Technische Universität München
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Sensor-based Running Diagnostics

From Validation to Application

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With warm thanks to all my family and friends.
Especially to Evelyn, Paul and Eric:
Thank you for your support and presence!

Abstract

This dissertation is a compilation of three publications aimed at advancing the scientific understanding of running analysis by using sensor data for the detection of athletes' movements. The research progresses through three key stages: first, validating the technology; second, developing a methodology for data collection in real-world scenarios; and third, leveraging the collected data for performance analysis (PA). In addition, two co-authored publications covering these topics are integrated.

The first study, "Validation of Player and Ball Tracking with a Local Positioning System" evaluates the accuracy of LPSs in tracking players and balls in sports settings. By comparing positional data, speed, acceleration and distance measures against an infra-red motion capturing system as criterion reference, the study investigates tracking accuracy and, ultimately, the error margins of resulting Performance Indicators (PIs). The study's results show a positional error (RMSE) of $\approx$8cm and $\approx$15cm for player and ball tracking in a small-sided game scenario.

The second study, "Detection of Ground Contact Times with Inertial Sensors in Elite 100-m Sprints under Competitive Field Conditions" explores the use of IMUs to accurately measure PIs, such as Ground Contact Time (GCT), in sprinting movements. This study was conducted in a field setting with German elite sprinters as participants to demonstrate practical applicability and relevance. The findings show that IMUs can reliably capture detailed temporal data on performance, indicating parameters essential for understanding sprint mechanics and optimizing performance variations.

The third study, "A Pilot Study in Sensor Instrumented Training (SIT) - Ground Contact Time for Monitoring Fatigue and Curve Running Technique," examines the possibilities of SIT in enhancing mid-distance running sessions. This research investigates GCT variations between straight and curved running as well as the use of GCT as a fatigue indicator in interval training. This study's findings illustrate the potential of SIT in mid-distance running for the practical use case of refining running technique and monitoring fatigue based on GCT measurement.

The ability to capture granular kinematic data offers coaches and athletes a data-driven approach to enhance training regimens and optimize performance. SIT represents an advancement in the application of sports technology, enabling more tailored and effective training methodologies in the near future.

Two co-authored studies, "Drone-Based Position Detection in Sports: Validation and Applications" and "Simulating Defensive Trajectories in American Football for Predicting League Average Defensive Movements" further expand on running analysis using positional tracking data. The former study demonstrates how drone-based systems can capture detailed positional running data, enhancing traditional methods of sports analysis. The second study shows the integration of imitation learning algorithms, a variant of reinforcement learning, as a possible analysis tool in sports. This makes running data, for example, a promising asset for real-time performance monitoring and strategic planning.

The dissertation contributes to the current scientific development of PA and sports informatics and provides insights for coaches, athletes and researchers. It also demonstrates the potential of advanced tracking systems to enhance training methodologies and improve athletic performance.

Contents

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Acronyms

AOA Angle of Arrival

DSP Digital Signal Processing

GCT Ground Contact Time

GNSS Global Navigation Satellite System

GPS Global Positioning System

HPE Human Pose Estimation

IC Initial Contact

IMU Inertial Measurement Unit

IR Infra-red Motion Capturing

LAVEG Laser Velocity Guard

LPS Local Positioning System

OG OptoGait

PA Performance Analysis

PD Position Detection

PI Performance Indicator

PPA Practical Performance Analysis

RSS Received-signal Strength

SF Step Frequency

SIT Sensor Instrumented Training

SL Step Length

SSG Small-sided Game

ST Step Time

StP Stance Phase

SwP Swing Phase

TC Terminal Contact

TDOA Time-Difference of Arrival

TG Timing Gate

TOF Time-of-Flight

TPA Theoretical Performance Analysis

TS Training Science

UWB Ultra-wideband

VBT Video-based Tracking

Publication list

The present work is a cumulative dissertation that incorporates three peer-reviewed full papers from internationally distributed journals as main author.

Publications as first author

Blauberger, P., Marzilger, R. & Lames, M. (2021). Validation of player and ball tracking with a local positioning system. *Sensors, 21*(4), 1465. https://doi.org/10.3390/s21041465

Blauberger, P., Horsch, A. & Lames, M. (2021). Detection of ground contact times with inertial sensors in elite 100-m sprints under competitive field conditions. *Sensors, 21*(21). https://doi.org/10.3390/s21217331

Blauberger, P., Fukushima, T. , Russomanno, T. G. & Lames, M. (2024). A pilot study in sensor instrumented training (sit) - ground contact time for monitoring fatigue and curve running technique. *International Journal of Computer Science in Sport, 23*(1), 80-92. https://doi.org/10.2478/ijcss-2024-0005

Publications as co-author

Schmid, M., Blauberger, P. & Lames, M. (2021). Simulating defensive trajectories in american football for predicting league average defensive movements. *Frontiers in Sports and Active Living, 3*, 669845. https://doi.org/10.3389/fspor.2021.669845

Russomanno, T. G., Blauberger, P., Kolbinger, O., Lam, H., Schmid, M. & Lames, M. (2022). Drone-based position detection in sports — validation and applications. *Frontiers in physiology, 13*, 850512. https://doi.org/10.3389/fphys.2022.850512

Fukushima, T., Blauberger, P., Guedes Russomanno, T., & Lames, M. (2024). The potential of human pose estimation for motion capture in sports: A validation study. *Sports Engineering, 27*(1). https://doi.org/10.1007/s12283-doi.org/024-00460-w

Monteiro, R. L. M., Dos Santos, C. C. A., Blauberger, P., Link, D., Russomanno, T. G., Tahara, A. K., Chinaglia, A. G., & Santiago, P. R. P. (2024). Enhancing soccer goalkeepers penalty dive kinematics with instructional video and laterality insights in field conditions. *Scientific reports, 14*(1), 10225. https://doi.org/10.1038/s41598-024-60074-x

1 Introduction

1.1 Technology and Sports

Technological support can be frequently found in almost all areas of modern life. Every day, we can recognize the improvement of ordinary products by implementing technology to form new achievements. This progress also includes not-so-prominent use cases like sports. The implementation and analysis of data has gained more and more importance for various stakeholders (Link, 2018). In this intersection of sports and technology, the evolution of sensor-based diagnostics provides new methods for understanding and enhancing athletic performance (Baca et al., 2022). Different Position Detection (PD) methods, like Global Positioning System (GPS) or Local Positioning System (LPS), work with sensors attached to the athlete (Buchheit & Simpson, 2017). The integration of Inertial Measurement Units (IMUs) sensors can help to understand human motion and, ultimately, an athlete's performance. The exploration of this field needs scientific support on the way from theoretical understanding to the practical application of sensor technologies.

Running, a fundamental element in most sports, requires understanding various areas, such as biomechanics, human physiology and performance metrics. Sensor technology's applicability has promised a beneficial development in this domain, offering objective insights into athletes' movements. Robertson et al. (2023) describe that technology in sports should be integrated with care. This includes the assessment of the accuracy of a new technology, e.g. by validation of a methodology (pillar A & B: Quality Assurance & Measurement and Established Benefit). In pillar C & D (Ethics & Security and User Experience), the feasibility of an implementation is highlighted. Pillar D & E (User Experience and Data Management) provide guidance for the integration into training. Therefore, the journey from a technological concept to a practical diagnostic tool involves challenges, including validating accuracy, determining the feasibility of implementation and integrating it into athletes' training programs.

Using this guideline, in the first step, the adequateness of different sensor-based systems needs to be evaluated. Commonly used systems include LPS and IMU. The findings from these initial investigations provide a scientific basis for selecting appropriate technologies and highlight the complexities involved in accurately capturing and interpreting athletic movement. Afterward, such a system can support athletes and coaches by providing data for Performance Analysis (PA). Ultimately, all sensor systems need to be integrated into athletes' daily training and monitoring regimes. This includes examining user-friendliness, data interpretation and the ability of these systems to provide interoperatability (Robertson et al., 2023) for athletes and coaches. This integration leads to various assessments of different measurement data, which can be combined to provide a more holistic understanding of the movements.

1.2 Motivation

This dissertation examines sensor-based technologies and their application in running diagnostics. Ultimately, the project aims to advance the field of PA and guides the way towards Sensor Instrumented Training (SIT). It not only contributes to the theoretical understanding of sports but also has practical implications for athletes and coaches in competitions, as well as for everyday training and competition.

Identification and Validation of Sensor-Based Position Detection Methods

The first aim of this thesis is to identify and validate a sensor-based PD method for accurately measuring running performance components. The outcome of this aim should be the adequate usage of scientific validation methodology that can serve as the foundation for research and practice in the following parts. Ensuring accurate and reliable measurements is critical for the development of further analytical techniques and for building confidence in the use of these technologies in various sports settings. Therefore, every technology that is used afterward (e.g., for PA) needs to be validated in this setting.

Integration of Sensor-Based Analysis Methods in Real-World Running Scenarios

The second aim focuses on the integration of a sensor-based analysis method in real-world running scenarios. Beyond the development of an appropriate method, it is crucial to validate this method within the context of its intended use case (Luteberget & Gilgien, 2020). This involves testing the method in actual sports environments to demonstrate its usability (Robertson et al., 2023) and, ultimately, effectiveness. The successful integration of the assessment method into sports practice should illustrate its applicability and utility for further PA.

Demonstration of Sensor-Instrumented Training

The final aim is to combine and showcase different methods as a demonstration for SIT in the context of running. This aim should highlight the advantages of SIT, exploring its potential as a powerful tool in sports science and PA. By showcasing the benefits of integrating various sensor-based methods (Baca, 2015), this dissertation aims to illustrate how SIT can enhance performance analysis, optimize training regimens, and provide valuable insights for athletes and coaches.

2 Context of Sports Science and Informatics

2.1 Training Science

Training Science (TS) is a discipline within sports science, characterized by its scientific approach to optimizing actions in sports (Lames, 2023). It incorporates principles from the sports variation of disciplines like medicine, psychology, biomechanics, sociology and pedagogy (Hohmann et al., 2020). From the perspective of sports science, this work focuses on the field of TS.

As the scientific books of Hohmann et al. (2020) and also Lames (2023) describe, TS investigates the interplay of training, competition and capabilities (Figure 2.1). The sections of training and competition refer to the process of preparing for and participating in sports events. Capabilities denote the attributes of athletes necessary for successful performance in competition, which can be enhanced through training. Its prerequisites include all personal attributes affecting performance, such as inherent capabilities and untrainable factors (e.g. arm/leg length). Environmental factors and performance prerequisites can be seen as the basis of a pyramid with its top in competition results. Thus, the ultimate goal is to maximize performance in competition (Hohmann et al., 2020). The results of a performance can be measured with Performance Indicators (PIs). A PI is a single or combined variable that describes parts or all determinants of performance (M. D. Hughes & Bartlett, 2002; Lames, 2023).

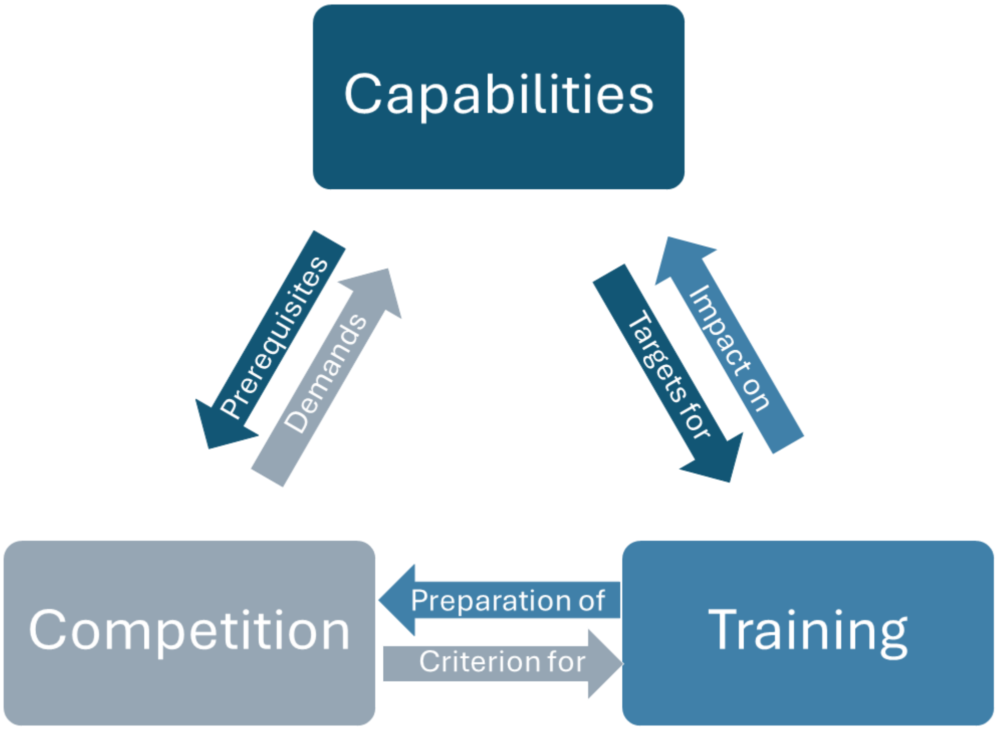

Figure 2.1 The interplay between training, competition and capabilities. Taken from Hohmann et al. (2020) with permission of Limpert-Verlag. Translated after Lames (2023).

Within this framework, PA is placed:
"Performance analysis (PA) is the assessment of competition, parts of competition, and performance prerequisites with different methods for different purposes." (Lames, 2023).
This rather broad concept of PA can be further divided into Theoretical Performance Analysis (TPA) and Practical Performance Analysis (PPA), which have evolved, encompassing theoretical and practical approaches (Lames & McGarry, 2007). The following gives a quick overview of both categories. Afterward, a short section will deal with distinguishing both concepts.

Theoretical Performance Analysis

TPA aims to uncover general laws that assess behavior in different sports contexts, utilizing various methodologies from behavioral research and, increasingly, computational approaches like machine learning. This sub-discipline is dedicated to measuring the influence of various determinants on competition results, like losing or winning (Lames, 2023). TPA aims to distill complex sports performances into relationships and models to provide a profound, law-like understanding of the dynamics in sports. Through statistical analysis and the search for appropriate models, TPA offers a scientific foundation to sports, which often shows unpredictable and emerging behavior (Lames, 2023).

Practical Performance Analysis

In contrast to TPA, PPA aims at clearly supporting practitioners like coaches and athletes. The practical usefulness of the research is one of the primary objectives (Lames, 2023). However, the provision of short- or real-time feedback is no primary aim of PPA. Tools such as PD systems (Linke, Link, Weber, et al., 2018), wearable sensors and action detection methods enable the measurement and analysis of various performance metrics or PIs. These include parameters like speed, acceleration, number of occurrences, or combined evaluations of these. This data-driven approach allows for an objective and quantifiable assessment of performance, facilitating adapted training programs that address athletes' specific needs and goals.

Difference between Theoretical Performance Analysis and Practical Performance Analysis

From the short descriptions follows that TPA is not always designed for creating actionable insights. This void is filled by PPA. There are big methodological differences like sample size, statistical methodology or research design between both disciplines. Therefore, clearly distinguishing between TPA and PPA may be seen as a solution to the dilemma. Nevertheless, both disciplines are not completely independent, as TPA can often give a broader framework for PPA (Lames, 2023).

Integration of Technology in Performance Analysis

Integrating technology in PA represents a continuing process in TS. From its classical roots, e.g. notational analysis (M. Hughes & Franks, 2010), to modern data-driven approaches, e.g. sports analytics (Link et al., 2018), PA plays a crucial role in understanding and improving athlete performance. Electronic data collection and analysis can provide immediate feedback, allowing for adjustments to be made on the fly. This technological integration enhances the possibility of

PA and might connect even more theoretical concepts with practical applications in training.

One example is the incorporation of load monitoring towards understanding and optimizing athlete training and performance. PD technologies enable the precise measurement of an athlete's workload, capturing various metrics like intensity, duration and frequency of training sessions (Polglaze et al., 2015; Scott et al., 2013). This data can be used to prevent overtraining and injuries and ensure athletes maintain an optimal equilibrium between training stress and injury recovery. Load monitoring uses a data-informed approach, allowing coaches and athletes to make evidence-based decisions that enhance training outcomes to ultimately raise the performance in competition (Akenhead & Nassis, 2016; Gabbett, 2016).

However, not all technological achievements are also useful in practice. The practical impact debate within PA emphasizes on the need for further research to connect theoretical knowledge and practical application. This debate calls for researchers to provide strong justifications for their work, underlining its relevance and applicability in real-world sports settings. The argument suggests that while theoretical advancements are valuable, the ultimate goal of PA should be to offer actionable insights that can influence coaching strategies and ultimately improve athlete performance. By aligning research objectives with practical needs, PA can ensure that its developments are not only scientifically robust but also practically impactful, thereby enhancing the professional practice and understanding of performance in sports (Carling, 2013; Carling et al., 2014; Mackenzie & Cushion, 2013).

2.2 Sports Informatics

Sports Informatics can be seen as the intersection between sports science and information technology. It encompasses the study, design and implementation of informatical methods to enhance various aspects of sports, including, e.g. training assessment (Dellaserra et al., 2014), PA (Lames & McGarry, 2007), coaching strategies (Schmid et al., 2021) and fan engagement (Panchanathan et al., 2017). This field implements theoretical constructs and data manipulation methods to extract meaningful insights from sports data.

According to Perl (2006), the area of sports informatics was already developing in a fast pace at this time. The term "Sportinformatik," or "Computer Science in Sport," was first introduced by German sport scientist Herbert Haag in 1976, initially referring to "Sport Information". Additionally, Jürgen Perl founded the Institute for Informatics at a University in 1985 and established a section dedicated to sports informatics (Lames and Link in Baca (2015)). While the International Association of Sport Information (IASI) has been operating in this field for decades, the development of Computer Science in Sport lagged behind due to the late availability of necessary hardware and software tools. It wasn't until the mid-eighties, with the advent of more powerful personal computers capable of analyzing complex interactive systems like sports games, that interest in this area began to grow rapidly (Perl, 2006).

Since the nineties, computers and computer-based analysis methods and concepts have formed the foundation for the expanding field of Computer Science in Sport (Perl, 2006). Baca (2006) added informatics topics with potential applications in sports science that can be summarized as follows:

- Data collection, processing, and analysis
- Modeling and simulation
- Databases
- Multimedia visualization

These broad categories are captured within current science at the time of this dissertation. The article collection of the spinfortec 2020 conference by Fehr (2020) clustered the presented topics of current research as follows:

- Information and Feedback
- Data collection and data analysis
- Sport equipment and material
- Modeling and simulation

- Multimedia, E-learning, E-sport
- Wearables and intelligent sports equipment

This dissertation primarily includes work about data collection and analysis but also includes part of modeling and visualization. Therefore, the next chapter will deal with this topic in more detail.

Data Collection, Processing, and Analysis

A multitude of parameters must be collected to describe and analyze athletic performance. For instance, biological measurements like pulmonary function, oxygen saturation, or heart rate are measured. Also, positional data of playing balls and athletes make the analysis of technical and tactical patterns in team sports possible. All these data need to be measured, processed, and analyzed to create value in the relevant application field. Additionally, practical requirements, such as low latency for real-time applications, influence the requirements for the transmission medium during data collection (Baca, 2015). Therefore, measurement technology that abstractly converts analog into digital signals is needed. A summarizing term for this technology is sensors.

Sensors

According to Baca (2015), in the context of sports, there are several measurements of increased interest. The following variables can be measured with sensors:

- Acceleration:
  Can be measured using piezoelectric or capacitive sensors. Modern sensors can now be built as microelectromechanical systems, systems that can be built on a micrometer scale (Nicolau, 2005). This sensor is commonly included in IMUs. An exemplary acceleration signal of a tennis racket is shown in figure 2.2.
- Angles and Angular Velocities:
  Can be measured optically, mechanically, or with gyroscopes. Usually included in an IMU.

- Spatial Orientations:
  Are measured using IMUs. Most commonly, an IMU combines gyroscopes and accelerometers to measure spatial orientation.
- Distance and Speed:
  Distance can be measured using changes in electric resistance or a potentiometer. Speed can be measured by using the Doppler effect or be derived from the rate of change in distance data.
- Temperature:
  It can be measured with liquids, temperature-dependent materials, or infrared radiation. Some IMUs contain a thermometer.
- Time:
  Time differences can be measured optically (e.g. Timing Gates (TGs)), electronically (e.g. stopwatches), or mechanically (e.g. sprint starts).
- Forces and Pressure:
  Are primarily measured by strain gauges, capacitive sensors, or piezoelectric.
- Oxygen concentration and Respiratory frequency:
  Spiroergometry can measure oxygen uptake and breath frequency, whereas the frequency alone can also be measured in other ways (e.g. strain gauges).
- Sound:
  Microphones, for example, can measure sound pressure, which is translated into the sound a human can hear.
- Biosignals:
  Skin electrodes are usually used to measure electromyographic (EMG), electroencephalographic (EEG) and electrocardiographic (ECG) parameters.

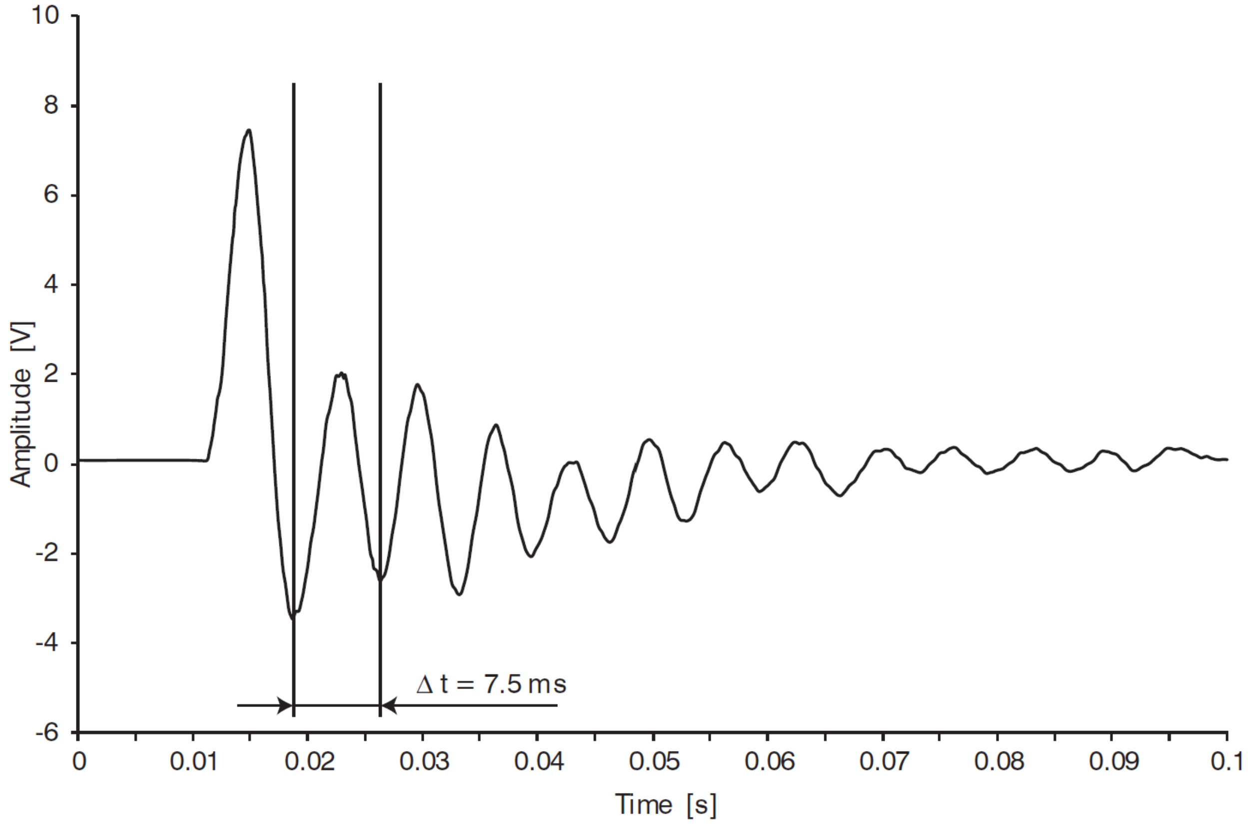

Figure 2.2 Accelerometer signal from a tennis racket. The scale of the x-axis (time) illustrated, how fine-grained these sensors must operate to answer certain questions. Graph taken from Baca (2015) with permission of Taylor & Francis Group.

To ensure an unbiased capture of the sensory signals, the athletes must be distracted as little as possible. This is where "Ubiquitous computing" or "Pervasive computing" offers solutions (Baca et al., 2009; Baca et al., 2022). This concept evaluates the application possibilities of a variety of small connected computing units. Different sensor-based measurement systems such as GPSs, LPSs, and IMUs can be used within for this purpose. GPS and LPS are already effectively utilized in sports for monitoring and helping to manage athletes in training and competition (Robertson et al., 2023). Their non-intrusive application and technological capabilities make it an appropriate tool for sports. Additionally, IMUs offer measurements with a high frequency at the exact spot where the sensor is placed. By providing data on accelerations, their rotation and finally direction of the movement, IMUs support the creation of detailed movement analysis.

Given that sensor-based data collection comprises a significant part of this work, a detailed description of these fields is provided in chapter 3.2. In this context, the sampling frequency of any measurement sensor needs to be considered.

Sampling Frequency

The sampling frequency (or sampling rate) indicates how often an analog signal is converted into a digital value. The conversion process needs to transform an electrical signal into a digital value. The frequency of this conversion should be selected to ensure that no important information is lost between the following measurement points while keeping the number of values manageable for further storage and processing (Baca, 2015).

Figure 2.3 illustrates how different sampling rates can influence the signal reconstruction. The example shows, that a sampling rate of 25 Hz is not representing the first peak within the signal. Increasing the rate to 50 Hz begins to reveal a feature in the ascending part of the curve. At 200 Hz, the peak becomes clearly recognizable. However, further increasing the sampling rate only adds minimal information to the signal but highly increases data storage and requires more processing at different steps (Baca, 2015). The sampled and saved signal can then be further processed.

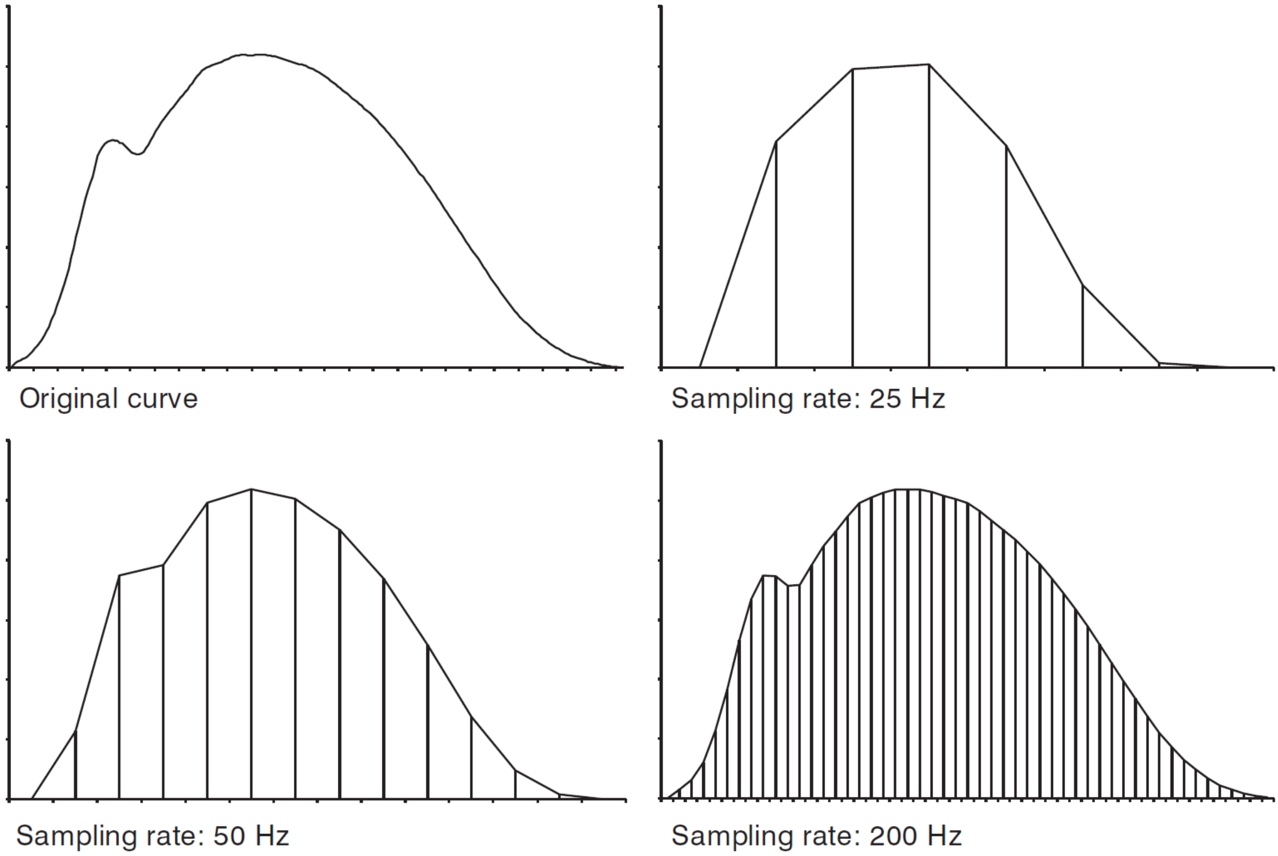

Figure 2.3 Signal curves with different sampling frequencies. The representation of the original signal can be adapted by a change in the sampling frequency. The effect of detecting smaller peaks in the curve with 25 Hz, 50 Hz and 200 Hz is clearly visible. Sampling signals at a higher frequency has upsides and downsides. Taken from Baca (2015) with permission of Taylor & Francis Group.

Signal Manipulation and Filtering

The processing, adjustment, revision or improvement of digital signals can be summarized under the term Digital Signal Processing (DSP) (Baca, 2015). DSP transforms the collected data to make it usable for further application purposes. For example, data can be manipulated to improve signal quality or compressed for long term storage.

Measured data often need to be scaled, for example, to convert from unit to another. This step involves multiplying the signal by a linear or individual factor or adding and subtracting offsets. With upsampling or downsampling, measurement data can be synchronized. Different interpolation algorithms add data points for upsampling, while data points are dropped for downsampling (Baca, 2015). This was done in study 1 of this dissertation. Also, the sampling rate can play a huge role for PA (Polglaze et al., 2016). With a signal normalization step, we can better compare signal values, as the data can be transformed into interpretable intervals. Normalization can also be particularly useful when comparing signals with different units (Baca, 2015).

With a Fourier transformation, the signal can be categorized into frequency ranges. This step can enable the separation and aggregation of frequencies of interest. This can help to determine an appropriate cutoff frequency for a filter (Winter, 2009).

The application of different filters can be seen in figure 2.4. Measured data often contain artifacts and noise, which can result from inaccuracies or errors in the measurement equipment. Analog and digital filters can be used to remove unwanted parts of a signal. They are usually applied as software routines to the data. Well-known types of such filters are band-pass, low-pass and high-pass filters, which filter out low-frequency or high-frequency parts of a signal, respectively. A combination of those is the band-stop filter. These techniques can be used independently of the measurement technology to improve the quality and usability of the data (Baca, 2015).

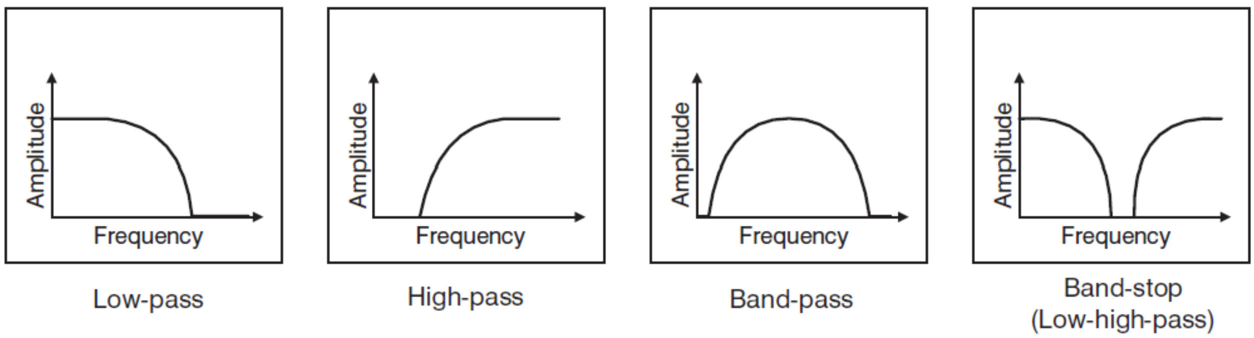

Figure 2.4 Different filtering techniques. This illustration shows the different filters and the need for threshold choices. For low-pass and high-pass filters, one threshold must be chosen to cut off higher or lower signal frequencies. Band-pass and band-stop filters use two threshold to adapt the signal. Taken from Baca (2015) with permission of Taylor & Francis Group.

Once the relevant data have been gathered and processed, analysis can be carried out. The needed context can now be given to the results, or statistical analysis is carried out. Also, the visualization of the data can be improved and adapted using domain knowledge.

However, Sports Informatics extends beyond athlete tracking and raw data collection. It also involves analyzing and interpreting large volumes of data — often called big data — generated in sports settings. By applying machine learning algorithms and advanced statistical models, sports computer scientists can uncover patterns and trends that might not be immediately apparent. This analytical prowess aids in decision-making, strategy formulation and long-term athlete development. Umpires can be supported by using technological advancements (Kolbinger & Lames, 2017). Furthermore, sports informatics plays a crucial role in transforming the fan experience. For example, the reaction of fans during soccer matches was investigated using text mining (Kolbinger & Knopp, 2020).

Sports Informatics represents an interdisciplinary field that blends the physicality of sports with the rapid development of information technology. From interactive smartphone apps that provide real-time statistics and analytics to virtual reality experiences that bring fans closer to the action, the integration of technology in sports is reshaping how fans engage with their favorite teams and athletes. Through the use of technologies like LPSs, GPSs and IMUs, coupled with appropriate data analysis, it offers a data-driven approach to understanding and enhancing various dimensions of sports. As the field continues to evolve, it unlocks new possibilities and will further influence sports science.

2.3 This Work

This dissertation implements elements from both training science and sports informatics by applying technological methodologies within sports contexts.

The scientific validation of the accuracy of tracking technologies forms the foundation of this project, assessing their integration into practical sports and running applications. This process involves comparing new methods against established standards to evaluate their accuracy in real-world sports settings. The basis of the validation process in a robust methodological framework ensures, that the proposed measurement techniques adhere to scientific standards while also meeting the demands of PA.

The initial phase of the project focuses on the validation of tracking technologies. This involves a detailed comparison with gold-standard methodologies to determine the accuracy of the new sensor-based methods. Such validation is crucial, as it provides the scientific community and practitioners with confidence in the measurement tools and ensures that the data collected are both precise and actionable.

Following the validation phase, the project explores the practical integration of these validated methods into PA applications. This stage examines how the newly validated technologies can enhance the granularity and accuracy of PA, influencing training methodologies and informing strategic decision-making. The integration process involves deploying the technology in real-world scenarios, such as different training sessions, to assess its effectiveness and usability. The goal is to ensure that these tools not only provide accurate data but also seamlessly integrate into existing training routines, offering real-time feedback and insights that coaches and athletes can directly apply.

Additionally, the dissertation investigates the broader impact of these advanced measurement tools on understanding athlete performance. By providing detailed data on various performance metrics, such as speed, acceleration, or Ground Contact Time (GCT), these technologies offer a more nuanced view of an athlete's capabilities and areas for improvement. This comprehensive understanding can lead to more tailored and effective training programs, ultimately enhancing overall athletic performance.

In the later stage of this work the potential of these technologies to enhance PA and training in sports is highlighted. Advanced measurement tools, when properly validated and integrated, can offer significant insights that extend beyond traditional methods. They provide a data-driven foundation for making informed decisions about training regimens and performance optimization. By bridging the gap between theoretical research and practical application, this work contributes to the advancement of sports science, demonstrating how innovative technologies can be harnessed to improve athletic performance and training outcomes.

3 Running Diagnostics

3.1 Principles of Human Gait and Running

Human motion spans a spectrum from a complete standstill to reaching maximum velocity (Figure 3.1). Especially normal and pathological gait is a well-researched field within science (Peruzzi et al., 2011). The shift from walking to running is characterized by a change in the gait cycle: from a phase where both feet are simultaneously on the ground (double support) to a period where neither foot touches the ground (double float) (Perry, 1992). This transition is illustrated at point A in figure 3.1. The transition from running to sprinting, indicated as Point B, is less distinctly defined. As this dissertation only discusses humans' running motion, the large area of walking is not individually mentioned. Typically, running is associated with longer distances and relies predominantly on aerobic metabolism. In contrast, sprinting involves shorter distances at higher speeds, engaging different metabolic processes (Cheetham et al., 1986).

A notable distinction in technique can be observed between sprinters and regular running athletes. Sprinters generally make the first ground contact with the forefoot during their stride, often without the hindfoot ever making ground contact. Conversely, most runners in longer distances tend to make the first contact with the ground with either the midfoot or the rearfoot. The changeover from a midfoot or rearfoot strike to forefoot striking is typically what defines Point B in figure 3.1.

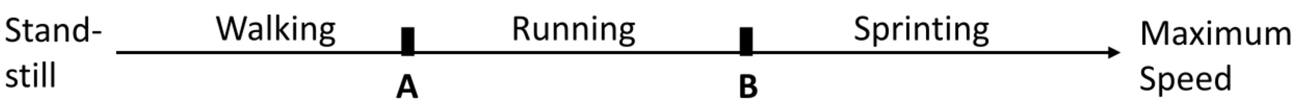

Figure 3.1 Schematic description of human gait phases. Point A symbolizes the transition from walking to running. Point B indicates the transition from running to sprinting. Figure adapted after Novacheck (1998).

3.1.1 Gait Cycle

The human gait cycle is defined as the interval between consecutive Initial Contacts (ICs) of the same foot (H. Zhang et al., 2020). This cycle, similarly to the understanding of walking patterns, has been described using different terminologies. In alignment with the current literature and publications, this thesis adopts the currently predominant set of terms to maintain consistency with current research in the field.

Whittle (2014) describes that each gait cycle comprises two main phases: The Stance Phase (StP) and the Swing Phase (SwP). The StP begins with the IC of the foot with the ground and ends with the Terminal Contact (TC) (often called toe off), marking the foot's departure from the ground (Novacheck, 1998). The time window between these events is defined as the StP. StPs of the left and right foot overlap during walking, where both feet are in contact with the ground at the same time. The SwP follows after the StP, starting from the TC and ending at the next IC of the same foot, as depicted in figure 3.2.

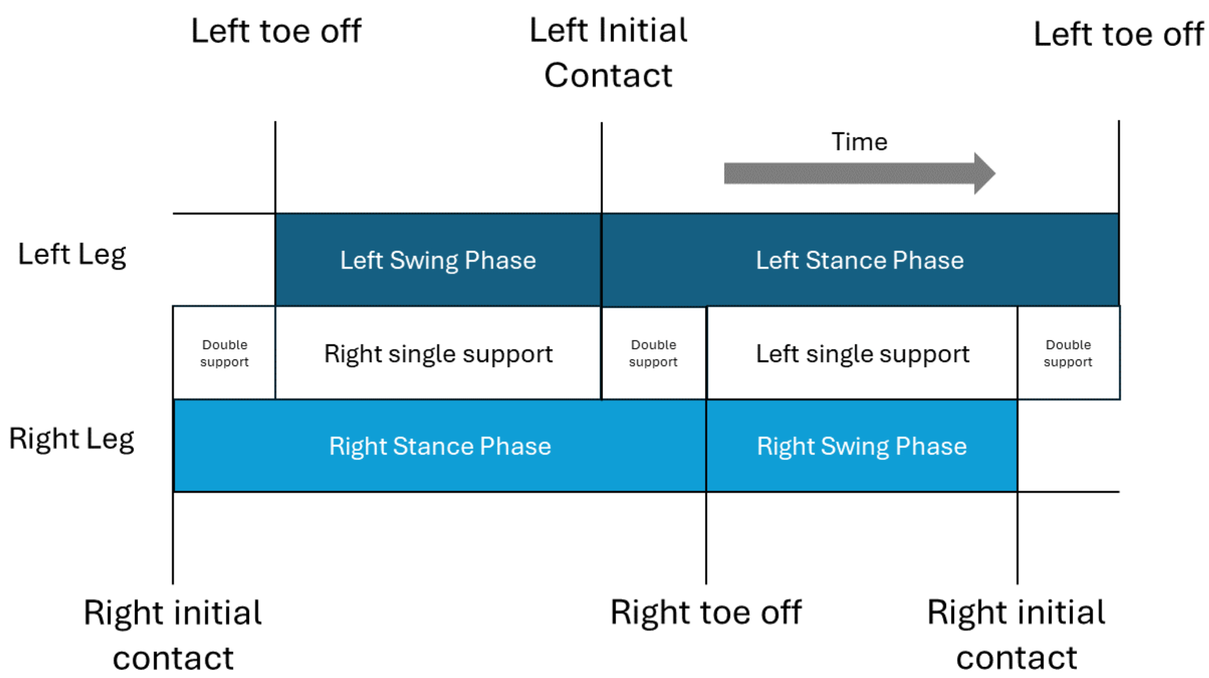

Figure 3.2 Illustration of one gait cycle. The left leg (dark blue) and right leg (light blue) asynchronously go through the Stance and Swing Phase. This leads to either one or both feet maintaining contact with the ground. Figure adapted after Whittle (2014).

The StP consists of three intervals marked by different patterns of ground contact by the feet. This phase begins and concludes with periods of double support phases, where both feet are in contact with the ground (Novacheck, 1998). Between these sections is the single support phase, during which only one foot maintains ground contact. Figure 3.2 illustrates the phases within a single left and right foot gait cycle. This visual representation aids in distinguishing between the movements of the right (light blue) and left (dark blue) sides of the body (Whittle, 2014).

In gait analysis, *stride* and *gait cycle* are often used interchangeably to describe the movement pattern of one limb. The term *step* refers to the movement from one foot to the opposite foot. For instance, the movement from left IC to right IC is defined as a right step, and the opposite is a left step, as shown in figure 3.2.

3.1.2 Sprint Cycle

The phases of the running gait cycle and the sprint gait cycle are identical and are, therefore, both described in this subsection. Strides and steps in sprinting are described similarly to walking (Novacheck, 1998). Each stride can be divided into the StP and the SwP. However, there is no time frame for both feet to make contact with the ground simultaneously. Instead, both feet are in the air at the same time twice during the sprint cycle (Barberis, 2007). The StP begins with the IC when the foot first touches the ground and ends with the TC, when the foot leaves the ground (Vu Thi Thu, 2023). The SwP starts with the toe off and ends with the IC of the next stride. As speed increases, the time spent in SwP increases, stride time decreases, and the entire cycle shortens.

Typically, the phases of a maximal sprint can be subdivided into four phases:

1. Start Phase:
   This includes reaction time and block clearance.
2. Acceleration Phase:
   The step length increases during this phase. It can further be divided into the initial, middle and final stages of the acceleration phase (Nagahara et al., 2016).

3. Maximum Velocity Phase:
   Where step length peaks and stride time reaches its minimum (Mattes et al., 2014).

4. Deceleration Phase:
   Occurs after maintaining maximum velocity.

Each phase has different characteristics of spatiotemporal parameters. During the acceleration phase, Step Length (SL) increases rapidly and levels off around maximum velocity. Stride time decreases rapidly and reaches its minimum at maximum velocity. Step Frequency (SF) increases rapidly in the initial 10 meters and then remains fairly constant throughout the sprint.

In the context of velocity during the StP it is typically assumed that the foot's velocity is zero. This is based on the observation that the foot rolls from the outer edge to the inner edge during this phase (Peruzzi et al., 2011). Although the foot is in motion, its velocity is considered negligible or zero, particularly in the brief period leading up to and including the heel off (Wang et al., 2015). This assumption would lead to a clear distinction between steps. However, contrary to casual walking, elite sprinters try to minimize the time of StPs which makes this period rather short at high running speeds.

3.1.3 Events and Terminology

The gait cycle, an essential concept in running diagnostics and human locomotion analysis, consists of a series of key events that collectively describe the complex process of walking or running. A gait cycle with its terminology is illustrated in figure 3.3. IC marks the beginning of the StP, signaling the foot's first contact with the ground. This event is crucial for absorbing impact and transitioning body weight onto the leading limb. Therefore, it can be detected by ground reaction forces (van Oeveren et al., 2024). Following IC, the Mid Swing occurs, providing critical support and stability as the body's weight is fully transferred over the foot. This phase is pivotal for maintaining balance and facilitating forward movement.

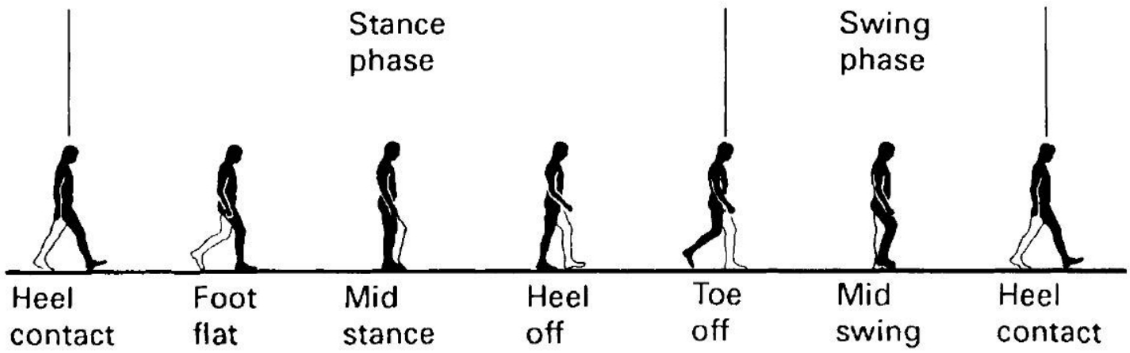

Figure 3.3 Terminology of gait events after Whittle (2014). A gait cycle consists of a Stance Phase and a Swing Phase that can be further distinguished by the described events.

As the StP progresses, TC prepares the foot for lift-off, with the toes generating the necessary thrust and accelerating the body forward. This leads into the Initial Swing, where the limb begins its forward trajectory. Mid-swing follows, with the limb advancing further. Terminal Swing completes the cycle, bringing the limb forward in preparation for the next IC, thereby continuing the rhythmic pattern of gait.

Within this cycle, two overarching phases are identified: the StP, where the foot remains in contact with the ground, supporting body weight and facilitating propulsion, and the SwP, characterized by the foot's absence of ground contact, allowing the limb to move forward (Kharb et al., 2011). SL and SF are critical metrics in this context, measuring the distance covered per stride and the rate of steps per unit time, respectively, both of which significantly influence running efficiency and performance. The time a step takes is referred to as Step Time (ST). Conversely, Ground Contact Time (GCT) is the duration the foot spends in contact with the ground This value serves as a vital indicator of running dynamics and efficiency, affecting speed and stability (Coh et al., 2001; Di Michele & Merni, 2014). Several studies state the importance of this PI within sprinting (Mattes et al., 2014; Morin et al., 2012; Purcell et al., 2005).

Understanding these key events and terminology is fundamental in analyzing and optimizing gait, providing insights into individual running mechanics, identifying areas for improvement, and tailoring training interventions to enhance performance.

3.1.4 Running Training

The structure of a running training session encompasses various components designed to improve different aspects of a runner's performance. The following covers four fundamental concepts: Permanent load training, repetitive training, competition training and interval training. They provide a theoretical background for the individual studies of this dissertation project.

Permanent Load Training

Permanent load training can be described by its low intensity, long duration, and continuous execution without any pauses (Hohmann et al., 2020). This form of training is designed to build endurance by maintaining a steady, manageable effort over an extended period. Typically used in aerobic conditioning, permanent load training helps improve cardiovascular health, increase stamina, and enhance the body's ability to sustain prolonged physical activity. It is a fundamental training method for endurance athletes, such as long-distance runners and cyclists, who require the ability to perform consistently over long durations.

Repetitive Training

Repetitive training is characterized by high intensity efforts followed by full regeneration during pauses, resulting in a long total duration (Hohmann et al., 2020). This form of training involves performing multiple high-intensity exercises or sprints, each followed by sufficient rest periods to allow for complete recovery. The goal is to maximize performance during each high-intensity interval while ensuring the body can fully recuperate before the next effort.

Competition Training

Competition training is designed to activate all of an athlete's physical and mental reserves (Hohmann et al., 2020). This training method involves a level of intensity that is marginally higher than what the athlete can normally achieve, requiring additional motivation and support. The purpose is to simulate the demands of actual competition, thereby enhancing endurance and preparing the athlete for competitive performance.

Intensive Interval Training

Intensive interval training is characterized by numerous series of intervals with high intensity (Hohmann et al., 2020). This type of training is aimed at improving anaerobic endurance. A common characterization is a quite brief interval at high speed. Runners perform short distances, such as 200m to 400m intervals, at close to maximum effort, with recovery intervals to allow the heart rate to recover partially. Sufficient recovery is critical in intensive intervals to ensure that each effort is performed with maximum focus and energy. The recovery period often includes walking or light jogging.

Extensive Interval Training

Extensive interval training involves a moderate intensity, focusing on enhancing aerobic capacity through the cardiovascular system and, therefore, endurance (Hohmann et al., 2020). Often, this is characterized by longer intervals. These intervals are run at a challenging but sustainable pace, with short recovery periods. Sometimes, tempo or threshold runs are included. These are sustained efforts at a controlled, hard pace. They are implemented to improve metabolic fitness and increase the body's ability to sustain high-intensity efforts over a longer period. Unlike intensive intervals, recovery during extensive intervals is usually active and consists of continued running at a lower intensity. The training is within the aerobic zone and enhances the body's cardiovascular system (Hohmann et al., 2020).

Incorporating warm-up routines into a running program can also improve an athlete's performance. The warm-up prepares the body for the demands of high-intensity work, while the intervals contribute to various performance factors, such as speed, endurance and efficiency.

3.1.5 Current Diagnostics

The methodology used for running diagnostics is constantly evolving. This paragraph should only give a brief overview of the technologies currently used in running diagnostics from the perspective of their application. A more detailed description of all mentioned systems will follow in the next chapters.

Among the leading tools in this domain are TGs, GPSs, LPSs and IMUs, each offering unique data sets that can be harnessed for analysis.

- Timing Gates:
  Timing gates are often used in speed and agility drills. They provide precise measurements of an athlete's speed at various intervals. The data collected can help assess an athlete's acceleration, speed consistency and reaction times.

- Global Positioning Systems:
  Widely used in outdoor sports, GPS devices track an athlete's position, velocity and trajectory over time. This technology is commonly used by distance runners, offering insights into endurance, pacing strategies and movement patterns across different terrains. Most wearables like running watches or small trackers include GPS receivers.

- Local Positioning Systems:
  LPSs are ideal for indoor sports or environments where GPS signals are unreliable. By providing accurate positional data, LPS can provide the same or even more accurate data.

- Inertial Measurement Units:
  These sensors capture detailed data on an athlete's acceleration, rotation and orientation, offering a quantifiable view of their movements. IMUs can help to identify asymmetries or inefficiencies in an athlete's gait pattern and many other variables.

The data derived from all these technologies can be utilized in various ways, enhancing sports analytics' scope and depth. For instance, tracking data can inform individualized training programs, optimize tactic strategies, and contribute to injury prevention by identifying risk factors (Decroos et al., 2018; Rossi et al., 2018). In rehabilitation contexts, these diagnostics can monitor an athlete's recovery progress and readiness to return to sports.

A notable application of sports analytics, as demonstrated in our research on ghosting (Schmid et al., 2021), uses data from one of these diagnostic tools to simulate and analyze player movements and positioning in team sports. By creating 'ghost' versions of players based on real data, potential movements, strategies and outcomes were shown. This can provide a powerful tool for coaches and analysts to refine tactics and enhance player understanding of game dynamics.

3.2 Position Detection

The following chapter introduces the functioning of the most common PD methodologies that are used to raise spatiotemporal data in sports. It needs to be emphasized, that not all of these technologies are currently used in running sports. As Link (2018) stated, tracking data are already used by stakeholders such as media coverage, betting industry, data providers and many others. Additionally, tactical analysis can be conducted based on positional data (Memmert et al., 2017). Also, these data are scientifically used to enhance and evaluate mathematical models in sports (Beetz et al., 2005; Bialkowski et al., 2016; Dick & Brefeld, 2019). In recent years, predominantly three PD methodologies have come to the broader appliance in sports: GPS, LPS and Video-based Tracking (VBT) (Buchheit et al., 2014; Memmert & Raabe, 2018). For further analysis, the sensor-based solutions GPS and LPS are often supported by measurements of IMUs. Therefore, the underlying principle of IMU measurements is also explained. The previously mentioned methods (Chapter 3.1.5) were used within this dissertation project and are explained in more detail.

3.2.1 Global Positioning System

GPS has become a widely used technology in tracking outdoor athletic activities (Schutz & Herren, 2000). As there exist numerous other systems (e.g. GLONASS, Galileo, Beidou), the correct term would be Global Navigation Satellite System (GNSS). GPS, however, is predominantly used in the literature and will therefore be used synonymously in this dissertation. This is especially true in team sports like football, rugby and handball, but also for many athletes in individual sports like running or cycling (Aughey, 2011). In study three, this dissertation project used GPS to add further insights for SIT. As the methodology of GNSS was first used by the American military, the term of GPS has become widely common, although it is only one of several satellite clusters.

GPS's ability to provide spatio-temporal data on an athlete's position, velocity and distance covered makes it valuable for TS, especially PA. Besides the indisputable scientific use case of positional data (Rawstorn et al., 2014), also the sports market applies GPSs commonly (Malone et al., 2017). The market shows a variety of systems, such as SPI ProX (Köklü et al., 2015), GPSports (Linke, Link, & Lames, 2018) and newer versions that support real-time data from companies like Kinexon (Schmidt et al., 2023). Some studies have demonstrated the validity and reliability of GPS in capturing macro-level data such as total distance covered and average speed, which are crucial for sports (Di Salvo et al., 2006; Gløersen et al., 2018).

The functioning of GPS PD is based on the triangulation principle. A simple illustration of this is shown in figure 3.4. The location of the target point can be determined by acquiring the position of a minimum of three reference points and intersecting the resultant circles. The distance from the target point to the reference point can be calculated by knowing the elapsed time and the speed of the signal which is the speed of light. When the receiver captures signals from over three reference points under standard conditions, the precision of the positional determination is enhanced (Teeuw et al., 2005). Additionally, the speed of a receiver can be calculated using the Doppler-shift phenomenon (J. Zhang et al., 2006). This exploits the difference of received electromagnetic wavelengths from a moving object. The speed measurements from GPS devices are not as precise at higher velocities (Nagahara et al., 2017).

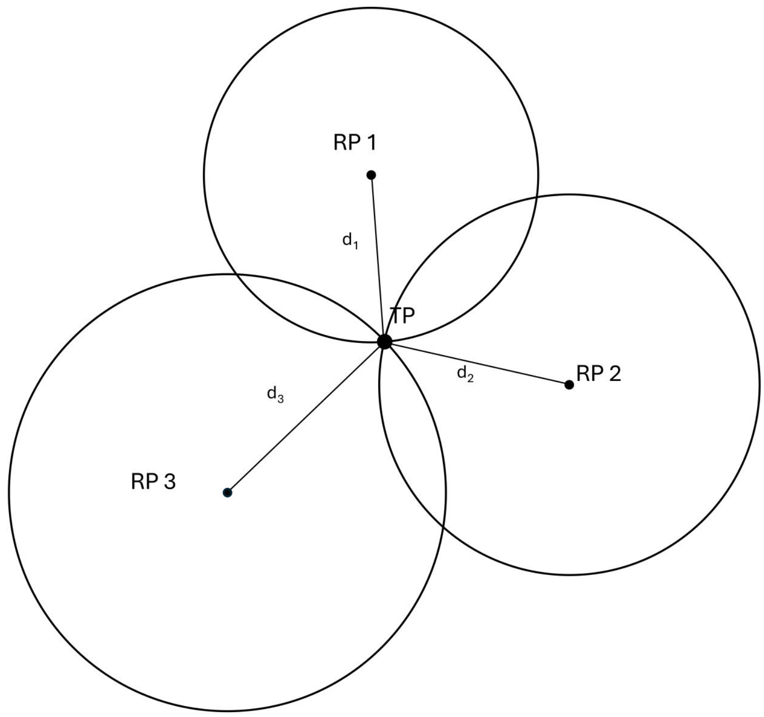

Figure 3.4 Illustration of the triangulation principle. By acquiring the position of three reference points (RP) and intersecting the resultant circles, the location of the target point (TP) can be determined. Each circle has a radius of d, which is determined by the traveling time of the signal wave and its speed (the speed of light).

Several validation studies have evaluated the accuracy of GPS tracking in sports settings (Akenhead et al., 2014; Beato et al., 2016; Gilgien et al., 2014; Gray et al., 2010). Also, the reliability of different sensors (Coutts & Duffield, 2010; Duffield et al., 2010) and the influence of sampling frequency was assessed (Castellano et al., 2011; Rampinini et al., 2015).

However, GPS technology has limitations, particularly in terms of signal accuracy in densely built areas or under tree cover. Generally, as a stable signal transmission from the satellites needs a direct line of sight, GPS measurements should only be conducted outdoors. Additionally, GPS is less effective in assessing fine-grained positional data like the location of limbs (Linke & Lames, 2019).

3.2.2 Local Positioning System

LPS represents another sports tracking technology that utilizes various radio frequency-based methodologies to achieve precise local/indoor PD. These methodologies cover a broad spectrum, including infrared, ultrasound, Radio-Frequency Identification, Wireless Local Area Networks, Bluetooth and Ultra-wideband (UWB) (Elkarim et al., 2015; Gu et al., 2009).

Among these, UWB systems are commonly used in sports tracking (Bastida Castillo et al., 2018). Notable implementations of UWB systems in sports include Ubisense's Real-Time Location System, Inmotio's Local Position Measurement system (Aughey et al., 2022; Frencken et al., 2010), ChyronHego's ZXY Arena (Medbø & Ylvisåker, 2023), Kinexon (Alt et al., 2020; Fleureau et al., 2020) and RedFIR by Fraunhofer IIS (Seidl et al., 2017).

In contrast to GNSSs, which passively receive signals from satellites, LPSs require athletes to wear devices that actively transmit signals to local static base stations, also known as anchor nodes. These stations then calculate the position of the player based on the characteristics of the received electromagnetic waves.

The core of LPS functionality lies in four primary position determination techniques: Time-of-Flight (TOF), Time-Difference of Arrival (TDOA), Received-signal Strength (RSS) and Angle of Arrival (AOA) (Vossiek et al., 2003).

- TOF estimates the location by measuring the time radio signals travel from the transmitter to various anchor nodes.
- RSS calculates the location based on the difference between transmitted and received power and often requires advanced models or algorithms like neural networks to account for complex signal behaviors.
- TDOA assesses the time difference between signals reaching the base stations, utilizing nonlinear regression to translate this data into hyperbolic coordinates, which, when intersected, pinpoint the player's location. This calculation is based on the triangulation principle (Figure 3.4).
- AOA involves calculating the incoming angles of signals at the anchor nodes to determine the position of the player's transmitter.

These methodologies enable LPSs to achieve an impressive overall sampling rate of up to 1000 Hz (shared among transmitters) and static accuracy to within approximately 0.1 m. However, dynamic accuracy, vital for tracking fast-moving athletes, ranges between 0.08-0.28 m, highlighting some limitations in the technology's current implementation (Blauberger, Marzilger, et al., 2021; Linke, Link, & Lames, 2018; Ogris et al., 2012; Sathyan et al., 2012).

The deployment of LPSs in professional sports settings is not without challenges. The complexity of system installation, including base station setup, calibration and software configuration, varies dramatically across different systems. This process can range from being relatively straightforward and automated to complex and time-consuming (Linke, 2019).

Additionally, the environmental context of the sports venue can impact data quality. Factors such as external radio frequency interference and the proximity of large or metal structures can influence signal transmission and, therefore, accuracy. Similarly, a player's proximity to pitch boundaries or obstructions like advertising boards may also influence data quality. Another commonly known issue is occluding objects (Manafifard et al., 2017).

LPSs have expanded the way athlete performance can be monitored and analyzed, offering another methodology in position tracking. As technology advances, the costs associated with LPS usage decrease. Therefore, it can be anticipated that these systems will become more accessible, which could lead to their broader application in sports.

Validation of LPS in sports settings is crucial for ensuring their reliability and accuracy. Various studies have been carried out, focussing on the usage in indoor or outdoor environments (Sathyan et al., 2012), different sports (Rhodes et al., 2014), or outcome parameters (Seidl et al., 2016). The topic of validation is summarized in a systematic review by (Rico-González et al., 2020).

3.2.3 Video-based Tracking

VBT systems offer a solution to some of the limitations posed by sensor-based measurements like GPS or LPS. These systems use the view of cameras to capture athletes' movements, preferably showing the whole field or pitch in the scene. With further processing methods, the detected athletes are tracked as pixel locations. These locations are then transferred into real-world distance measurements (Di Salvo et al., 2006). The images can also be used for further tactical analysis (Oskouie et al., 2014).

As an adaptation to the fundamental tracking technique, the image data can be captured with drones, which established another sub-category: Drone-based

PD. This possibility was investigated for sports movements in an article by Russomanno et al. (2022) which was co-authored within this dissertation project. The integration of machine learning algorithms in VBT has further enhanced the capacity of these systems to provide appropriate feedback. VBT requires a controlled environment for optimal data capture and can be resource-intensive regarding equipment and data processing.

Validation of VBT systems is essential to ensure their accuracy and reliability in capturing athletes' movements. According to Aughey et al. (2022), validation against established standards like GPS or LPS confirms that VBT can offer a viable alternative, particularly in scenarios where traditional sensor-based systems may fall short. By comparing the real-world distance measurements derived from VBT systems against those obtained from gold-standard tracking methods, researchers can assess the accuracy of VBT (Redwood-Brown et al., 2012).

Human Pose Estimation

Human Pose Estimation (HPE), particularly through advancements in markerless motion capturing, represents a current approach in the field of computer vision. This technology allows for the detailed analysis of athletes' movements without the need for physical markers, which are traditionally used in motion capture systems (like Infra-red Motion Capturing (IR)). Instead, sophisticated algorithms and computer vision techniques are employed to detect and track the human body's key points from video data.

Recent studies have investigated the accuracy (Fukushima et al., 2024) and highlighted use cases (Monteiro et al., 2024) for HPE technologies. Both studies were co-authored by the author of this dissertation. These innovations have leveraged deep learning models and artificial intelligence to enhance the accuracy and efficiency of pose estimation in complex, dynamic sports environments. Such technologies are capable of providing real-time feedback and biomechanical analyses, which can be used to assess performance.

The application of HPE in sports science offers numerous advantages. For example, without the encumbrance of markers, athletes can perform movements more naturally, providing more authentic data for analysis. This method is particularly beneficial in environments where traditional motion-capturing setups are impractical, such as outdoor fields or in competition scenarios. The data collected can be used to assess techniques, align training practices with performance outcomes and conduct injury risk assessments.

Despite its benefits, HPE faces challenges, particularly in terms of environmental variability and the potential for decreased accuracy under certain conditions (Fukushima et al., 2024). However, ongoing research and technological improvements continue to address these issues, with the goal of making HPE as accurate and reliable as traditional marker-based systems.

3.2.4 Inertial Measurement Unit

IMUs are micro-technology-based sensors offering precise measurements of angular rate, acceleration and sometimes magnetic field orientations. These compact devices provide inertial data, enabling the measurement of an object's dynamics without the need for external reference objects.

IMUs typically comprise a combination of accelerometers, gyroscopes and magnetometers. Accelerometers measure linear acceleration, while gyroscopes detect angular velocity, and magnetometers detect orientation relative to the Earth's magnetic field. As the previously mentioned variables are usually measured in three dimensions, the whole sensor is often described as a 9-axis motion sensor. This trio of sensors allows for comprehensive motion tracking, capturing translational and rotational movements.

Figure 3.5 Inertial Measurement Units for running. The labeling was done for the left foot (LF) and the right foot (RF). The data output of both sensors is the same. The attachment is done in the manufacturer's rubber case.

The data from each sensor component is synthesized through a process known as sensor fusion (Dehzangi et al., 2017; Zhao et al., 2019). This integration often employs sophisticated algorithms like Kalman filters (Bailey & Harle, 2014) or Madgwick filters, which combine the diverse data streams into a unified output (Amaro & Patrao, 2016). The data can be combined with information from other sensors, e.g. GPS (Mertens et al., 2018). The result is the representation of an object's motion, accounting for various forces and movements.

Accurate data collection requires calibration of the IMU to counteract systematic errors and reduce noise. Calibration processes adjust for the sensor frames, mounting frames and anatomical frames, ensuring the sensor's accuracy (Bonnet et al., 2009). Noise reduction techniques, such as signal smoothing and filtering, are also used to reduce the impact of random fluctuations.

In sports science, IMUs have been increasingly used in the past years for analyzing athletes' movements. They allow for the assessment of speed, acceleration, jump kinematics, gait analysis and more, offering data that can inform training adjustments, technique improvements and rehabilitation strategies. The running of athletes was already investigated by several studies using (foot-mounted) IMUs (Bergamini et al., 2013; Bergamini et al., 2012; de Ruiter & van Dieën, 2019; Falbriard et al., 2018; Falbriard et al., 2020; Falbriard et al., 2021; Gurchiek et al., 2019; Macadam et al., 2019; Potter et al., 2019; Schmidt, Rheinländer, et al., 2016; Schmidt, Rheinländer, et al., 2016). IMU data from the athletes' feet were also already leveraged to quantify tactical parameters (Marris et al., 2021). However, also some limitations, e.g. in running power estimation, were found (Baumgartner et al., 2021). The sensors used in this dissertation are illustrated in figure 3.5 (Physilog5, Gait Up SA, Lausanne, Switzerland, size: 47.5 mm × 26.5 mm × 10 mm, weight: 11 g).

The key advantage of IMUs lies in their versatility and self-sufficiency. Unlike optical motion capture systems, IMU do not require an external frame of reference, allowing for their use in various environments, including outdoors or in confined spaces. Their compact size and ability to provide real-time data make them appealing for a wide range of applications.

3.2.5 Ball Tracking

Ball tracking can be achieved with various technologies and, therefore, should be seen as an individual methodology. However, it is covered in an individual section, as its utility for providing insights into game dynamics, player interactions and overall strategy in various sports gives it standalone value. Currently, the two primary methodologies for continuously tracking the ball are VBT and the use of LPS.

VBT utilizes (sometimes high-speed) cameras positioned around the playing pitch to capture the ball's movement. These systems employ sophisticated image processing algorithms to detect and track the ball's position frame by frame. The technical functioning is mainly the same as for players.

Alternatively, an LPS chip can be embedded within the ball to provide positional data. This method provides continuous tracking data that is then used for both position and velocity calculations. As a chip needs to be installed inside of the ball, additionally, an IMU can be integrated into the installation. However, it requires modifications to the ball.

Both methods have individual advantages and limitations, and the choice of the method may depend on the sport's specific requirements. Usually, both systems are integrated within the tracking of player data, as described in the sections above.

3.3 Method Validation

Each study within this dissertation project relied on measurement equipment that has undergone scientific validation. This commitment to using validated tools is inevitable for research findings. Given the significance of validation in scientific inquiries, subsequent sections of this dissertation will look into the methodological importance of the validation process. These aspects of validation are especially pertinent to the studies at hand and provide an understanding of validation efforts.

3.3.1 Validation Theory

In the realm of sports science, validating the accuracy of tracking technologies is important to ensure reliable data collection, e.g. for PA (Linke, Link, & Lames, 2018). In this context, the validity involved using comparative systems with known and, in some cases, superior accuracy. This approach aligns with the concept of concurrent validity, where the performance of one measurement tool is evaluated against a gold standard or a well-established benchmark. By comparing the outputs of the tracking technologies under investigation against these established systems, researchers could determine the degree to which the new methods provide accurate and consistent measurements. This validation process is critical, especially where precise data on player and ball positioning, speed and other metrics can significantly impact training, game analysis and strategic planning. The use of a gold standard in this validation theory ensures that the findings are grounded in a reliable comparison, providing confidence in the technology's utility and applicability in real-world sports settings.

In a review study, Luteberget and Gilgien (2020) enumerated three main important points a proper validation and, therefore, a gold standard should be tested in sports settings.

1. Validating a system's instantaneous dynamic position measurement is important as deviations in position can affect derived parameters (e.g. speed). Discrepancies in data processing between devices and manufacturers can amplify these errors.

2. Firmware updates or changes can alter data processing (e.g. parameter calculation and filtering) without changing the basic measurement of position, affecting parameters like distance and speed. Therefore, position measurements serve as a more consistent parameter for long-term system validity.

3. Validating the instantaneous dynamic position in GPSs, LPSs and VBT systems is crucial for further tactical analyses and ensures long-term stability across firmware versions, ultimately saving time and costs.

Additionally, a methodology should be validated in the context of where this exact method will be used in the future. Therefore, Small-sided Games (SSGs) and running courses have been established for tailoring validation settings to replicate sports scenarios. SSGs (Aguiar et al., 2015) and courses (Hoppe et al., 2018) are subjected to different validation studies to ensure they mirror the targeted athletic skills and performance metrics. Both training forms have been evaluated together, too (Blauberger, Marzilger, et al., 2021; Linke, Link, & Lames, 2018).

3.3.2 Reference Measurements

All studies in this thesis were supported by various measurement technologies to ensure precise temporal and spatial information. The three used methodologies IR, TGs and OptoGait (OG) were chosen as tools for data collection in the publications and will shortly be summarized in the following paragraphs. Additionally, as marker-less motion capturing plays an important and still developing role, it will also shortly be described.

Infra-red Motion Capturing

IR, exemplified by systems like Vicon or Qualisys, is a technology widely used in biomechanics, sports science and entertainment to capture and analyze movement. These systems consist of multiple high-speed cameras equipped with infrared sensors positioned around a designated capture area. A measurement setup at the Technical University Munich can be seen in figure 3.6. The cameras emit infrared light, which is reflected by small markers attached to the subject's body. The cameras then detect the reflected light, and sophisticated software triangulates the data to construct a precise three-dimensional representation of the marker's movements over time. Many markers' positions can enable the fitting of a defined body or object, e.g., a subject skeleton, in the detected area. The resulting data provides detailed insights into kinematics, allowing researchers and practitioners to analyze biomechanical properties such as angles, velocities and accelerations of various body segments. This technology is crucial for detailed movement analysis, performance enhancement, injury treatment, and realistic animation in films and video games.

Figure 3.6 Measurement systems at the university's diagnostics hall. An infrared motion-capturing system (Vicon) is mounted on the rail system around the hall. OptoGait strips (blue) are placed on the floor.

Timing Gates

TGs are electronic devices used to measure the time it takes for an athlete to cover a certain distance, making them indispensable tools for evaluating speed and agility. These systems typically consist of a sending device emitting an infrared beam and a receiving device detecting this signal. When an athlete passes through this infrared beam, this event triggers a recording of the passed time.

Figure 3.7 Timing Gate usage in running. The elapsed time until an athlete reaches the precisely marked position on the track is captured by TGs that are placed on tripods. The signals of the TGs are forwarded wirelessly to a central stopwatch.

This basic mechanism is the foundation of accurate measurement of sprint times and other time-dependent metrics (Figure 3.7). Beyond sprint testing, TGs are versatile tools used in various drills, such as shuttle runs, or for the assessment of reaction times. The benefit of TGs lies in their precision and ease of setup, allowing for the measurement of reliable and accurate data with minimal interference with the athletes. However, their reliance on a clear path between the gates can pose challenges in certain environments, and they primarily measure linear speed, offering limited insights into complex, multi-directional movements. Additionally, the passing of a linear beam at one specific point means that unwanted events can be detected. Hence, a sprint athlete's limb (e.g. the arm) can pass this point first, leading to erroneous (here too short) tracked times.

OptoGait

OG is an optical measurement system designed for gait and motion analysis. The OG system employs two strips of linear floor-level photoelectric cells, creating corridors of light-emitting and light-receiving diodes (Lienhard et al., 2013). These two strips are arranged parallel to each other and perpendicular to the running path. As an individual walks or runs through this corridor, their feet interrupt the light beams, allowing OG to detect all interruptions and subsequently calculate temporal variables, such as SF, GCT and one-dimensional spatial indicators, such as SL. In a post-processing step within the software, it offers a comprehensive view of a person's movement. Its applications extend from running (Schmidt, Rheinländer, et al., 2016) or jumping analysis (Castagna & Castellini, 2013) in sports to rehabilitation settings, where monitoring gait changes is used to support recovery. OG's ability to measure a wide array of metrics in real-time is its most significant advantage, providing detailed feedback that can inform training adjustments and injury prevention strategies. The system's requirement for indoor environments and its higher cost can limit its accessibility and applicability in some sports settings. The deployment of OG strips in a hall is shown in figure 3.6. An example of in-field usage in this project is illustrated in figure 3.8.

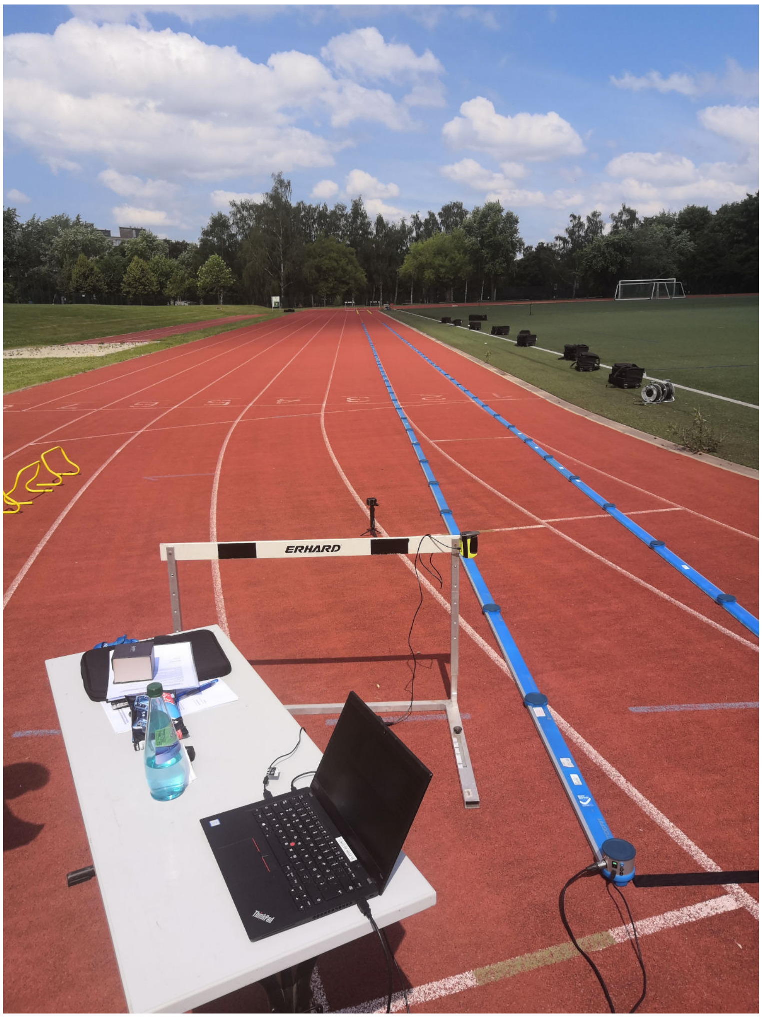

Figure 3.8 Measurement setup of Optogait at a running track. OptoGait strips are placed on the track over the course of 50 meters for tracking the first half of a 100-meter sprint.

While both technologies offer valuable insights, TGs excel in simplicity and measuring speed over predetermined distances, whereas OG provides a deeper analysis of movement patterns. The choice between TGs and OG often hinges on the specific needs of the assessment, with TGs being more suited for straightforward speed and agility tests and OG for detailed biomechanical analyses. TGs and OG provide precise timing measurements which were assessed in different studies (Ammann et al., 2016; Ammann & Wyss, 2014; Schmidt, Rheinländer, et al., 2016; Schmidt, Rheinländer, et al., 2016). In a validation study, the agreement limits for GCT were determined to be 95% within 7.7% when compared to a contact mat (Lienhard et al., 2013). Another investigation found no significant discrepancies in GCT measurements when contrasted with a high-speed video camera (Alvarez et al., 2017). The selection between TGs and OG should be guided by the objective of the PA, considering factors like the environment, type of data required and budget constraints.

Laser Velocity Guard

The Laser Velocity Guard (LAVEG) is an instrument for measuring distances with high precision, utilized for industrial applications or in fields such as engineering or sports science. LAVEG operates by emitting a laser beam towards a target and measuring the time it takes for the reflection to return. This time interval is then converted into distance using the speed of light, allowing for calculating distances and deriving velocities. The device's ability to capture minute position changes over short intervals makes it an invaluable tool for detailed motion analysis.

In sports science, LAVEG is used for tracking the speed and position of athletes during training and competitions, offering data for further analysis and performance enhancement (Bezodis et al., 2012). LAVEG's contribution to precision measurement has made it a valuable tool in domains demanding distance and velocity measurements, such as running diagnostics.

3.3.3 Statistical Analysis

In method validation, statistical analysis plays a crucial role in assessing the accuracy and reliability of the data obtained. Different methods are often used to validate new measurement methods against established standards.

One widely recognized approach is the Bland-Altman analysis, Altman and Bland (1983) introduced this method, which compares two different measurement techniques by plotting the difference against the mean of the two measurements to assess agreement (Figure 3.9). This technique is beneficial for determining the consistency across methods when measuring the same variable. This method can be used to visually detect and present non-systematic or systematic errors and biases in a measurement.

Additionally, root mean square error and mean absolute error are robust statistical tools used to measure the differences between values predicted by a model and observed values (Figure 3.10). While the former gives a relatively high weight to large errors, making it sensitive to outliers, mean absolute errors

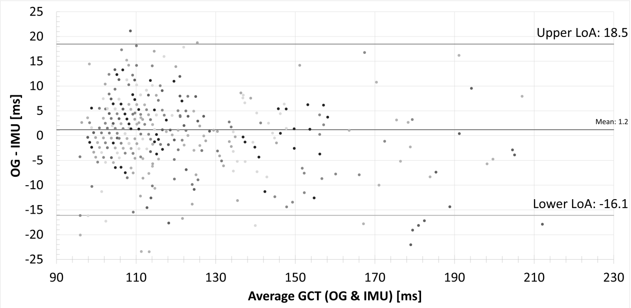

Figure 3.9 Exemplary Bland-Altman plot. The axes represent the difference between the two systems (y-axis) and the average measurement of both systems (x-axis). Each data point represents a measurement value of the ground contact time. A line is drawn for the mean value, and an upper/lower limit of the agreement line is added. Same data as in (Blauberger, Horsch, et al., 2021).

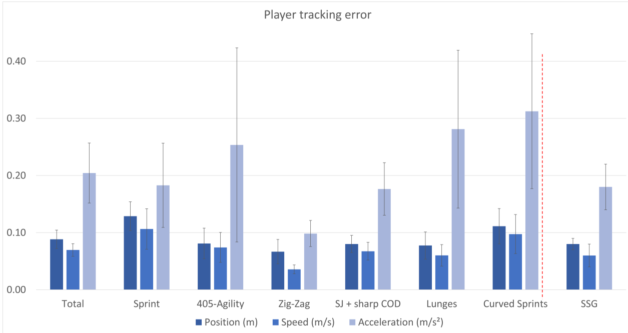

Figure 3.10 Exemplary visualization of RMSE values. The mean root mean squared error for position, speed and acceleration measurements of players are shown for different exercise types (columns 1-7) and a football game scenario (column 8). Same data as in (Blauberger, Marzilger, et al., 2021).

provide a linear score that makes absolute differences easier to interpret. Both error calculations respect the unit of the input values.

The percentage difference is used to express the relative difference between two quantities as a percentage. It offers a normalized metric of deviation that can be intuitively interpreted and facilitates this interpretability even when comparing very low and large magnitudes.

4 Publications

This chapter summarizes all publications that were developed within this doctoral project. For each paper, a short introduction with bibliographic facts, followed by a summary in the context of the whole project, is given. The first three publications (sections 4.1, 4.2 & 4.3) are the main contributions of this dissertation author within the topic. The respective published version is printed thereafter. Additionally, two publications as co-authors are briefly summarized (section 4.4). The full text of these two publications can be found in the Appendix (section 6.2).

4.1 Validation of Player and Ball Tracking with a Local Positioning System

Bibliographic Facts

The first study is entitled "Validation of Player and Ball Tracking with a Local Positioning System". It was authored by Blauberger, P., Marzilger, R. & Lames, M., and published in 2021 in the MDPI Sensors journal (Blauberger, Marzilger, et al., 2021). At the time of the publication, the journal had an impact factor of 3.847 and was ranked in Q2. The network platform ResearchGate counts 33 citations and 1885 reads for this study (as of 07-02-2024).

Content

This study addresses the critical aspect of accuracy in sports tracking technology and focuses on using an appropriate validation methodology in sports settings where the system is put to use (Figure 4.1). The main aspect of this research involves validating the effectiveness of a LPS in tracking players and balls, a developing element in the analysis of sports performance. It specifically looks into the errors associated with LPS technology, highlighting its applicability for game sports like handball or football.

While it shows promise in these use cases, its current error margin might still be too high for accurately measuring granular running performance metrics such as GCT. The accuracy of this measurement system, particularly in the context of these errors, is of special interest for the advancement of the dissertation project.

Contribution of the Main Author

Patrick Blauberger (P.B.) conceptualized the study alongside Martin Lames (M.L.) and developed the methodology with M.L. and Robert Marzilger (R.M.). The Data acquisition was executed by M.L., P.B. and R.M.. P.B. was responsible for the software development, validation, formal analysis, investigation and data curation. Furthermore, P.B. wrote the draft of the manuscript and contributed to the visualization of the data. He took on responsibilities in project administration, ensuring the smooth progress and completion of the study. The final manuscript version was accepted by all authors.

Figure 4.1 Measurement hall of the study. As the objectives of the study required a precise infrared motion-capturing system, an indoor facility was used. The marks at the ground and the electronic placement arm were used for precise position tracking.

sensors

MDPI

Communication

Validation of Player and Ball Tracking with a Local Positioning System

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Abstract: The aim of this study was the validation of player and ball position measurements of Kinexon's local positioning system (LPS) in handball and football. Eight athletes conducted a sport-specific course (SSC) and small sided football games (SSG), simultaneously tracked by the LPS and an infrared camera-based motion capture system as reference system. Furthermore, football shots and handball throws were performed to evaluate ball tracking. The position root mean square error (RMSE) for player tracking was 9 cm for SSCs, the instantaneous peak speed showed a percentage deviation from the reference system of 0.7–1.7% for different exercises. The RMSE for SSGs was 8 cm. Covered distance was overestimated by 0.6% in SSCs and 1.0% in SSGs. The 2D RMSE of ball tracking was 15 cm in SSGs, 3D position errors of shot and throw impact locations were 17 cm and 21 cm. The methodology for the validation of a system's accuracy in sports tracking requires extensive attention, especially in settings covering both, player and ball measurements. Most tracking errors for player tracking were smaller or in line with errors found for comparable systems in the literature. Ball tracking showed a larger error than player tracking. Here, the influence of the positioning of the sensor must be further reviewed. In total, the accuracy of Kinexon's LPS has proven to represent the current state of the art for player and ball position detection in team sports.

Keywords: validity; accuracy; local positioning system; player tracking; ball tracking; position; speed; acceleration; team sports

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1. Introduction

The analysis of sports performance in training and competition often relies on automatic position detection. Various decisions are based on metrics derived from player tracking variables of these systems. Positional data are used for monitoring players' training loads [1,2], activity profiles [3] or tactical performance analysis [4,5]. Additionally, positional information about the ball can be used for further analysis, such as the integration of ball possession [6,7].

To acquire positional information, three methods are commonly used in sports practice, as well as scientific investigations: Global positioning systems (GPS), local positioning systems (LPS) and semi-automatic video tracking systems (VID) [1,8,9]. Regardless of the tracking method, an individual, sport-specific validation of each system is necessary to allow a proper interpretation of the position information [8,10–13]. Much effort can already be found in the validation of GPS [8,14,15], LPS [8–11,15,15–19] and VID [8,20]. Different sports like football [8,15,20–23], handball [24], ice hockey [18] or general sport-specific settings [8,9,17,20] are evaluated. Furthermore, some studies investigated comparability of results obtained from the three methods [8,25,26]. For some of these systems, the continuous positional tracking of balls is possible. However, none of the aforementioned validation studies accounted for the accuracy of ball tracking. The tracking of balls is solely validated in separate studies. Seidl et al. investigated tracking accuracy of a RedFir radio-based tracking system and compared the results to lighting gates. A mean bias of 2.6% was found, meaning a slight overestimation of the ball speed measured by the LPS [27]. The continuous accuracy of ball tracking was not assessed, highlighting a shortcoming of lightning gates. Witt and colleagues investigated the detection of single ball contacts with help of a LPS. Ball tracking turned out to be sufficient for detection of events [28].

Generally, the methodology of validation studies of LPS in sports turned out to be complex and therefore requires many specific considerations. An individual, sport-specific evaluation of each system is necessary [11–13]. For validation purposes, the usage of a proper gold standard reference system is necessary to validate instantaneous position, speed and acceleration [12]. Further critical points are the adaptation of filter parameters or the correction for gait patterns [8,9,20].

Kinexon's LPS is a widespread and commercially available system in the segment of sports tracking. This system is used in the first division of the German handball national league and also the Velux EHF Final4 to record matches since the 2019/2020 season [7]. A recent study from Fleureau et al. looked at the validity of peak speed and acceleration of Kinexon's LPS in handball specific movements [24]. They compared values to the results of simultaneous motion capture and concluded an acceptable validity. Care should be taken near the border of the playing field [24]. Alt et al. investigated the running based validity of Kinexon's LPS in a sport-specific circuit. They found a good to moderate tracking validity with better results in outdoor tracking [9]. Hoppe et al. focused on validity and reliability of a GPS and Kinexon's LPS by comparing the results of both systems to timing gate reference values. They found superior overall LPS values, although more outlier measurement errors occurred [10]. A validation study including player or ball position measurements with Kinexon's LPS and an infrared camera-based criterion reference system was not found in the literature.

Therefore, the aim of this study was the validation of Kinexon's player and ball tracking capabilities, specifically for applications in handball and football. To achieve this validation, the LPS system's position tracking was compared to an infrared camera-based reference system with superior accuracy.

2. Materials and Methods

2.1. Participants

Eight adolescent male players from a professional handball club (age: 14.9 ± 1.2 years, height: 1.8 ± 0.1 m, weight: 75.5 ± 5.0 kg) participated in this study. Prior to the study, all players received verbal and written information about purpose, procedure and requirements of the test. All captured data was anonymized. The protocol accorded to the ethic standards of the Technical University of Munich and was in accordance with the Declaration of Helsinki. Each participant and their parents gave written informed consent to participate in this study.

2.2. Tested System

A commercially available LPS (KINEXON Precision Technologies, Munich, Germany) was investigated in this study. Firmware versions and application software versions corresponded to the latest releases on the testing date (APP version: 7.11.21, Stream processor version: 7.11.2). The installation and calibration of the system was guided by technicians of the manufacturer. Around the playing field 26 antennas and two base stations were evenly distributed at three different height levels above the ground (Figure 1). The calibration required the exact assessment of all antennas' 3D positions with respect to the local measurement area, using a Tachymeter with millimetre accuracy. With the help of these reference positions, the LPS determines the location of the player and ball tags. This calibration procedure is necessary if the system is installed at a new place. The different height of the assembled antennas enabled 3D measurements of the ball tags. The player tag was positioned between each player's shoulder blades utilizing a pouch sewn into the player's jersey (Figure 2).

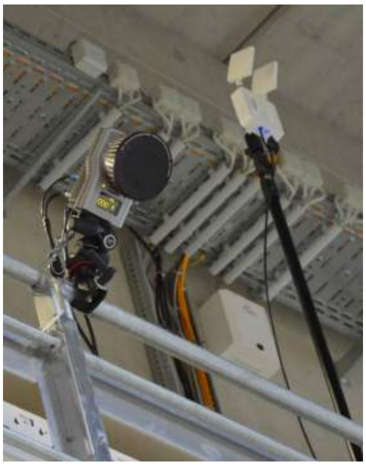

Figure 1. Balcony-mounted Qualysis camera (left) and Kinexon antenna (right).

The sensors transmitted time information via radio-technology to the antennas, which then forwarded the signal via a wide local area network to the local static base stations. Afterwards, the time information of all antennas were aggregated by a central computer and combined into positional data. The momentary position of a player was determined with a frequency of 20 Hz. Certified handballs and footballs were equipped with sensor tags underneath the spherical surface. This arrangement is similar to what is approved in professional leagues (Figure 2).

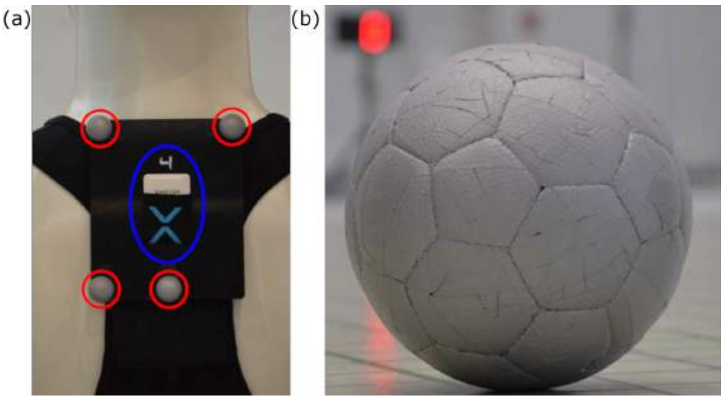

Figure 2. (**a**) Kinexon tag attachment (blue circle) and reference system marker arrangement (red circles). (**b**) Ball as reflective reference system marker with Kinexon sensor inside.

2.3. Testing Site and Reference System

The test took place in the test and application center L.I.N.K. (Figure 3) at the Fraunhofer Institute for Integrated Circuits (Nuremberg, Germany). The setup covered an area of $26 \times 16 \times 6$ m (base area: 416 m^2) for measurements with both systems. The size of the field was limited by the dimension of the measurement hall. All cameras of the reference system were mounted on a gallery above the measurement area.

Figure 3. Test setup at the Fraunhofer L.I.N.K test hall in Nuremberg.

Criterion positions for dynamic accuracy determination were captured by a 30-camera motion capture system (28 Oqus 700+ cameras, 2 Miqus Video cameras, Qualisys, Sweden; Figure 1). Based on infra-red determination of reflective markers a precise calculation of the 3D-positions of the markers with a sample rate of 120 Hz was achieved.

To test the spatial accuracy of the reference system, a calibration object with known dimensions was moved within the measurement area [8]. Deviations of the known spatial distance between the markers and distance measured by the motion tracking system resulted in a mean deviation of 2.89 mm (SD = 1.66 mm, 95% CI [−3.22 mm, +3.27 mm]). The root mean square error (RMSE) was 1.7 mm.

For player tracking, several markers were placed on the upper thoracic spine between the scapulae (Figure 2). The software recognized the different marker patterns for each player and automatically calculated the center as current tracking position (Qualisys track manager 2019.3).

Both, handballs and footballs were completely covered with reflective foil. This enabled the reference system to track the ball as a single object, meaning the center of the tracked marker is corresponding to the center of the ball (Figure 2).

2.4. Testing Protocol and Sample Size

The test setup contained both handball and football specific exercises to cover a variety of game sport relevant situations.

All participants conducted four trials of a sport-specific course (SSC), containing typical exercises of team sports. The elements were selected to test different critical capabilities of player position tracking in high speed, acceleration and changes of direction (COD) periods [19]. The exercises and intensities used are common practice for testing the accuracy of position detection systems in sports [8,11,17,20,22]. The course consisted of a linear sprint (1), 405 agility test (2), zig-zag jogging (3), squat jump (SJ) followed by sharp COD (4), multi-directional lunges (5) and two curved sprints (6). An exemplary trajectory of the course is shown in Figure 4.

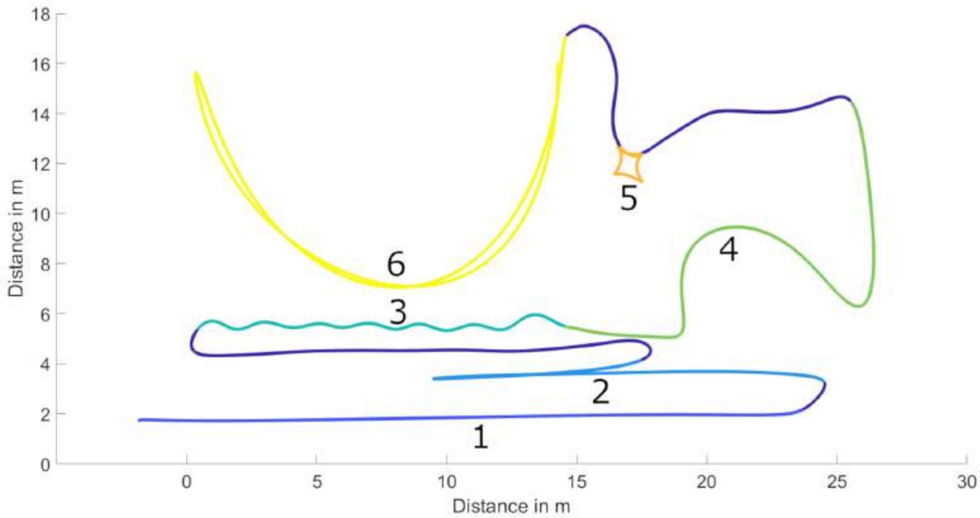

Figure 4. Sport-specific course (SSC) example with Qualisys data. Exercises in chronological order: 1 = linear sprint; 2 = 505 agility test; 3 = zig-zag jogging; 4 = squat jump and sharp changes of direction; 5 = multi-directional lunges; 6 = two curved sprints

To test game specific patterns 4 vs. 4 and 3 vs. 3 small-sided football games (SSG) without goals were conducted within the test area. Each game lasted for 2 min, followed by 1 min of passive rest. The players followed the aim of keeping ball possession within the team and were instructed to keep the intensity at a high level. If the ball left the playing field, it was immediately returned by assistants around the field. This ensured a high net playing time in the SSGs.

Ball shots and throws were tested in 46 football 11-meter penalty kicks and 72 handball 7-m throws without a goalkeeper. A 2 × 3 m goal was placed at the respective distance. As this study aims only at validation, the same setup was used for shots and throws. The participants were instructed to distribute the shots and throws equally over the whole area of the goal. In total, 36 of the 7-m throws were executed as bounced shots.

Table 1 shows the sample size divided into player and ball tracking. For player tracking no trial had to be removed, which resulted in a total sample size of 32 SSC and 36 SSG trials. Ball positions were acquired for all 6 SSG, 46 football penalty shots and 71 handball seven-meter throws. The handball throws altered between direct and bounced shots. All SSG and shot trials were included in the analysis. One throw had to be excluded, due to synchronization problems. In the post processing of the data, tracking errors of the reference system such as out-of-bounds sample points were excluded from the analysis. Shots and throws had a very short duration, thus time and frame data are omitted in Table 1.

Table 1. Overview of trials and sample points, used for player and ball tracking in SSCs and SSGs.

	Player Tracking		Ball Tracking		
	SSC	**SSG**	**SSG**	**Shots**	**Throws**
Trials valid	32	38	6	46	71
Trials excluded	0	0	0	0	1
Sample points valid	55,783	83,086	24,374	-	-
Sample points excluded	2147	4788	7230	0	0
Net time (min)	46.5	69.2	8.1	-	-

2.5. Data Processing

Position data of both systems were exported as raw data to local text files. Data of the Kinexon LPS-System was sampled at 20 Hz for players and 50 Hz for the ball. Reference system data was sampled with a frequency of 120 Hz. All further steps were executed in MATLAB (R2019b, The MathWorks Inc., Natick, MA, USA). The criterion data was downsampled to the Kinexon sample frequency, using a linear interpolation algorithm.

Raw positional data of all players were filtered with a fourth order Butterworth low pass filter. The filtering method was adopted from validation studies with similar exercises [20]. In previous studies an appropriate cut-off frequency of 1 Hz was determined by analysing occurring gait frequencies of football players with a method described by Winter [29]. Raw ball positions were filtered with a 4th order Butterworth low pass filter and a cut-off frequency of 10 Hz.

Many use cases in sports require the analysis of speed and acceleration. Most commercial systems provide these variables in their output. However, to assure better comparability in this study, the filtered positional data were used as basis for the calculation. Speed (rate of change in XY position) and acceleration (rate of change in speed) were derived by differencing two consecutive data points. This procedure was applied to player as well as ball data. Peak speed, peak acceleration and peak deceleration represents the maximum or minimum momentary value in the respective data.

The alignment of both signals was accomplished in two steps. Initially all trials were synchronized temporally. Therefore, the system data was time-shifted until the minimal total RMSE between the speed values was found. For spatial synchronisation, a Procrustes analysis (Euclidean similarity transformation) was conducted to find the best fitting rotational and translational parameters and align both systems.

3D ball accuracy was investigated by comparing the tracked impact positions of shots and throws crossing the goal line. The start and end of each shot and throw were manually tagged. The intersection point of the ball with the goal plane was calculated using the manually defined start position and the closest tracked position to the goal plane. The coordinates of the goal were measured manually and did not change in during whole test. Position errors are recorded in 2D (XY), height (Z) and 3D (XYZ).

As tracking devices are usually meant to show the gross movement of a player and to avoid overestimation of covered distances by body sway when standing still, the data was gait neutralized before the distance covered was calculated [8]. Waypoints were created every 60 cm, the positions in between were interpolated using a shape-preserving piecewise cubic spline algorithm [8]. Finally the distance between each frame was summarized, resulting in the total distance covered. In addition to the total value, distances are given in speed zones, using the following thresholds: Zone 1 (<6 km·h^{-1}), Zone 2 (≥ 6 to <15 km·h^{-1}), Zone 3 (≥ 15 to <20 km·h^{-1}), Zone 4 (≥ 20 to <25 km·h^{-1}), Zone 5 (≥ 25 km·h^{-1}).

2.6. Statistical Analysis

Measurement errors of positional data are stated by means of root mean square error (RMSE) and mean absolute error (MAE):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(measured\ distance - actual\ distance)^2}{number\ of\ measurements}} \tag{1}$$

$$\mathrm{MAE} = \sum_{i=1}^{n}|measured\ distance - actual\ distance| \tag{2}$$

Both error indicators are stated for three variables. Position (m): Position RMSE and MAE, Speed (m·s^{-1}): Instantaneous speed RMSE and MAE and Acceleration (m·s^{-2}): Instantaneous acceleration RMSE and MAE. For position measurements, the circular error propable (CEP) as the median and the CE95 as the the 95th percentile of error values are calculated.

Three indications of percentage differences occure in the results: Tables 3 and 5 include the percentage difference for measured peak speed, peak acceleration and peak deceleration values. Table 3 also shows the absolute percentage difference; Table 4 shows the absolute percentage difference for shot and throw position errors; Table 6 elaborates normal and absolute percentage differences between measured covered distance in the speed zones. Speed zones 4 and 5 are excluded (-) for SSGs, as only two athletes reached zone 4 and none reached zone 5. Percentage deviation is calculated for covered distances above 0 m in both systems. In both cases, the omitted covered distances are added to the total distance. All differences are stated as the average percentage deviation of the former variable in the respective trials.

3. Results

The results are structured in three different sub-sections: Position, speed and acceleration (1), Peak values (2), and Shot and throw tracking (3). All table values are rounded after calculation which can lead to small inconsistencies in printed outcomes.

3.1. Position, Speed and Acceleration

Table 2 presents the 2D deviations of momentary position, speed and acceleration between the reference system and Kinexon.

Table 2. Position, speed and acceleration errors measured for SSC and SSG. For each category, root mean square error (RMSE) and mean absolute error (MAE) as well as their standard deviation (SD) is shown. CEP indicates the median position error, CE95 the 95th percentile of error values.

		Position (m)		Speed ($m \cdot s^{-1}$)		Acceleration ($m \cdot s^{-2}$)			
		RMSE ± SD	**MAE ± SD**	**CEP**	**CE95**	**RMSE ± SD**	**MAE ± SD**	**RMSE ± SD**	**MAE ± SD**
SSC	Total	0.09 0.02	0.08 0.01	0.07	0.15	0.07 0.01	0.05 0.01	0.20 0.05	0.12 0.01
	Sprint	0.13 0.03	0.12 0.02	0.12	0.19	0.11 0.04	0.09 0.03	0.18 0.07	0.14 0.05
	405-Agility	0.08 0.03	0.07 0.02	0.07	0.13	0.07 0.03	0.06 0.02	0.25 0.17	0.15 0.05
	Zig-Zag	0.07 0.02	0.06 0.02	0.06	0.10	0.04 0.01	0.03 0.01	0.10 0.02	0.08 0.02
	SJ + sharp turns	0.08 0.01	0.07 0.01	0.07	0.13	0.07 0.02	0.05 0.01	0.18 0.05	0.12 0.03
	Lunges	0.08 0.02	0.07 0.02	0.07	0.12	0.06 0.02	0.05 0.02	0.28 0.14	0.19 0.09
	Curved sprints	0.11 0.03	0.10 0.03	0.10	0.17	0.10 0.03	0.07 0.02	0.31 0.14	0.16 0.05
SSG	Player	0.08 0.01	0.07 0.01	0.6	0.13	0.06 0.02	0.04 0.01	0.18 0.04	0.10 0.02
	Ball	0.15 0.03	0.12 0.02	0.11	0.22	1.61 0.75	0.86 0.09	36.06 14.57	19.22 2.21

3.2. Peak Speed, Peak Acceleration and Peak Deceleration

Table 3 shows the mean and standard deviation (SD) of peak speed, peak acceleration and peak deceleration for the different stages of the SSC. Differences between both systems are shown as relative and absolute percentage deviations.

Table 3. Table with peak speed, peak acceleration and peak deceleration of the reference and Kinexon system for different parts of the SSC. Percentage values indicate the differences between both systems.

	Peak Speed ($m \cdot s^{-1}$)				Peak Acceleration ($m \cdot s^{-2}$)				Peak Deceleration ($m \cdot s^{-2}$)			
	Ref Sys ± SD	Kinexon ± SD	% Diff	Absolute % Diff	Ref Sys ± SD	Kinexon ± SD	% Diff	Absolute % Diff	Ref Sys ± SD	Kinexon ± SD	% Diff	Absolute % Diff
Linear Sprint	7.43 0.39	7.51 0.40	1.0%	1.0%	3.82 0.62	3.76 0.48	−0.5%	5.2%	−4.64 0.49	−4.75 0.51	2.4%	2.4%
405 Agility	5.90 0.32	5.98 0.32	1.4%	1.4%	7.01 0.57	6.92 0.52	−1.3%	2.7%	−7.45 0.44	−7.42 0.41	−0.3%	2.1%
Zig-Zag	1.66 0.16	1.69 0.16	1.7%	2.4%	0.91 0.33	1.00 0.35	10.2%	12.9%	−1.02 0.33	−1.03 0.35	−0.1%	7.3%
SJ and COD	4.43 0.35	4.51 0.36	1.7%	1.7%	4.52 0.49	4.63 0.51	2.4%	3.1%	−4.58 0.47	−4.70 0.50	2.7%	3.4%
Lunges	1.21 0.28	1.22 0.27	1.5%	3.2%	1.99 0.62	2.04 0.61	2.9%	5.7%	−2.01 0.55	−2.09 0.54	4.3%	6.1%
Curved sprints	5.82 0.22	5.86 0.21	0.7%	0.8%	6.08 0.50	6.10 0.49	0.5%	3.0%	−6.64 0.41	−6.71 0.38	1.1%	2.5%

3.3. *Shot and Throw Tracking*

Deviations of the tracked position the ball passing the goal line are show in Table 4, Table 5 shows the measured ball speed peaks in shots and throws.

Table 4. Football shot and handball throw: Deviation of impact position at the goal. The percentage difference states the deviation between shot and throw errors.

	Shot Pos Error ± SD (m)	Throw Pos Error ± SD (m)	% Diff
2D	0.13 0.08	0.13 0.15	2.4%
Height	0.09 0.07	0.15 0.13	38.7%
3D	0.17 0.08	0.21 0.18	18.9%

Table 5. 2D peak speed of shots and throws.

	Ref Sys ± SD ($m \cdot s^{-1}$)	Kinexon ± SD ($m \cdot s^{-1}$)	% Diff
Shot	24.65 3.49	25.05 3.50	1.8%
Throw	17.78 1.64	18.20 2.27	2.6%

3.4. *Covered Distance*

Table 6 presents the covered distance measured by the reference system and Kinexon.

Table 6. Covered distance in SSCs and SSGs, shown in five speed zones and the total trial. In SSGs, zone 4 was only reached in two occasions and is therefore excluded. No player reached speed zone 5 in all SSGs.

		Ref Sys ± SD (m)	Kinexon ± SD (m)	% Diff	Absolute % Diff
SSC	Total	173.9 6.7	174.9 6.8	0.6%	0.6%
	Zone 1	48.8 7.8	48.9 7.9	0.2%	1.3%
	Zone 2	50.1 8.5	50.3 8.8	0.3%	1.3%
	Zone 3	46.7 7.2	45.0 7.5	−3.7%	4.1%

Table 6. *Cont.*

		Ref Sys ± SD (m)	Kinexon ± SD (m)	% Diff	Absolute % Diff
	Zone 4	21.2 8.9	22.7 9.1	8.5%	9.1%
	Zone 5	7.2 3.9	8.0 3.8	14.5%	15.5%
SSG	Total	165.5 27.4	167.1 27.6	1.0%	1.0%
	Zone 1	61.5 10.4	61.2 10.6	−0.5%	1.4%
	Zone 2	98.3 29.2	99.6 29.4	1.4%	1.7%
	Zone 3	5.4 6.6	6.0 7.0	15.3%	16.5%
	Zone 4	-	-	-	-
	Zone 5	-	-	-	-

4. Discussion

4.1. Discussion of Results

The RMSE of 9 cm for positional measurements for the whole course did not differ largely from the RMSE of 8 cm for SSG tracking. Both mean absolute errors turned out to be 1 cm smaller (Table 2). The small advantage in accuracy of SSG compared to SSC is to be expected as SSC contains more critical events for position detection. Table 7 shows the accuracy of player position tracking from studies using a similar reference system.

Table 7. Results from studies using similar validation procedures.

Article	Tested System	Reference System	Exercises	Result
Ogris et al. [2012] [22]	LPS	Vicon	Courses, SSG	MAE: 23.4 cm
Linke et al. [2018] [8]	GPS, LPS, VID	Vicon	Courses, SSG, Shuttle runs	RMSE GPS: 96 cm RMSE LPS: 23 cm RMSE VID: 56 cm
Luteberget et al. [2018] [11]	LPS	Qualisys	Courses	MAE: 21 cm
Linke et al. [2020] [20]	2 × VID	Vicon	Courses, SSG	RMSE VID1: 9 cm RMSE VID2: 8 cm
Hodder et al. [2020] [17]	LPS	Vicon	Courses	RMSE: 20 cm

A similar result pattern was found for general speed and acceleration errors. Looking at the specific exercises of the course, tracking in high velocity phases (e.g., linear and curved sprints) was less accurate compared to other sections (Table 2). Small differences between RMSE and MAE (Table 2) hint towards a constant tracking error instead of several peak errors, as calculation of RMSE squares all errors before taking the mean and the root. Table 6 presents the difference of measured covered distance, divided into five speed zones and the total value. In total, the percentage deviation was 0.6% for SSCs and 1.0% for SSGs. The positive differences indicate, that all covered distances were slightly overestimated by the Kinexon system. These results are comparable to other studies investigating LPS [11,20,23].

Table 3 demonstrates errors in peak speed, peak acceleration and peak deceleration and the percentage deviations between Kinexon's and Qualisys's measured values. The percentage deviation of measured peak speed in the six exercises of the course were in the range of 0.7–1.7%. The error ranges got bigger for acceleration (−1.3–10.2%) and deceleration (−0.3–4.3%). The exercises with the highest percentage peak speed deviation were zig-zag jogging and the squad jump followed by CODs. Additionally, a high peak acceleration discrepancy was found for zig-zag jogging. The linear sprints with the highest peak speed also showed an overestimation by the LPS. Such overestimations can be found in other studies' results, assessing Kinexon's peak speed measurements. Fleureau et al. mention a mean bias of 0.15 ($m \cdot s^{-1}$) and 0.17 ($m \cdot s^{-1}$) for side- and center-field sprints [24]. These results indicate difficulties with the system in the assessment of speed and acceleration for alternating trajectories and are in line with similar shortcomings of LPS systems stated for LPS systems [19].

The 2D tracking accuracy of the football showed a position RMSE of 15 cm for SSGs. Compared to player tracking accuracy, this turns out to be almost twice as high (player tracking RMSE 8 cm; Table 2). Even the increased sampling frequency of 50 Hz (ball) compared to 20 Hz (player) could not compensate for that. This is to be expected, because the ball shows more critical kinematics, e.g., acceleration and speed than players' movements. Additionally, the systematic error mentioned, caused by the location of the LPS sensor in the ball, influences the results. For ball tracking, the error should be interpreted respecting the intended usage of the data. Although the positional error of ball tracking was higher then the error found for player tracking in this study, the height of this error was stated as acceptable for player tracking in other studies [17]. Therefore, ball tracking accuracy could be appropriate for purposes like ball possession analysis [28]. For officiating purposes such as hawkeye in tennis, where error rates of well under 1 cm are achieved [30] the ball tracking should not yet be used.

Table 4 shows a deviation of 17 cm (shot) and 21 cm (throw) between the tracked 3D ball impact locations in the goal. This is a difference of 18.9% between the tracking of handballs and footballs. When looking at the composition of the error, rather big differences occur in height measurements, whereas the 2D position error was 13 cm for both ball types. In total, ball position tracking was more error prone than player tracking. The measured peak speed of the ball in shots and throws was slightly overestimated by the LPS (Table 5). This discrepancy was in the same range for both balls.

4.2. Discussion of Methods

There are different designs for validation studies of a position tracking system [19]. As Luteberget and Gilgien [12] mention, a gold standard design is indispensable and preferential to just comparing results of position tracking systems. A 3D-motion capture system based on infrared cameras with passive markers may be seen as the presently most effective reference system [12].

In this study, different stations of a sport-specific course were chosen to mimic relevant movements in team sports, with a focus on critical situations for position tracking devices. However, not all common and imaginable movements could be integrated. This should be taken into account, especially for sports with focus on other movement patterns.

The data processing in this study was chosen to be appropriate and applicable to recordings of two individual systems. However, the adaptation of the data processing to one specific system might be beneficial for optimizing this system's results. Differential filtering settings are commonly used by manufacturers to improve results. This filter adaptation might result in more precise tracking outcomes [9].

Player tracking was evaluated using a course with different sections and small sided games. The course was designed to cover exercises for various demands within the testing area. This area was limited to the coverage capacity of the reference system. To the best knowledge of the authors, currently available infrared camera-based motion capture systems cannot cover large areas like a whole handball or even football pitch. Nevertheless, the size of the pitch has a significant influence on player kinematics and tactical behaviour. Neither did the relatively short track for linear sprints allow for reaching top sprinting speed nor did the limited pitch dimensions of the SSG allow for reaching top speeds comparable to full pitch handball or football matches. Moreover, for the same reason only a small number of samples in high or very high speed sections could be compared. This can be seen in the low availability of high speed covered distance in SSCs and the lack of high speed occurrences in SSGs (Table 6). Although this limitation is caused by the state of the art in validation methodology, it has the unpleasant consequence that we are not able to validate systems in speed zones, where accuracy gets increasingly critical.

Ball tracking accuracy for handballs and footballs is demonstrated in 2D (Table 2) and 3D (Table 4). Shots and throws were conducted with a large distribution of height differences and therefore allowed the analysis in 3D. Here, the Z-coordinate (height of the ball) was taken into account. In SSGs, the players' aim of keeping ball possession led to the passes predominantly with the ball on the ground. Ball position measurements in SSGs were compared in 2D. The height accuracy in game-like scenarios should be more specifically addressed in further studies.

The tracking of the ball depends, among other things, on the positioning of the sensor, which is right underneath the surface of the ball. For a football (around ø 22 cm) and a handball (around ø 18 cm), this results in a maximum dislocation of 11 cm/9 cm to the center of the ball in the XY plane. As the ball is spinning, there is a variable systematic error ranging from 0 cm to 11 cm. This error is part of the deviation between reference and tested system, but may not really be seen as a measurement error.

5. Conclusions

This study investigated the sport-specific validity of Kinexon's LPS for both, player and ball tracking data. The comparison with an infrared camera-based motion tracking system as criterion reference system allows for precise and continuous evaluation of the tracking accuracy. The exercises in the course were chosen to reflect typical movements of athletes in team sports, especially handball and football. It has to be considered, that the coverage area of the reference system falls short of original handball and football pitches thus not allowing for long phases of high velocities and coverage of a real-sized pitch.

The position measurements of players in the SSC showed just minor differences within all exercises, depending on position, speed and acceleration. For the game-like test setting, the error was slightly lower. These results are in line or even better compared to previous studies on LPS or video-based systems and better than GPS. Ball tracking showed a higher error than player tracking. The 3D accuracy for shots and throws depends on measurements in the Z direction and shows differences between handballs and footballs. The speed of the ball was slightly overestimated by the LPS.

Based on the results of this study, the accuracy of Kinexon's LPS represents the current state of the art regarding player and ball position detection in handball and football. The system can be confidently used to track player and ball positions in team sports.

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4.2 Detection of Ground Contact Times with Inertial Sensors in Elite 100-m Sprints under Competitive Field Conditions

Bibliographic Facts

The dissertation's second study, "Detection of Ground Contact Times with Inertial Sensors in Elite 100-m Sprints under Competitive Field Conditions" was authored by Blauberger, P., Horsch, A. & Lames, M., and published in 2021 in the MDPI journal Sensors (Blauberger, Horsch, et al., 2021). The journal had an impact factor of 3.847 and ranked in the second quartile at the time of its publication. The study has garnered nine citations and 535 reads on ResearchGate (as of 07-02-2024).

Content

Central to this study is the exploration of a feasible methodology for employing inertial sensors to accurately measure GCT in elite-level 100-meter sprints. This research was applied under field conditions, ensuring that the outcomes are directly applicable to high-stakes athletic environments (Figure 4.2). The study's participant pool, comprised of experienced elite sprinters, adds a layer of practical relevance and authenticity to the research. This choice of participants underscores the study's commitment to generating findings that are not just theoretically robust but also directly transferable to high-performance sports settings.

One key outcome was the sensors' ability to provide detailed temporal data regarding the athletes' foot contact with the ground during the sprint. This information is essential for the understanding of sprinting, particularly in the context of elite performance, where fractions of a second are decisive. The study showed that the variations in GCT as measured by the sensors were aligned with the athletes' sprinting phases, offering insights into the efficiency and technique of each sprinter. Moreover, the research found that these measurements could be obtained reliably under competitive field conditions, indicating that such technology can be feasibly integrated into regular training and competition without disruption. This aspect is crucial for coaches and athletes who seek to incorporate data-driven techniques into their training regimes without hindering the sport's natural flow. The study's results open up new possibilities for coaches and sports scientists in tracking and enhancing sprint performance. By providing accurate, real-time data, these sensors can help fine-tune training programs, identify improvement areas and develop strategies that can give athletes a competitive edge. The potential of this technology focuses on sprinting but could also be applied in other sports where GCT is evaluated as a PI.

Contribution of the Main Author

The main author (P.B.) was involved in conceptualizing the study alongside Martin Lames (M.L.) and also played a key role in developing the methodology with Alexander Horsch (A.H.) and M.L.. P.B. was responsible for the software development, validation, formal analysis and data curation, demonstrating a comprehensive involvement in both the execution and analytical aspects of the research. A.H. and M.L. were significantly involved in data interpretation. P.B. led the writing of the original draft and contributed to the visualization aspects of the study. While M.L. provided supervision and project administration, P.B.'s contributions included operational execution, data analysis and manuscript preparation. All authors approved the final research paper.

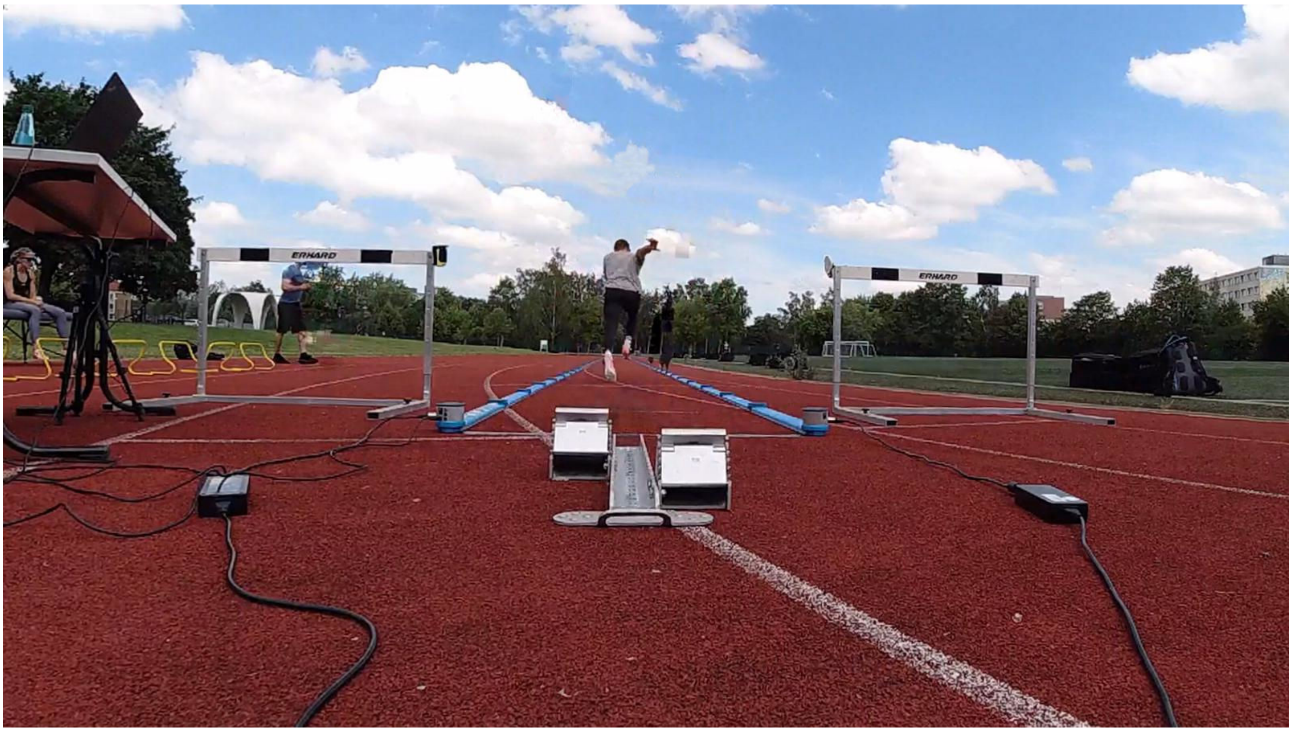

Figure 4.2 Measurement setup and athlete. The blue OptoGait strips acquired reference data. Both feet of the athlete were equipped with Inertial Measurement Units.

sensors

Article

Detection of Ground Contact Times with Inertial Sensors in Elite 100-m Sprints under Competitive Field Conditions

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Abstract: This study describes a method for extracting the stride parameter ground contact time (GCT) from inertial sensor signals in sprinting. Five elite athletes were equipped with inertial measurement units (IMU) on their ankles and performed 34 maximum 50 and 100-m sprints. The GCT of each step was estimated based on features of the recorded IMU signals. Additionally, a photo-electric measurement system covered a 50-m corridor of the track to generate ground truth data. This corridor was placed interchangeably at the first and the last 50-ms of the track. In total, 863 of 889 steps (97.08%) were detected correctly. On average, ground truth data were underestimated by 3.55 ms. The root mean square error of GCT was 7.97 ms. Error analyses showed that GCT at the beginning and the end of the sprint was classified with smaller errors. For single runs the visualization of step-by-step GCT was demonstrated as a new diagnostic instrument for sprint running. The results show the high potential of IMUs to provide the temporal parameter GCT for elite-level athletes.

Keywords: running; sprinting; contact time; sports analytics; inertial sensors (IMU); field application

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1. Introduction

In recent years, the acquisition of performance parameters with sensors for application in sport science and practice has been a developing topic. The evolution towards smaller and lighter devices like inertial measurement units (IMU) allows for field usage in professional sports. With the availability of increased sample rates, even sports with fast and abrupt movements get in the scope of detailed sensor-based analysis.

In sports with high speeds, such as sprints, little direct feedback is available to the athlete. Hence, scientific assistance needs to assess objective indicators to give detailed feedback and enhance future performances. Temporal parameters like ground contact time (GCT), step duration, and step rate are common features of running analysis. These parameters were linked to enhanced performances in several studies [1–3], underlining their helpfulness for coaches and athletes in training and competition. Additionally, the influence of GCT on the running economy was stated [4]. In sprinting, a negative correlation between GCT and performance in a sample including french elite-level sprinters was found [5]. Especially GCT is an essential parameter in sprinting [6] but is not commonly available in training and competition settings until now [7].

Temporal parameters, in which tiny deviations can play a decisive role, and can only be captured with technological aid. Established methods like video footage, timing gates, contact mats, motion capturing, or force plates are used to determine exact temporal sprint parameters [8–10]. The feedback obtained by these methods can improve the quality of the running technique. However, they require notable effort or preparation and cannot be commonly applied in the field or competition settings, where the most valuable information may be collected. Non-invasive position detection methods with less overall (Global positioning system—GPS) or on-court preparation (Local positioning system—LPS) can eliminate these problems. Seidl et al. investigated the determination of temporal parameters with a LPS. For the detection of ground contact times, the most precise commonly used position detection method, LPS, does not work [11,12]. This also implies that GPS is not suitable for this detection. For reliable sprint parameter detection, photoelectric systems like Optogait or Optojump are commonly used [7,12–14]. However, before the measurement, these systems need to be set up on the running track carefully, thus requiring a large effort and not suited for analyses of official competitions. Moreover, only straight runs of one athlete at a time can be assessed.

To substitute these time intensive and costly systems, the integration of IMUs for diagnostics in gait [15–17], runs [18–20], or sprinting [13,21–25] received much attention in the last decade. Various studies introduced new or adapted sprint performance metrics based on data of IMUs. In a systematic review, Macadam et al. gathered several studies investigating one or more types of temporal parameters for sprint kinematics. They conclude, among other things, that a more distal sensor placement (e.g., foot, shank, shoe-mounted) enhances the validity and reliability of sensor measurements [26]. Also, a sampling frequency of >200 Hz improved results in the examined studies. A recent study proposed combining data from a LPS with integrated IMUs positioned near the participant's sacrum for a more holistic view of gait parameters [27]. They stated good results for speed and stride length while not addressing ground contact time. Schmid et al. investigated the validity of IMU measurements with real-time quantification of the collected data. They report detection errors of -2.5 ± 4.8 ms for GCT and a correct step detection rate of 95.7% [13]. In a recent study, Falbriard et al. investigated temporal parameters during hurdle running. Besides a perfect hurdle clearance detection (with the help of magnetic sensors) and determination of the leading leg, they found an increase in GCT during one race [28]. Schmid and colleagues suggested a discussion regarding the GCT values, mentioning a correction procedure based on the previous study of Falbriard et al. [22,29].

From the current literature, it remains unclear whether the detection of sprint parameters with IMUs can determine the GCT of elite-level 50 and 100-m sprinters in the field. Precise GCT information could be beneficial for coaches, athletes, and science to investigate training and competition success. This study aims to validate the detection of GCTs for elite sprinters in the field with shoe-mounted IMUs.

2. Materials and Methods

2.1. Sample and Protocol

The sample consists of 1140 steps from 34 maximum 50 and 100-m sprints performed by five elite national sprinters, with three participants of the Tokyo Olympics (age: 22.6 ± 2.7 years; weight: 69.6 ± 11.5 kg; 3 male, 2 female; test year's best official 100 m time: f: 11.65 s, f: 11.11 s, m: 10.76 s, m: 10.77 s, m: 11.27 s); 889 of these steps were simultaneously measured with the photoelectric Optogait system. The trials were performed on official sprinting tracks during three separate training sessions. Before the study, all athletes were instructed verbally and received written information about the procedure and purpose of the study. The study has been approved by the ethical committee of Technical University Munich and all subjects gave informed consent.

2.2. Measurement Systems

Two IMUs (Physilog5, Gait Up SA, Lausanne, Switzerland, size: 47.5 mm $\times$ 26.5 mm$\times$10 mm, weight: 11 g) were attached to each athlete's shoes, positioned right above the ankle of the foot (Figure 1). The IMUs were chosen to be easily applicable, light, and least obstructive for the athletes' performance. The positioning was reported not to be of any problem by each athlete. The IMU included an accelerometer (512 Hz, $\pm$16 g operating range) and gyroscope (512 Hz, $\pm 2000^{\circ}$/s operating range) and a barometric sensor. In this project, only the 3D accelerometer and 3D gyroscope are used. For ground truth data acquisition, a 50 m corridor of photoelectric bars on the ground (Optogait, Bolzano, Microgate, Bolzano, Italy) was used. Optogait was used already as criterion measurement system in previous sprinting studies [7,13,30]. This system is modularly composed of 1 m bars, which can be connected to cover an arbitrary distance. Over the area of 100 cm $\times$ 80 cm, 96 light diodes are evenly located 3 mm above the running track. One validation study reported 95% limits of agreement of 7.7% for GCT with a contact mat [31], whereas another study did not find significant differences in GCT compared to a high speed video camera [32]. To acquire data for the total 100 m distance, the Optogait corridor was repositioned to the second 50 m sector for 6 of the sprints. With this procedure, ground truth data for 77.98% of the steps were captured (76.72% on the first 50 m and 23.28% steps of the last 50 m).

Figure 1. Sprint shoes with IMUs attached to the ankles (red circles).

2.3. Data Processing

Initially, all raw data of both systems were exported as local text files, and personalized data was anonymized. The software MATLAB (R2021b, The MathWorks Inc., Natick, MA, USA) was used for further data processing steps. The built-in functions *butter*, *filtfilt*, and *findpeaks* were used in the algorithm. X, Y, and Z signals from the IMUs' Accelerometer and Gyroscope were acquired at 512 Hz and extracted with the company's software tool. The sensor's respective information about the direction of acceleration and angular velocity is described relative to the sensor's position, which is constantly changing during a movement. The current study summarized Accelerometer and Gyroscope outputs to one vector as vector magnitude unit (VMU) to circumvent this problem. Both VMUs were filtered using a 2nd order Butterworth low pass filter with a cut-off frequency at 70 Hz [28]. These filter parameters were successfully applied to the training data and achieved the best results. The automatic detection of step events was achieved based on two relevant episodes of a step cycle: Initial contact (IC) and terminal contact (TC). IC describes the moment in time when the heel initiates the very first contact with the ground. TC, also known as toe-off, refers to the moment when the tip of the foot leaves the ground. The precise temporal location of these events can be determined with different procedures. It turned out to be most promising to use patterns in accelerometer as well as gyroscope data [22].

For algorithm development, repetitive patterns in the IMU signals were analyzed and used to extract GCT. Six randomly selected runs served as training data. After the development, no further adaptations were made to the detection, which was applied to the rest of the runs. This procedure helps ensure that the algorithm does not over-fit the data. Figure 2 exemplary illustrates the algorithmic determination of those time points for one single step of a sprint. The IC of the foot causes an abrupt change of the acceleration induced by the touchdown. In this study, IC was defined as the moment of the local minimum in acceleration when the heel impacts the ground (Figure 2A). Using this definition of IC, the location of TC time points was determined with the help of the ground truth data in the training set. The foot's movement at the end of the contact phase causes two peaks in the combined angular velocity. TC was defined by the local minimum between these two bursts (Figure 2B). The graphs show synchronous signals of the accelerometer and gyroscope of the IMU for one single step, together with the Optogait signal for ground contact.

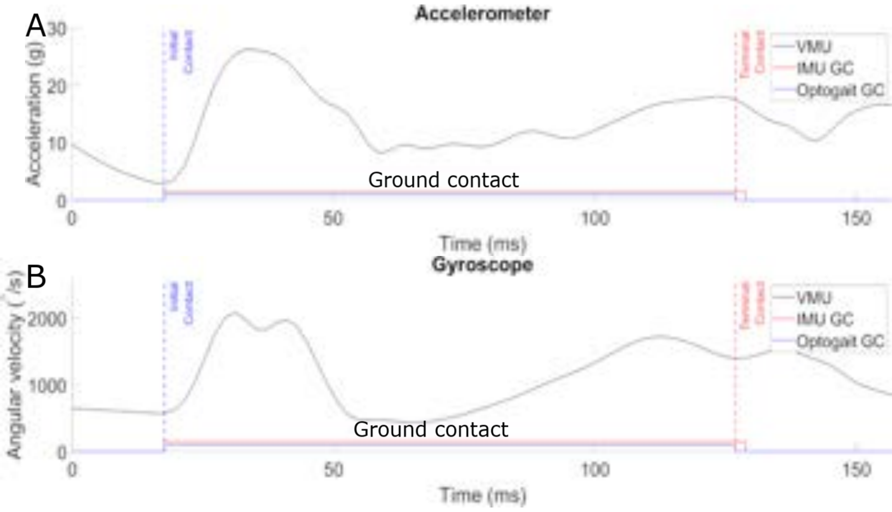

Figure 2. Vector magnitude unit (VMU) of x, y, and z acceleration (**A**) and angular velocity (**B**) throughout one single sprint step. The blue dashed line marks the initial contact event; the red dashed line the terminal contact. The solid red line indicates the resulting ground contact period for the inertial measurement unit (IMU). The photo-electric-measured (Optogait) ground contact time is represented by the solid blue line.

2.4. Statistical Analysis

Results regarding the whole sample include all steps which at least two athletes performed. This discrepancy comes from the different step lengths of the tested athletes. This leads to a maximum of 50 steps for any 100-m sprint.

All Graphs were created with Microsoft Excel (2016, Microsoft Corporation, Redmond, WA, USA). Percentage differences are calculated as the percentage deviation of the photo-electric measured value. To show error distributions, a well-known procedure is the visualization of data in a Bland-Altman-Plot. Step-wise deviations are indicated by means of root mean square error (RMSE) between the calculated GCT and the GCT of the ground truth.

3. Results

Section 3.1 addresses results on the validity of the GCT detection. Section 3.2 illustrates the distribution of the measured GCT. Moreover, based on IMU data, exemplary evaluations of individual runs regarding reliability and gender comparison are visualized. Results are shown as percentage values, averages, standard deviations, and Bland-Altman plots.

3.1. Results on Validity

The algorithm correctly detected 863 of 889 ground contact events, corresponding to a false detection rate of 2.92%; 6.47% of the first five steps and 13.33% of the last five steps of the respective sprint were incorrectly detected. The remaining sprint steps were incorrectly detected in 0.56% of the cases. The IMUs detected a mean GCT of 119.95 ± 22.51 ms, and Optogait detected 117.13 ± 24.03 ms for all simultaneously measured steps. The step-wise average relative time difference between IMU- and Optogait-GCT was 3.55 ± 6.16 ms, which translates to a 3.03% average deviation of GCT. A mean absolute time difference of 5.46 ± 4.55 ms (4.66% deviation) was measured. The deviation of each step results in a total root mean square error of 7.97 ms.

Measurement errors for the detected GCT are illustrated in a Bland-Altman plot (Figure 3). All steps with both IMU and ground truth data are shown independently of the respective trial. The first five steps are marked with red dots, steps 6–50 are shown in blue color. The solid black line represents the mean bias of all detected steps: 3.55 ms. Limits of Agreement ($2 * SD$) were obtained at −8.53 ms and 15.63 ms and are represented by the black dashed lines.

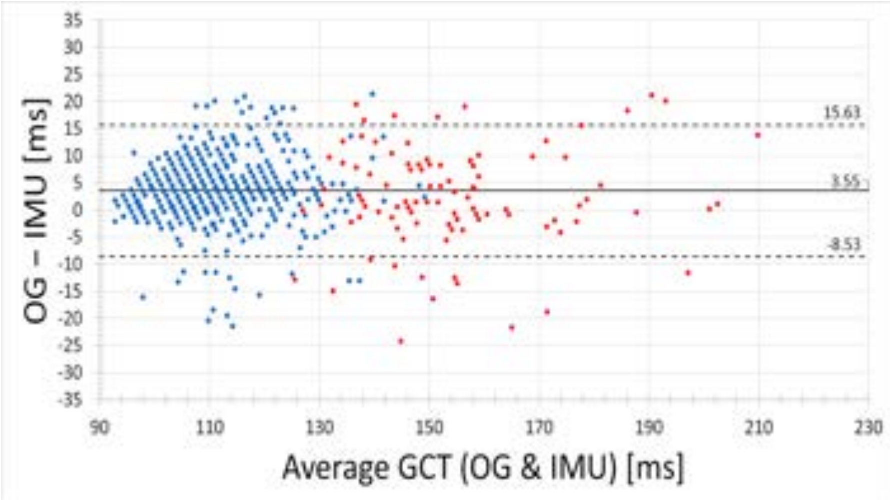

Figure 3. Bland-Altman-Plot of IMU- and Optogait (OG) measured ground contact time (GCT). Dashed lines show Limits of Agreement ($2 * SD$): −8.53 ms and 15.63 ms, the dotted line the mean: 3.55 ms. Red data points represent steps 1–5 at the beginning of the sprint. Blue-colored dots indicate all other steps (i.e., step 6–50).

Figure 4 shows the average step-wise measured GCT with Optogait (blue) and IMUs (red).

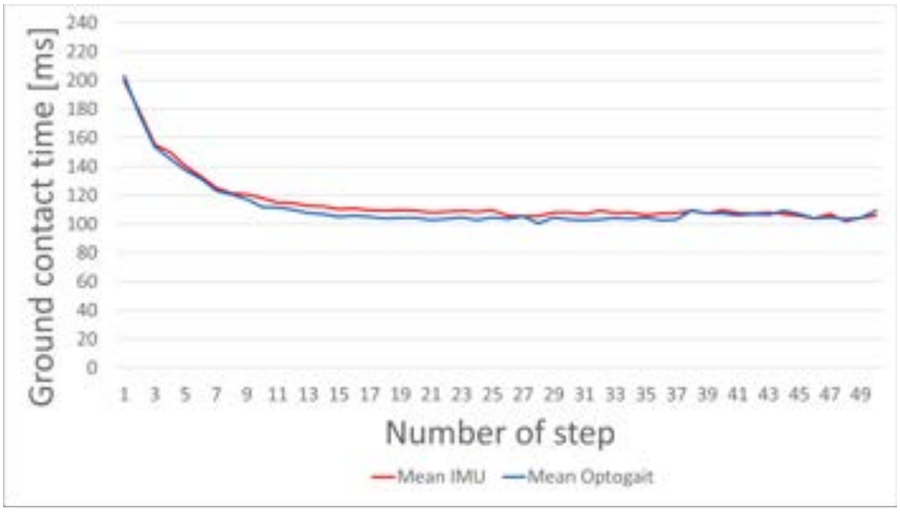

Figure 4. Average GCT of Optogait (blue) and IMU (red) measurements. Only these steps are included, which at least two different athletes performed. All measured data points are summarized to one value for the respective step in the sprint.

Table 1 shows the distribution of GCT throughout step ranges of five and ten steps. The measured mean and absolute percentage deviation to the reference system in the respective step range is displayed. Steps 6–46 show a constant deviation in the range from 3% to 6%. The first five steps indicate a lower relative difference (1.17%). The absolute values are in the range above. For the last five steps, a lower relative (0.22%), as well as absolute (2.13%) deviation is found.

Table 1. Mean IMU measured ground contact time (GCT), and its relative and absolute percentage deviation to the reference system for various step ranges of all 100-m sprints. The first and last intervals are summarized into five steps. All other intervals combine ten steps. The last five steps showed the lowest percentage difference.

Step	GCT ± SD	% Diff ± SD	Absolute % Diff ± SD
ine 1–5	163.45	1.17%	4.33%
	24.73	1.77%	0.36%
ine 6–15	118.43	3.28%	4.61%
	9.45	1.52%	0.78%
ine 16–25	109.32	4.28%	4.98%
	6.40	0.52%	0.69%
ine 26–35	107.12	5.14%	5.72%
	9.12	2.18%	1.27%
ine 36–45	107.86	4.24%	5.86%
	9.01	2.27%	1.13%
ine 46–50	104.80	0.22%	2.13%
	6.71	1.26%	1.11%

3.2. Results on GCT

The following result section illustrates the IMU-detected GCT of exemplary single runs. The first graph visualizes the reliability of the measured GCT by showing two runs of the same athlete. The following graph emphasizes the application of this method, comparing GCT from single runs of athletes from different genders.

Figure 5 shows two separate sprints of the same athlete. Chronologically, blue represents the first and red the second sprint. The difference between the GCT of both runs is on average 0.48 ms per step For steps 1–5, an average decrease of 27.36% in both runs can be seen.

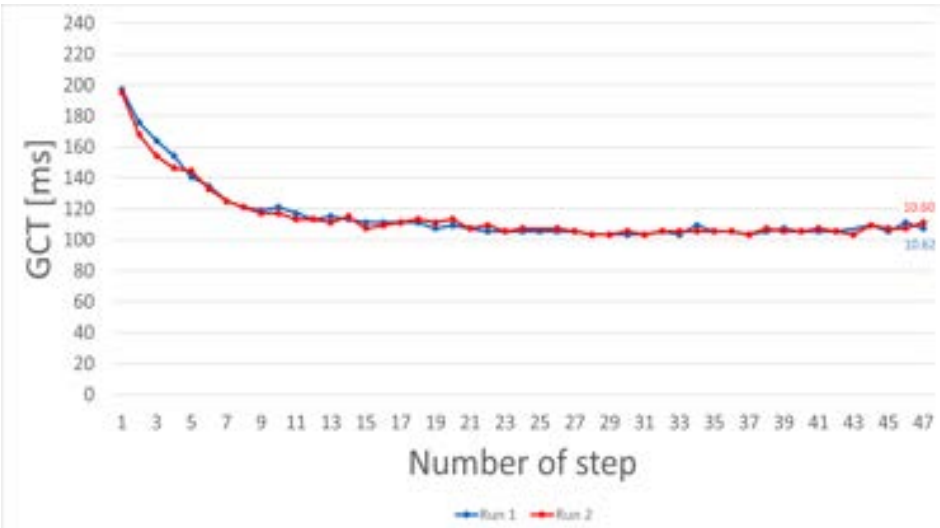

Figure 5. IMU-measured GCT of two 100 m sprints of the same athlete. Run 1 (blue) was conducted approximately 30 min before Run 2 (red). The graph illustrates reliable intra-subject results.

An exemplary comparison of GCTs of a female and a male sprinter is given in Figure 6. These two individual runs were chosen to illustrate the possibilities of this method. Each ground contact is represented by a dot on the respective line. The time between the last and the first step of this 100-m dash was 10.66 s for the male and 11.12 s for the female sprinter. The number of steps altered with 50 steps for the female athlete and 47 for the male athlete. No gender dependent differences occur in the top speed phase of the run.

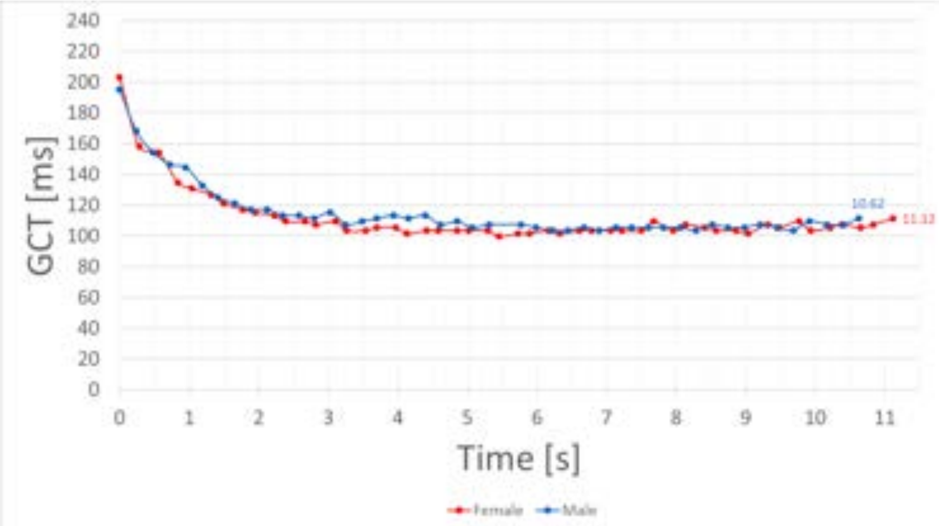

Figure 6. IMU-measured GCT of a female (red) and a male (blue) sprinter over 100 m. The marked dots on each line represent ground contacts. The connecting line between the dots is added for better visual separation. The time of the last contact represents the total period between the first and the last step of the respective sprint.

4. Discussion

The current study was conducted to explore and prove the benefits of sensor-based running parameters in top-level sports.

4.1. Discussion of Methods

The detection of gait events from sensor data progressed in recent years. Various sensor outputs can be used to extract time points of interest. In addition, the procedure during data processing also plays a decisive role in the development. This study does not claim to extract the most precise or correct signals or features to estimate IC and TC. In other proposed methods, specific components of the accelerometer and gyroscope are tested for detection and applied to running signals [13,22]. Schmidt and colleagues used minima in an acceleration component of one direction to detect IC and TC. Falbriard et al. identified several different time points for IC and TC as possible ground contact indicators. They found a combination of acceleration and angular velocity as promising by comparing these time points to the detection of a force plate as the criterion reference system.

Especially for validation purposes, the study design should focus on an appropriate criterion measurement system. The criterion measurement system in the current study, Optogait, is a commonly accepted method for ground truth data acquisition [7,13]. The recent study's setup—including the alternation of the 50-m corridor—was also used in other studies [7]. Additionally, the time-synchronization of all systems could improve the insights during the algorithm development. Although the burst in the accelerometer at IC was used to synchronize the events a posteriori by minimizing the least square errors of the first IC, it is possible to circumvent this error source with a technical synchronization. Hence, this time-synchronization would allow for a more accurate assessment of the IC and TC detection.

The results for GCT in Figure 6 are exemplary and must be further compared to inter- and intra-subject results. Additionally, more incorrectly detected steps occurred during the first five (6.47%) and last five (13.33%) steps. Therefore, improvements to the used algorithm should be achieved, especially since the methodology of pattern detection from IMU signals has been a fast developing topic in recent years; for example, the early steps of a sprint (see Figure 3) show greater discrepancies.

A relatively small sample was chosen for this study to represent high-level sprinters from different gender, age, weight, height, and other variations. However, it cannot be assumed to have covered all discrepancies within this population. Therefore, no conclusions about general differences can be drawn within this small sample size. For further quantification of elite sprint performances, a broader data basis should be established while considering that the evaluation of individual athletes should also be supported. With the increasing usage of IMU sensors in recent commercial products, future studies can also account for combining further sensory data to a more holistic acquisition of running parameters of professional athletes.

4.2. Discussion of Results

The basic aim of a run analysis with IMUs should include the correct detection of sprint steps. The results on correct step detection can hint towards the algorithm validity. This study showed a detection rate of 97.1%. All false detected steps were missed real steps, corresponding to false positive detections. 80.8% of these detection errors occurred within in the first and last five steps of the respective sprint. This could be explained by the different coordination patterns at the beginning and end of the sprint which lead to unstable waveforms and ultimately false positives. To the best knowledge of the authors, the detection rate is only explicitly stated in one other study. Schmidt et al. reported the correct detection of 95.7% [13]. Thus, the proposed method showed results that are in line or even better.

Figures 3 and 4 show the distribution of measurement errors for each step of the sprint. The mean overestimation of 3.55 ms of IMU-based GCT detection compared to Optogait hints towards a systematic bias (Figure 3). As Falbriard et al. stated, correcting the GCT values based on previous results may help to achieve more precise results [22]. However, Figure 4 illustrates low deviations at the beginning and end of the sprints. This can also be seen in Table 1. The lower deviations of step range 1–5 and 45–50 indicate that an adaptive GCT recognition could be helpful. The first five steps occur especially important, as big relative changes can be observed in this time span (Figure 5. These indications need to be considered in a potential correction procedure.

The limits of agreement in the Bland-Altmann analyses of −9.28 ms and 16.14 ms (see Figure 3) appear to be relatively high compared to another study with a similar reference system, which stated lower bounds [13]. Besides a different detection of ground contact events, a possible reason could be the shorter contact time of elite sprinters who participated in this study. Also, a different running style of the individual participant could make a crucial impact because of the small sample size.

In Figures 5 and 6, individual runs are shown for application purposes. The temporal resolution of GCT enables the visualization of minor differences during a single run. The illustration of a female and a male sprinter in Figure 6 does not support a general gender comparison. However, as the tested sample performs on a high level and therefore experience individual improvements in running economy, the use case can show possibilities of individual analysis with IMU data. This representation of results does not contribute to the validity measurement or quantification of the tested population. In the individual analysis and comparison of these single runs, we can see indicators for running asymmetries (e.g., Figure 5—steps 43–47). As these asymmetries lie within the detected measurement error, the pure indication of IMU signals can not solely be referenced. This analysis can more easily be transferred to competition, as no counterparty or athletes are distracted by wearing such light and small sensors.

5. Conclusions

The step detection rate with the IMU data showed high reliability, whereas the deviation of the measured GCT depends on the section of the run. The early and late stages of the sprints tended to have lower deviations between IMU and Optogait measured GCT. These findings point out additional technical difficulties, such as problems of the algorithm. In total, the results encourage the field use of IMUs as a potential method for step detection and measurement of GCT in high-level sprints. This analysis can help to enhance our knowledge about performance on the highest levels. The findings of this study encourage the implementation of IMU-based measurements in high-level sprint competitions.

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Informed Consent Statement: Written informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available in the article.

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Abbreviations

The following abbreviations are used in this manuscript:

GCT	Ground contact time
IMU	Inertial measurement unit
GPS	Global positioning system
LPS	Local positioning system
VMU	Vector magnitude unit
IC	Initial contact
TC	Terminal contact
RMSE	Root mean squar error
SD	Standard deviation

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4.3 A Pilot Study in Sensor Instrumented Training (SIT) - Ground Contact Time for Monitoring Fatigue and Curve Running Technique

Bibliographic Facts

The third study within this dissertation, titled "A Pilot Study in Sensor Instrumented Training (SIT) - Ground Contact Time for Monitoring Fatigue and Curve Running Technique" is authored by the research team including Blauberger, P., Fukushima, T., Russomanno, T.G. & Lames, M., and was published in June 2024 (Blauberger et al., 2024). The paper was printed in the International Journal of Computer Science in Sport (IJCSS). It must be mentioned that this study was published online only a short time before the writing of this dissertation. Therefore, most bibliographic information cannot be stated.

Content

This study examines the utility of SIT in dissecting the nuances of mid-distance running, focusing on the variations of GCT during different running conditions and its potential as a fatigue indicator. Employing IMUs attached to the athletes' feet and using the developed methodology of the previous study, the GCT variations between straight and curved running across two training protocols were analyzed (Figure 4.3). Additionally, GPS sensors were used for location and speed tracking.

The results of the study include the observable GCT variation between the inner and outer feet during curve running, challenging some prevalent assumptions about curve running dynamics. Additionally, a pattern correlating GCT and speed with fatigue offers a new perspective to analyze athlete performance over training sessions. These results align with previous research on foot behavior during curve running and contribute to our understanding of training session dynamics.

By integrating advanced sensor technology, this study underscores the effectiveness of SIT in enhancing our grasp of running kinematics, particularly in the context of mid-distance running. The practical applications of these findings are vast, promising coaches and athletes a data-rich perspective on refining curve running techniques and optimizing training strategies. This research stands as a testament to the potential of sensor technology in elevating our understanding and approach to sports training, paving the way for more targeted and effective training methodologies in the future.

Contribution of the Main Author

P.B. is the main author of the study, collaborating closely with Takashi Fukushima (T.F.), Tiago Russomanno (T.R.) and M.L.. P.B. developed the methodology, working alongside all co-authors. P.B.'s responsibilities extended to software development, validation, formal analysis, and data curation, representing the execution and analytical phases of the research.

In addition to these technical contributions, P.B. led the drafting of the research manuscript and the visualization aspects of the study. While M.L. oversaw the project through supervision and administration, T.F. and T.R. contributed during data gathering. All authors agreed with the final version of the manuscript.

Figure 4.3 Running measurements in curved runs. IMU-sensors were attached to the athlete's feet.

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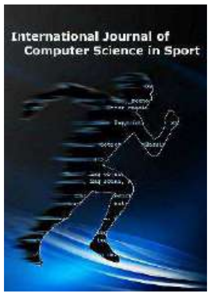

A Pilot Study in Sensor Instrumented Training (SIT) - Ground Contact Time for Monitoring Fatigue and Curve Running Technique

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Abstract

This study examines the possibilities of sensor-instrumented training (SIT) in mid-distance running training sessions. Within this framework, variations of ground contact time (GCT) between straight and curved running, as well as GCT as a fatigue indicator, are explored. Seven experienced runners, with two elite female athletes, participated in two training protocols: 15 sets of 400 m with 1-minute rest and five sets of 300 m with 3-minute rest. GCT was calculated using two inertial measurement units (IMU) attached to the athletes' feet. The running speed of all athletes was measured with wearable GPS devices. GCT showed variations between inner and outer feet, notably during curve running (300m: 2.56%; 400m: 2.35%). However, for the 300m runs, statistically insignificant GCT differences were more pronounced in straight runs (3.54%) than in curve runs (2.56%), contrasting with the typical assumption of higher differences in curve running. A fatigue-indicating pattern is visible in GCT, as well as speed curves. Other data of this study are consistent with prior research that has observed differences between the inner and outer foot during curve running, while our understanding of the development throughout the training session is enhanced. Using SIT can be a valuable tool for refining curve running technique. By incorporating novel sensing technology, the possibilities enhance our understanding of running kinematics and offer an excellent application of SIT in sports.

KEYWORDS: PERFORMANCE ANALYSIS, TRAINING CONTROL, SENSORS, CURVE RUNNING, GROUND CONTACT TIME

Introduction

Sports disciplines like mid-distance running, characterized by demanding speed and endurance, are predominantly staged on oval tracks with varying distances. Achieving peak performance in these disciplines necessitates athletes to undergo specialized training regimens, including a spectrum of different training protocols. Different running parameters can be measured throughout these training sessions and come under assessment.

For instance, ground contact time (GCT) is one important factor affecting a runner's performance and running economy (Joubert, Guerra, Jones, Knowles, & Piper, 2020; Mooses et al., 2021). GCT is the time a runner's foot spends in contact with the ground during each stride. A shorter ground contact time (GCT) is linked to swifter acceleration and exerts a positive impact on running economy, whereas a longer GCT can result in delayed finishing times and reduced force production (Lockie, Murphy, Schultz, Jeffriess, & Callaghan, 2013; Weyand, Sternlight, Bellizzi, & Wright, 2000). Research on mid-distance running has primarily focused on competition or race conditions (Renfree, Mytton, Skorski, & St Clair Gibson, 2014), with little attention given to GCT, especially during training. Inertial measurement units (IMU) application and appropriate data processing can monitor entire training sessions (Falbriard, Mohr, & Aminian, 2020; Schmidt et al., 2016). Understanding GCT during training is essential, as it can provide insight into a runner's technique. Generally, implementing feedback from measurements is essential within training control (Hohmann, Lames, Letzelter, & Pfeiffer, 2020). Furthermore, the effects of running on different track sections, such as straight and curved passages, on GCT during training have not been thoroughly investigated. Running on curved surfaces requires greater changes in direction and may lead to differences in GCT between feet compared to straight running (Alt, Heinrich, Funken, & Potthast, 2015; Churchill, Salo, & Trewartha, 2015).

Another aspect of training control is fatigue. It represents a multi-factorial phenomenon that impacts an athlete's performance capacity (Halson, 2014). Assessment of fatigue is crucial for optimizing training regimens and preventing injuries. One approach to assessing fatigue involves the study of stretch-shortening cycles within muscle contractions. Here, the muscle undergoes rapid transitions between eccentric and concentric phases, like, for example, within a ground contact in running, sprinting or jumping (Hennessy & Kilty, 2001). GCT has been proven a valuable parameter in this context for controlling fatigue in running, although mostly in lab settings (Apte et al., 2021). By monitoring GCT, coaches and sports scientists might gain insights into an athlete's fatigue status and make informed in-training decisions regarding training intensity, ultimately improving athletic performance and reducing the risk of injuries.

This example highlights that different variables need to be monitored to support training control (Fernandes, Garganta, & Anguera, 2012). The concept of ubiquitous computing in sports brings the integration of small, interconnected, and intelligent tools, particularly sensor technologies like IMUs and GPS sensors, within the pervasive computing paradigm (Baca, Dabnichki, Hu, Kornfeind, & Exel, 2022). These sensors, usually integrated into wearable devices, facilitate real-time data acquisition and analysis, enabling athletes and practitioners to integrate objective information. Especially over the past years, this field saw remarkable advancements driven by the convergence of wearable technology, cloud computing, and artificial intelligence.

IMUs, for instance, enable precise motion tracking, while GPS sensors provide geospatial data critical for performance assessment. This study mainly focuses on implementing IMU-measured data while additionally consulting GPS-measured data at specific sections and not analyzing it holistically. These innovations have impacted the landscape of sports analysis, offering the potential to capture data under field conditions. Numerous applications of these sensor-driven measurements can be found across a wide range of sports. In the following, we refer to this as sensor instrumented training (SIT). The current limitations in data acquisition, processing practices, and sensor functionalities, which hinder data-driven decision-making in the present technological and scientific context, must be acknowledged.

This study aims to explore the potential of conducting SIT in sports. Exemplary looking at GCT in curve running and indicators of fatigue within intensive and extensive running training sessions. While developing an entirely sophisticated solution is not the immediate goal, the feasibility and practicality of training control with SIT are shown.

Methods

Sample and protocol

The sample consists of seven experienced runners (age: 25.0 ± 3.2 years; weight: 61.7 ± 7.0 kg; height: 175.3 ± 10.1 cm; gender: 4f/3m). The data comprises five training sessions, with one participant completing both training protocols on different days. In order to cover a broad spectrum of practical training methods, one protocol each for the intensive and the extensive interval method (Hohmann et al., 2020) was included. During the different training protocols (extensive: 15*400 m, 1 min rest; n=4; intensive: 5*300 m, 3 min rest; n=4), GCT was measured using two sets of two IMUs (Physilog5 & Physilog6, Gait Up SA. Lausanne, Switzerland; Physilog5, size: 47.5 mm x 26.5 mm x 10 mm, weight: 11 g & Physilog6, size: 42.2 mm x 31.6 mm x 15.0 mm, weight: 15 g; Figure 1) each at the athletes' feet (Blauberger, Horsch, & Lames, 2021). The coach set the threshold based on individual training experiences regarding the intended running speed. The training protocol can be overviewed in Table 1. One athlete had to skip the final run within the intensive training protocol. The analysis included two female athletes who competed at the highest international level (WC/EC; official 800 m best times of 1:59.41 min and 2:00.36 min). Additionally, all athletes were equipped with GPS sensors (transponder (GPSports Sports Performance Indicator (SPI) Pro X, Canberra, Australia); Figure 1).

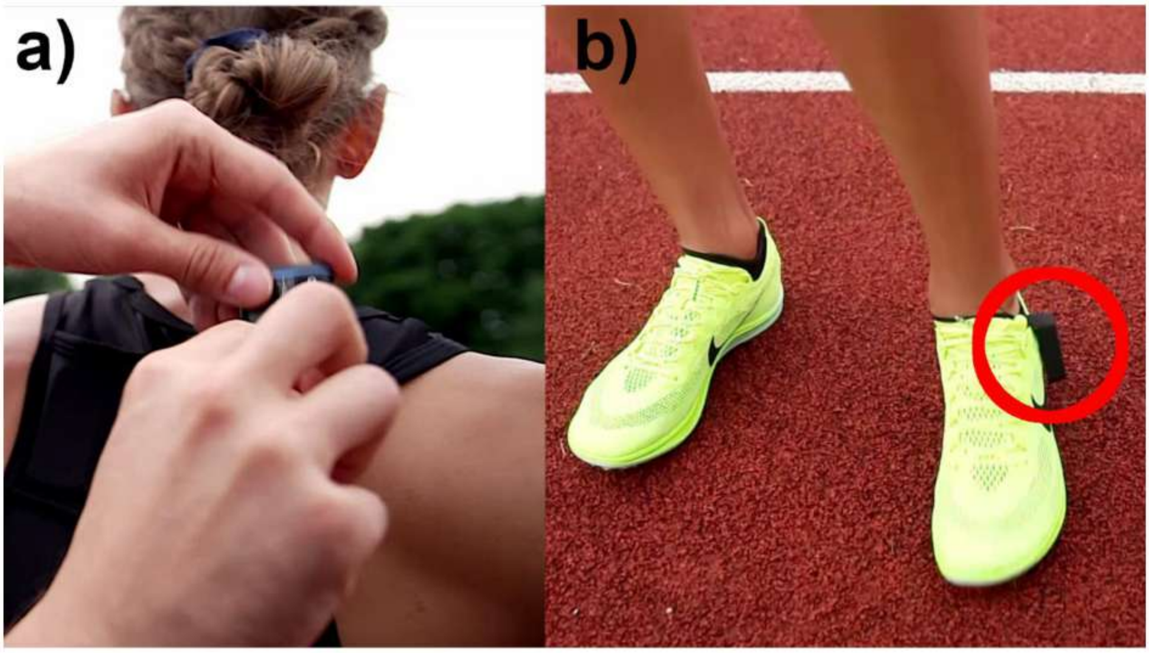

Figure 1: GPS receiver attachment location (a) and IMU sensor attachment location at both shoes (b).

The training was performed on an official running track (World Athletics, 2019) in five training sessions. Before each training session, the participating athletes were informed about the purpose of the study and the collected data. The study accorded to the ethical standards of the Technical University of Munich, and all subjects gave informed written consent. Additionally, all personal data were anonymized to ensure privacy. The study design corresponded to the recommendations of the Declaration of Helsinki.

Table 1: Description of running protocol and analyzed steps per athlete and run.

	300m	400m
Number of runs	5	15
Rest [min]	3	1
Number of athletes	4	4
Steps in curve per athlete per run	5	5
Steps on straight per athlete per run	5	5
Total steps in curve per run	20	75
Total steps on straight per run	20	75

Measurement systems

The IMUs were securely attached to the side of each running shoe. This methodology was chosen for its ease of application, lightweight design, and minimal impact on athletes' performance. The positioning of the IMUs on the ankle was also used in a previous validation study (Blauberger et al., 2021) to ensure data comparability. Athletes who participated in the study reported no issues with the sensor attachment. Each IMU includes a 3D accelerometer and a 3D gyroscope, both operating at a sampling frequency of 512 Hz. The accelerometer has a range of ±16 g, while the gyroscope has a range of ±2000°/s.

Additionally, the athletes were equipped with a GPS. The transponder was positioned on the upper thoracic spine, between the scapulae. All GPS transponders were activated 15 minutes before data collection for proper satellite signal acquisition. Only GPS signals that met the manufacturer's internal quality standards were recorded (Shergill, Twist, & Highton, 2021).

Data processing and analysis

The raw signals of the IMUs' accelerometer and gyroscope were used to find the step event of initial contact and toe-off. Therefore, data was filtered and analyzed using a previously developed and validated methodology (Blauberger et al., 2021). Each resulting ground contact can be associated with the precise event time relative to the start of the run. GCT was assessed using the average GCT of the five steps closest to the middle of the first curve and one linear running corridor. The total step counts per curve and straight section can be seen in Table 1. All total run values comprise all steps of the whole run. Additionally, GPS data enabled continuous measurement of speed and covered distance.

All values, tables, and graphs were developed using Matlab (R2022a, The MathWorks Inc., Natick, MA, USA). For the figures, data was filtered using a 4th-order Butterworth low-pass filter with a cut-off frequency of 1 Hz. Percentage differences were calculated as the percentage deviation of the former value. To compare GCT between the left and right foot during entire runs, we first assessed the normality of the data using the Shapiro-Wilk test. Depending on these results, a paired t-test (for normally distributed data) or Wilcoxon signed-rank test (for non-normally distributed data) was employed to display statistical differences in GCT values. The level of significance was set to $p<0.05$. Cohen's d effect sizes (ES) were classified as trivial (0-0.19), small (0.20-0.49), medium (0.50-0.79) and large (>0.80) (Cohen, 1992).

Results

The first result section includes GCT results on all 300 m and 400 m runs, emphasizing curve running. In the second part, results are shown for indications of fatigue with exemplary looking into the data of an elite athlete's training session. This athlete's runs are particularly interesting, as the coach signalled the athlete after the first run that the intensity was slightly too high to complete the planned training. This feedback arose only from the coach's "gut feeling" and the measurement of the final time.

Results on curve running

For the 300 m runs, a total difference of 1.44% between the inner and outer foot was found. This difference is not significant ($p = 0.35$) and shows a trivial ES (0.19). The mean contact time during straight sections (143.87 ms) was lower than in curve sections without statistical signifance (149.78 ms; $p = 0.18$; ES = 0.32). Also, the percentual disbalance was higher in straight sections than in curve sections. The overall mean GCT increased insignificantly but with a high ES ($p = 0.25$; ES = 4.74) from 140.57 ms (run 1) to 156.00 ms (run 5). Although the absolute GCT was longer, the difference between the feet did not show an increase. The progress within the training can be seen by showing run 1, run 3, and run 5 (Table 2). It needs to be emphasized, that none of the differences in Table 2 showed statistical significance.

Table 2: Mean IMU measured ground contact time (GCT) ± standard deviation in milliseconds and the percentage difference between inner and outer foot in 300 m runs. The total run aggregates the GCT of all steps. P-values are presented as $^{-}$ ($p > 0.05$) and * ($p < 0.05$). Cohen's d effect sizes were classified as ^{t} = trivial (0-0.19), ^{s} = small (0.20-0.49), ^{m} = medium (0.50-0.79) and ^{l} = large (>0.80). Both indicators are superscripted after the percentage difference value. No statistical significant differences were found.

		All runs	Run 1	Run 3	Run 5
Total run	Inner foot [ms]	146.46±7.97	139.04±7.39	146.83±6.28	152.21±9.97
	Outer foot [ms]	148.57±13.12	142.10±12.90	147.57±15.23	159.78±8.16
	Difference [%]	1.44^{-t}	2.20^{-s}	0.51^{-t}	4.97^{-l}
Curve section	Inner foot [ms]	151.72±9.69	141.70±7.02	155.08±10.46	158.33±11.59
	Outer foot [ms]	147.84±12.08	141.11±14.09	146.09±11.12	155.47±5.83
	Difference [%]	2.56^{-s}	0.41^{-t}	5.79^{-m}	1.81^{-s}
Straight section	Inner foot [ms]	141.37±9.14	134.77±9.74	144.43±7.39	146.52±9.43
	Outer foot [ms]	146.37±12.35	141.36±11.95	148.14±15.76	156.38±7.82
	Difference [%]	3.54^{-s}	4.89^{-s}	2.57^{-t}	6.73^{-l}

Overall, the GCT for 400 m runs revealed a deviation of 1.31% ($p = 0.01$; ES = 0.36) between the inner and outer foot. By separating the 15 runs into three equal groups, development within the training session can be tracked. The discrepancy of GCT between feet is smaller in the straight part of the runs than in the respective curved section. While the deviation between the inner and outer foot in curve running rose, the absolute GCT remained at the same level (Table

3). Out of 12 reported deviations in Table 3, four showed statistical significance.

Table 3: Mean IMU measured ground contact time (GCT) ± standard deviation in milliseconds and percentage deviation between inner and outer foot in 400 m runs. The total run aggregates the GCT of all steps. P-values are presented as $^{-}$ ($p > 0.05$) and * ($p < 0.05$). Cohen's d effect sizes were classified as ^{t} = trivial (0-0.19), ^{s} = small (0.20-0.49), ^{m} = medium (0.50-0.79) and ^{l} = large (>0.80). Both indicators are superscripted after the percentage difference value.

		All runs	Run 1-5	Run 6-10	Run 11-15
Total run	Inner foot [ms]	190.79±15.39	189.50±17.98	193.62±14.48	189.12±14.17
	Outer foot [ms]	188.30±12.85	186.59±16.71	192.28±6.72	185.84±13.26
	Difference [%]	1.31^{*s}	1.53^{-m}	0.69^{-t}	1.73^{*m}
Curve section	Inner foot [ms]	192.48±16.25	189.06±19.86	195.79±15.14	192.06±14.06
	Outer foot [ms]	187.95±14.76	184.88±19.92	192.95±7.06	185.54±14.84
	Difference [%]	2.35^{*s}	2.21^{-s}	1.45^{-s}	3.39^{*s}
Straight section	Inner foot [ms]	189.71±15.70	187.47±19.45	193.02±13.78	188.06±14.73
	Outer foot [ms]	188.37±14.85	186.73±17.67	192.47±8.11	185.44±17.29
	Difference [%]	0.71^{-s}	0.40^{-s}	0.29^{-t}	1.39^{-s}

Figure 2 illustrates the GCT of the inner and outer feet in 300 m and 400 m runs during straight and curve running. The inner foot's GCT was always more prolonged in the curve than during straight running. However, the outer foot's contact time did not differ substantially during straight and curve running.

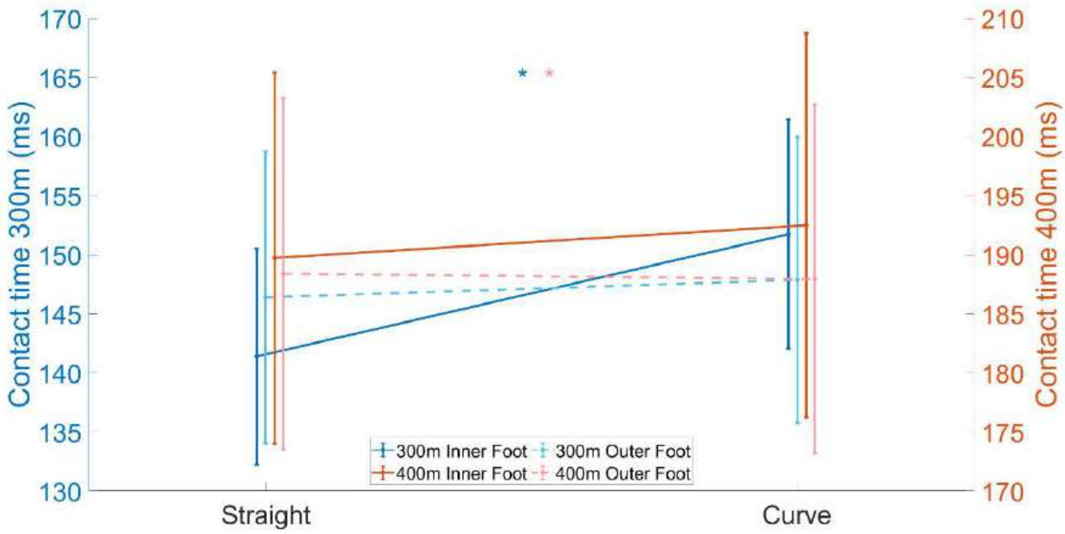

Figure 2: Mean IMU measured ground contact time (GCT) in milliseconds between straight and curve running for the inner and outer foot in 300 m and 400 m runs with standard deviations. Statistical significance ($p > 0.05$) is indicated with * in the respective colour.

Figure 3 displays the continuous development of the GCT in 300 m runs. The first part (a) presents the smoothed average GCT of both feet, while section (b) illustrates the GCT of the left and right foot individually. This exemplary figure indicates the influence of curve running on GCT. The running times are normalized, and display all runs' average times.

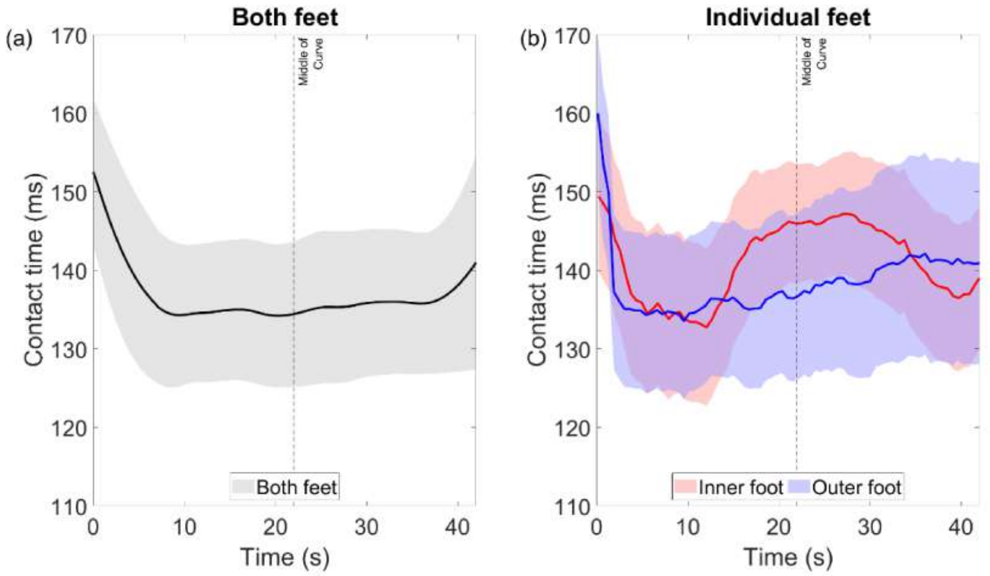

Figure 3: Illustration of ground contact time (GCT) across a 300 m distance run within an intensive training session. Plot (a) displays the smoothed average of the GCT for both feet, while the subsequent plot (b) presents the GCT of each foot separately. Both plots show the respective continuous standard deviations in transparent colour. A pattern concerning the laterality of the foot can be linked to running on the curved sections of the track.

Results on fatigue

To visualize results regarding fatigue during training, the data of one elite athlete is shown in detail. Figure 4 illustrates the GPS-recorded continuous speed during five 300 m runs within the same training. The blue and red lines are highlighted to underline the development between the first and second runs. The "too fast first run" found by the coach can be seen in the GPS data.

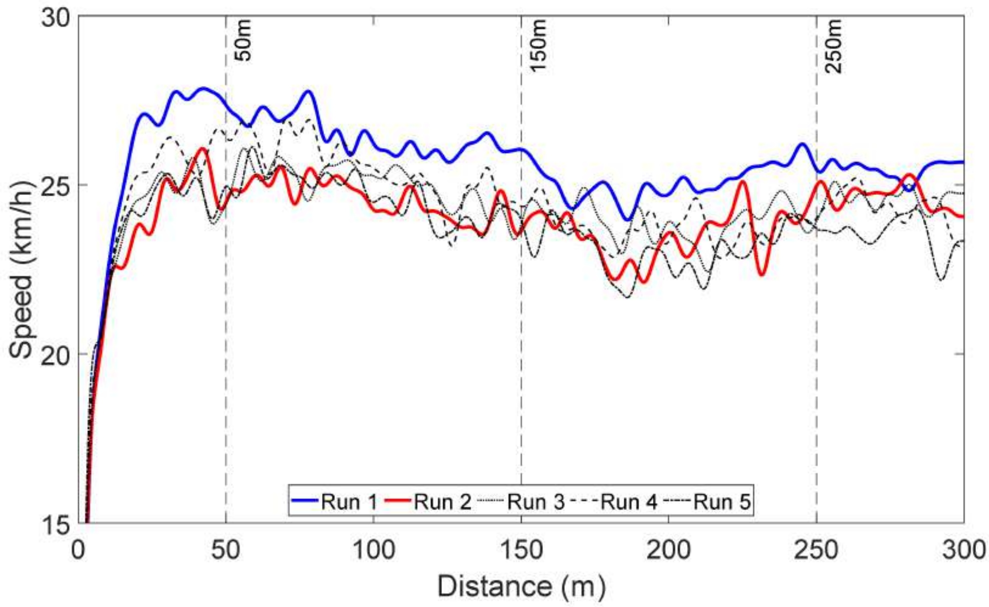

Figure 4: GPS-tracked speed, plotted over the distance of 300 m. The two bold lines (Run 1 & Run 2) show the athlete's fast start, leading to higher exhaustion than intended and needing to be controlled by the coach. After this intervention, the speed stayed at a comparable level.

In Figure 5, we revisit the training runs of the same athlete, this time focusing on the evolution of GCT. Notably, a major increase in GCT from the first to the second run indicates a change in running mechanics. This growth suggests that the athlete, likely prompted by the coach's intervention regarding their pacing strategy (as observed in Figure 4), adjusted their technique during the subsequent runs. Complementary to the GPS data, it can be distinguished between different step numbers. The first five steps are skipped in the graph to avoid the error-proneness of the methodology close to the start (Blauberger et al., 2021).

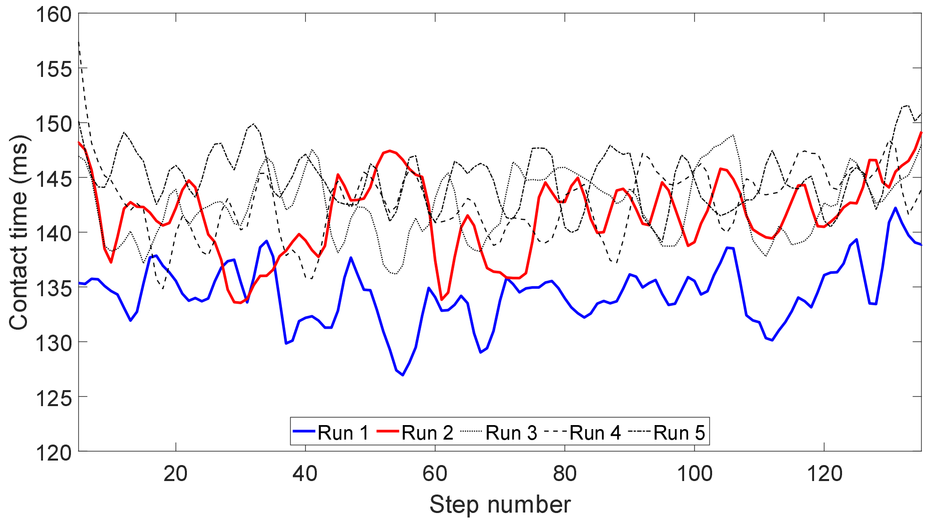

Figure 5: Mean ground contact time (GCT) of the same athlete within five 300 m runs. This data suggests a too-high intensity in the first run, which led to an intervention by the coach.

Discussion

Discussion of results

The results of this study, while indicative of specific trends, notably underscore the individuality in performance and response to training. Each athlete's data presents a unique profile, reflecting the interplay of physiological, biomechanical, and environmental factors. Although this individual variability limits the generalizability of our findings, it is crucial in demonstrating the potential and applicability of SIT. Especially, the statistical non-significance of many findings needs to be highlighted. Consequently, while the results may not provide an universal blueprint applicable to all athletes, they are showcasing the role of SIT for the application tailored training interventions. When customized to the individualities of each athlete, these interventions can enhance training outcomes. Thus, although our results are not broadly generalizable, they offer compelling evidence of the efficacy of SIT in a high-performance sports context, underscoring its utility in optimizing training strategies on an individual level.

The statistical results observed in our study should be interpreted with care. Table 2 shows no significant differences at all, while only 4 out of 12 comparisons in Table 3 show significant deviations. Therefore, also effect sizes are reported alongside p-values. Effect sizes offer a deeper insight into the substantive significance of our findings, revealing the magnitude of observed differences or relationships that do not state statistical significance, which might be harder to achieve in this study with a small sample size (Sullivan & Feinn, 2012). While interpreting the statistical outcomes of our study, it is crucial to note that even large effect sizes may not result in statistical significance, underscoring the importance of cautious interpretation, especially in the context of a small sample size.The results show that continuous step-by-step monitoring of the GCT of both feet provides valuable insights into the technique of curve running. Differences between the inner and outer foot in curve running (Figure 2) confirm previous findings in the literature based on an 8 m running corridor in the curve (Alt et al., 2015). To the best of the authors' knowledge, the increasing percentage differences throughout interval training were not reported before.

Moreover, the results show that continuous step-by-step monitoring of the GCT of both feet provides valuable insights into the technique of curve running. This study's training protocols are used commonly in practice (Fernandes et al., 2012) and, therefore, for training and competition analysis at the highest level. The 300 m runs of elite athletes show the necessity of assessing GCT continuously and for both feet separately. It is illustrated that inner and outer feet should be treated individually, showing different patterns (Figure 3).

However, an interesting finding emerged in our analysis of the 300m runs that diverged from common assumptions regarding GCT differences between legs in curved versus straight sections. Table 2 indicates that the observed differences in GCT were more pronounced during the straight sections (mean difference = 3.5%) compared to the curve sections (mean difference = 2.6%). This suggests that factors other than mere directional changes might contribute to GCT variations. This data thus highlights the complexity of GCT dynamics and underscores the importance of considering individual training developments.

In the scope of the discussion of the observed pattern, it is essential to note that while the data presented in Figure 3, 4 & 5 belongs to one elite athlete, similar trends were noticed among the other participants, including both elite and non-elite athletes. This underlines the value of SIT in capturing individual data. It also aligns with our emphasis on the individuality of results, illustrating that while our findings are demonstrative of the effectiveness of SIT, they also highlight the need for personalized training approaches for each athlete. This individual perspective remains central to our discussion and the broader applicability of our study.

The data shown in Figure 4 provides an in-depth look at the speed patterns of one elite athlete during a series of 300-meter runs, offering valuable information about their performance and how they manage fatigue. This figure highlights a notable trend, specifically a "too fast start," which occurs when the athlete begins their training session at a pace that is too quick to maintain throughout the exercise. Essentially, the athlete starts much faster than they can sustain, leading to potential early exhaustion. This pattern is crucial for coaches to observe. It demonstrates the athlete's tendency to exert too much effort too quickly, which can be counterproductive in training and competitive environments. By identifying this development, coaches can provide immediate feedback to the athlete, advising them to adjust their pacing. This might involve starting at a more controlled, sustainable speed, allowing the athlete to conserve energy and maintain a steadier pace throughout the run.

In Figure 5, we revisit the running performance of the same elite athlete, looking into the progression of GCT during the training session. Notably, this athlete's GCT data provides insights into the impact of training intensity and fatigue. The graph shows a visible increase in GCT when transitioning from the first run to the second run. This shift indicates a substantial alteration in running mechanics, potentially driven by the initial high-intensity effort in the first run. It is worth noting that this abrupt change in GCT could result from both the athlete's conscious adjustments and the body's natural adaptation to the running demands. Complementary to the GPS data (Figure 4), it can be distinguished between different step numbers. In combination, exact distances within the run can be associated with ground contacts. Observing such nuanced alterations in GCT underscores its value as a parameter for assessing fatigue and real-time technique modifications during training, emphasizing the crucial role of GCT monitoring in optimizing athletic performance.

Discussion of methodology

The methodology used in this study employed a combination of data collection techniques, including GCT measurements using inertial sensors and GPS data analysis. In other studies, these methods were already utilized to investigate the running characteristics of mid-distance runners during training.

The sample consists of seven experienced runners, focusing on one female athlete who competed at the highest international level (e.g., winning national championships). This selection ensures the inclusion of highly skilled athletes and provides valuable insights into the running characteristics of elite runners. P-values and effect sizes from pilot studies like this can help guiding the design of future studies, particularly in determining the necessary sample sizes to detect meaningful effects . By understanding the magnitude of the effects observed in a pilot study, researchers can more accurately estimate the sample size required for subsequent studies to ensure adequate statistical power.

Specific steps from each run were selected for evaluation. For the 300m runs, 20 steps from each curve and linear section were analyzed, amounting to 100 steps to the final assessment. Similarly, in the 400m runs, 20 steps per curve and linear section were examined, adding to 1125 steps across all runs. For the total run, every detected step was used. This methodological approach allowed for capturing the variations in GCT in different running sections. Another methodological procedure could have ended in slightly different results.

GCT is measured using four IMUs attached to the athletes' feet. This method is relatively new (Falbriard et al., 2020; Schmidt et al., 2016). The accuracy of GCT measurements using IMUs was previously tested and documented in another manuscript. Also, the positioning of the IMUs on the foot ankle follows this study's procedure to ensure consistency and comparability of the collected data (Blauberger et al., 2021).

To complement the GCT analysis, GPS transponders were utilized. These transponders were placed on the upper thoracic spine, between the scapulae, to capture and analyze the athletes' movement and speed during the training sessions. The GPS transponders were activated well before data collection to allow for satellite signal acquisition and ensure the quality of the recorded GPS data. Nevertheless, a margin of error can be found with this kind of tracking device, especially at higher speeds and curve running (Linke, Link, & Lames, 2018).

The collected data, GCT from the IMUs and GPS speed measurements are analyzed using appropriate statistical methods. The mean values and patterns of GCT for the inner and outer foot are examined, mainly focusing on the influence of running on the curved section of the track. The GPS speed measurements provide insights into the athletes' performance and allow for a comprehensive analysis of their running characteristics during different sections of the training runs.

The combination of IMUs and GPS data collection provides a validated methodology for analyzing the running characteristics of mid-distance runners. By incorporating both GCT measurements and GPS speed analysis, this study offers a comprehensive understanding of the athletes' running technique, performance, and the impact of different training conditions on their running characteristics.

Sensor instrumented training

The analysis of GCT dynamics within the training provides information about the athlete's adaptability and highlights the potential of SIT as a valuable tool for enhancing coaching decisions. By continuously monitoring GCT and other relevant metrics, coaches and athletes can adapt current training protocols to optimize performance.

Furthermore, the drop-off in GCT between the two more detailed analyzed runs underscores the importance of coaching intervention. These measurements can be implemented in the cycle of training control (Hohmann et al., 2020). Coaches control athletes' training and make informed decisions to optimize their training regimens. In this context, the observed changes in GCT provide a valuable cue for the coach to assess the athlete's level of fatigue and running efficiency. The coach's before-mentioned "gut feeling" can be supported with objective data.

The integration of real-time feedback mechanisms in sports training is a promising aspect to consider within the discussion of our study. In the context of our research, the continuous monitoring of GCT using sensor technologies like IMUs and GPS sensors presents an opportunity for real-time feedback to athletes and coaches. The data acquired could be directly processed and wirelessly distributed to provide live insights during training sessions (Baca et al., 2022). This real-time feedback empowers coaches to make required interventions, such as adjusting pacing strategies or refining running form, optimizing training regimens, and ultimately enhancing athletic performance. Furthermore, athletes can benefit from immediate feedback, enabling them to adapt even during the training. Thus, incorporating real-time feedback mechanisms based on GCT measurements possesses substantial promise for advancing sensor-instrumented training in sports. This study did not use real-time feedback but emphasized developing appropriate tools. For example, integrating various sensors into a mobile application could be tackled in future works.

Conclusion

This study adds to our current understanding of how running kinematics and training intersect. Commonly used information – like GPS-measured speed – can add information to regular training procedures. It is shown that this data can back up coaches' decisions regarding fatigue. Additionally, the application of sensing technology and specifically developed detection algorithms enable the continuous assessment of further parameters like ground contact time. Using this information, a prolonged GCT was found during curve running, especially in later phases of training.We advocate for further analysis of fatigue and curve run technique on a broader data basis, as their comprehensive understanding could potentially lead to enhanced training methodologies. We conclude that incorporating different sensor measurements showed indicators that could support the coaches' decisions during training and possibly competition.

Additionally, an improved comprehension of running techniques and their monitoring during training can benefit the effectiveness and quality of training in elite-level sports. We suggest that these applications can support sensor-instrumented training. This approach needs to be further investigated and developed to ultimately provide coaches and athletes with real-time feedback, for example, with a mobile application.

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4.4 Additional Publications

The following publications are not to be seen as the main achievement of this publication-based dissertation but contribute thematically and, therefore, are shortly explained. The full text of these publications can be found in the Appendix (section 6.2).

Drone Detection

The study titled "Drone-based Position Detection in Sports—Validation and Applications," authored by Russomanno, T. G., Blauberger, P., Kolbinger, O., Lam, H., Schmid, M., and Lames, M. was published in 2022 in the journal Frontiers in Physiology (Russomanno et al., 2022). The journal is focusing on advancements in physiological research. According to the ResearchGate platform, the paper shows a citation count of three and 1228 reads (as of 07-02-2024).

The primary aim of the research was to explore the efficacy and applications of drone-based technology in accurately detecting positions in sports. This investigation sought to bridge the gap in high-precision aerial tracking capabilities within the sports domain, providing a novel perspective on athlete monitoring with the potential to revolutionize training and analysis.

The results of the study underscored the accuracy and application potential of drone technology in sports settings. The research demonstrated that drones could be utilized for high-precision athlete tracking, providing a bird's-eye view that is advantageous for spatial analysis. This level of precision in positioning is pivotal for tactical evaluations and enhancing the quality of performance feedback. The study's successful validation of drone-based PD posits drones as valuable assets for real-time sports analytics, positioning them as versatile tools for future integration into diverse sporting disciplines.

In the context of running diagnostics, the study's advancements offer a promising avenue for integrating aerial surveillance to augment traditional tracking methods. The drone's vantage point provides a comprehensive view of athletes' movements, offering a new dimension to performance analysis that can influence and be influenced by ground-level diagnostics, enriching the data available for enhancing athletic training and strategies.

Ghosting

The study titled "Simulating Defensive Trajectories in American Football for Predicting League Average Defensive Movements" authored by Schmid, M., Blauberger, P., and Lames, M. was published in 2021 in the Journal Frontiers in the section Sports and Active Living (Schmid et al., 2021). The journal, with an impact factor of 2.7, publishes scientific contributions on all aspects of sports, physical activity and active living to investigate the benefits and risks of non-sedentary behavior. The paper was cited seven times and read 324 times, according to ResearchGate (as of 07-02-2024).

The research objective was to create a simulation model that could predict the defensive movements of American football players, focusing on reflecting the average behaviors seen across the league. This model was based on a reinforcement learning approach. The study contributed to the development of predictive analysis within the sports domain, aiming to provide scientists, coaches and players with actionable insights that could improve game planning and performance.

The findings of the study revealed that such a model could effectively forecast defensive player trajectories. This predictive ability is a game-changer for teams. It allows them to anticipate opponents' defensive strategies, which is crucial for offensive decision-making. The research proved the practicality of such simulations in professional sports environments, suggesting that this method could be broadly adopted in coaching and training to enhance strategic preparations and in-game adaptability.

This research's contribution indirectly supports the development of advancing running diagnostics by providing a framework that can be adapted to analyze and enhance an athlete's dynamic movements and decision-making in real-world scenarios. This has a reciprocal influence, as advancements in running diagnostics could feed back into the model, refining its predictive capabilities with more granular data on player speed, agility and endurance. Thus, the gap between theoretical models and their practical applications in sports science could be further closed.

5 Discussion

5.1 Study Summary

This project involves three studies to develop and refine a methodology for advancing sensor-based running diagnostics in sports. Additionally, two studies that analyzed the runs of athletes were co-authored.

Study one (section 4.1) starts the search for an adequate measurement system by validating the capability of a state-of-the-art sensor-based LPS for player and ball tracking (Blauberger, Marzilger, et al., 2021). It evaluates the accuracy of position, speed and acceleration measurements by comparing the output with a criterion reference measurement. This study contributes to the rating of one specific LPS for further usage within the dissertation project. It enhances our understanding of the importance of validation methodology for checking the appropriateness of systems in the sports context.

The second study (section 4.2) focuses on implementing IMU-based sprint step detection (Blauberger, Horsch, et al., 2021). The implementation is demonstrated by showing a robust detection pattern and diving into a more detailed analysis of one important sprint variable: GCT (Coh et al., 2001). The contribution of this study lays the basis for further analysis in running using IMUs.

The third study (section 4.3) uses the validated methodology of the previous work to show an example of PPA. The findings suggest that we can see differences in running variables per foot in mid-distance sprints. This is shown with the analysis of GCT. Finally, the integration of GPS data shows a more robust identification of training variables like fatigue. This supports the usage of additional sensor-based measurement data, which hints towards fatigue variables within the training, leading to SIT.

In this dissertation project, two co-authored studies are implemented: Russomanno et al. (2022) and Schmid et al. (2021) (section 4.4). They explore a simulation method, also called ghosting, and the usability of drone detection in sports. The former study provides a perspective on the use of sophisticated data analysis. Based on tracking data of all athletes' run paths, a probable movement pattern is predicted. The second study reveals ways drones can be utilized for gathering positional data, offering a low-cost alternative to assess positional data, which can then be used for sports and running analysis.

Both studies contribute to the understanding and application of tracking technologies in sports, offering implications for practitioners, researchers and athletes alike. The movements of tracked athletes focus on running and sprinting in both cases, which makes the results valuable within this dissertation project.

5.2 Validation

Validating tracking technologies for use in sports is important to ensure the reliability and accuracy of collected data. As this raw data is further used to create PIs, even small errors can cumulate into not neglectable differences (Linke, 2019).

Sensor Placement

As shown in study 1 (section 4.1), the placement of the sensor can make a huge difference in the outcome variable. For example, the influence of the location of the center of mass must be taken into account (Linke & Lames, 2019; Saini et al., 1998). For instance, placing a sensor inside a ball can lead to less accurate measurements compared to body-attached devices due to the dynamic and unpredictable nature of the ball's movement during play. This variability can bring errors in the detected data, which affects further analysis. A foot-attached sensor can cause comparable problems, as the inertial forces at common sensor placement locations (usually at the athlete's back) are different.

Limb Tracking

The accuracy of current tracking technologies may not be sufficient for precise limb tracking. However, detecting the precise position of the limb is inevitable to derive PIs like GCT. Seidl et al. (2017) highlight the appropriateness of an LPS in capturing the step parameters like SL and ST. However, GCT was not as precise as with different technologies. This is particularly relevant in running, where detailed kinematic parameters are essential for performance optimization and injury prevention, underscoring the need for more sophisticated tracking solutions, or the integration of additional sensors (Seidl et al., 2017).

Validation setting

Furthermore, tracking technologies must be validated within the actual sports setting they are intended for (Luteberget & Gilgien, 2020). The complexity and unpredictability of real-world sports environments can influence the performance of tracking systems. Validation in a controlled laboratory setting might not accurately reflect the challenges and interference these systems face during live sports scenarios, making in-situ validation important for ensuring the practical applicability and reliability of these technologies in sports contexts.

New Technologies

As shown in the study about drone tracking, this method can be used very well to create insights for PA. However, it is important to validate this method before usage. In the framework given by Robertson et al. (2023) this has to happen in Pillar A: Quality assurance & measurement. Drone tracking has shown to be a valuable tool for PD, but it definitely needs further development and validation on the way (section 4.4).

5.3 Method Development

The practical application of tracking methods in real-world sports settings raises several important considerations that must be addressed to ensure their effectiveness and relevance. Especially since different application cases require an adopted methodology to work within the fixed rules of a sport.

Required Accuracy

Another critical aspect is the method's needed accuracy. The level of precision required can vary significantly depending on the sport and the specific performance metrics being analyzed (Seidl et al., 2017). High accuracy is essential for methods intended to track fine-grained movements or minor performance changes. For example, in sprinting, even small inaccuracies can lead to misleading conclusions and ineffective training recommendations.

Moreover, the method's accuracy may vary with the context of its application. As shown in the gait basics (section 3.1), the biomechanics change for different running paces, for example, longer-distance runs. It can be expected that a method that delivers high precision in 100m sprints (study 2, section 4.2) or controlled environments might show lower accuracy over longer distances or in less controlled settings. This potential decrease in accuracy could be due to various factors, such as the initial contact difference from forefoot to rearfoot. Therefore, the usage of different technologies in the framework of SIT can be beneficial.

Usability in Practice

Usability in practice is a key factor in the development of new methodologies (Norman, 2013; Robertson et al., 2023). A method's success is determined not only by its technical capabilities but also by its ease of integration into daily training routines and accessibility for coaches and athletes. The utility of a method in a practical context, such as its adaptability to various training environments and its user-friendliness, is crucial for its adoption and sustained use in sports settings.

Filtering Techniques

To enhance the accuracy and reliability of tracking methods, particularly in noisy real-world sports environments, the implementation of appropriate filtering techniques is crucial. One commonly used approach is the application of low-pass filters (e.g. butterworth low-pass filter), which help to smooth the data by removing high-frequency noise (Falbriard et al., 2018; Linke, Link, & Lames, 2018). This is especially useful in scenarios where the measured data can be affected by rapid, insignificant fluctuations that do not reflect true movement patterns or performance metrics.

A low-pass filter operates by allowing signals with a frequency lower than a certain cutoff threshold to pass through while attenuating signals with frequencies higher than this threshold (Baca, 2015). The selection of the cutoff frequency is critical and should be based on the specific characteristics of the movement being analyzed. In the course of this dissertation, this filtering occurred on two different occasions: Filtering the raw signal of LPSs and IMUs (study 1, section 4.1 & study 2, section 4.2). LPS signals were further distinguished for ball and player tracking. In both cases, the cutoff frequency had to be chosen individually to preserve the essential motion characteristics while eliminating noise.

Therefore, choosing an appropriate threshold is an important step that is used to refine data. By setting specific cutoff values, data points outside a defined range can be excluded, which can be particularly useful for eliminating outliers or irrelevant fluctuations. For example, regarding GCT measurements, a threshold can be applied to filter out unrealistic GCT values that could arise from sensor errors or anomalous movements. Such a misdetected event should be counted as incorrect step detection, or no detection at all.

The integration of these filtering techniques into the tracking methodologies not only improves data quality but also enhances the precision of the derived metrics. This, in turn, ensures that the PA is based on accurate data, thereby providing more valid insights for training and performance optimization.

5.4 Feasibility in practice

Usage in competition

The allowance of technologies or methodologies in contests is an important consideration, as competition is the important setting for PA (Lames, 2023). Sports associations and regulatory authorities often have strict guidelines regarding the use of technology to ensure fair play and maintain the integrity of the competition. Any new method or system intended for use in tournaments must align with these regulations, and gaining acceptance can be a lengthy process involving demonstrations of the technology's value and safety. As summarized from Hohmann et al. (2020) and Lames (2023), the usage in training and for developing athletes' capabilities interplay with the final aim to maximize performance in competition. Therefore, the integration into competition settings needs to be considered right away.

Sensor Instrumented Training

Beyond regulatory approval, the practical implications of integrating new technologies or methods into sports settings are substantial. The ease of implementation, the adaptability of athletes and coaches, and the overall impact on the flow and nature of the sport have to be considered, especially since the concept of SIT proposes various new technologies (study 3, section 4.3). Technologies that are intrusive, overly complex, or significantly alter the nature of the sport may face resistance from stakeholders and could be less likely to be adopted widely. Moreover, the logistical aspects of deploying new technologies, such as the need for specialized equipment, operator training, and potential disruptions to established routines, must be considered. The costs associated with these implementations, e.g. in terms of financial investment and potential impacts on training and competition schedules, also play a role in determining the feasibility of new methods in practice.

Smartphone Application

The integration of PA technologies into user-friendly applications (apps) can be a beneficial advancement in the practical development of these methods. Apps can offer a streamlined and accessible interface for athletes and coaches to interact with complex data, making it easier to incorporate performance metrics into daily training routines. For instance, apps can provide real-time feedback on performance metrics such as speed, acceleration, and GCT, allowing for immediate adjustments during training sessions (Romero-Franco et al., 2017).

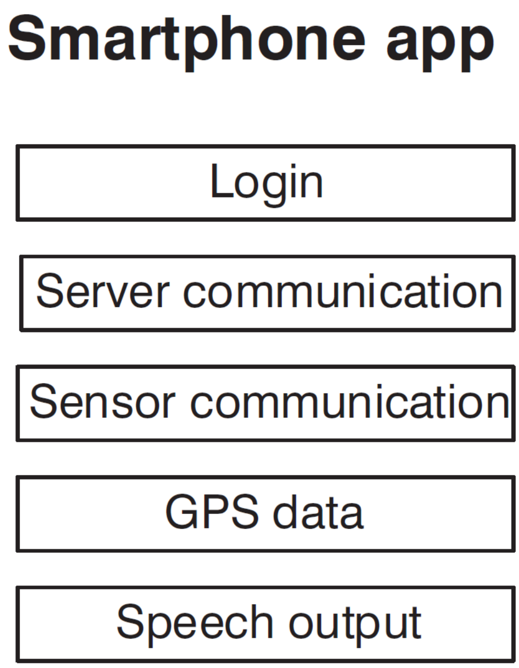

Figure 5.1 Implementation scheme for a smartphone app. The scheme describes the important pillars that must be incorporated into the development of a mobile sports application. Taken from Baca (2015) with permission of Taylor & Francis Group.

Moreover, apps can facilitate the visualization of data, enabling athletes and coaches to better understand performance trends and identify areas for improvement. By integrating data from various sources, including IMU sensors and GPSs, apps can present a comprehensive overview of an athlete's performance. This holistic approach not only enhances the accuracy of performance analysis but also supports the development of more tailored and effective training programs.

The development and implementation of such an app must consider critical components, ensuring that the interface is intuitive and that the data presented is actionable. Baca (2015) gave an outlook on how such an integration could look in sports environments (Figure 5.1). Training athletes and coaches to effectively use an app is also crucial for maximizing their potential benefits. Overall, app integration represents a significant step towards making the developed PA technologies more accessible and practical for everyday use in sports settings.

Simulation and Modelling

As described by Baca (2015), simulation and modeling are seen as the main areas of sports informatics. Other scientific works focus more on this topic (Wenninger, 2022). However, it should be discussed within the simulation background of the co-authored study about ghosting. As we saw in the results, the outcome of a simulated model adds context to its interpretability (section 4.4). Therefore, its acceptance and application in practice might be higher. On the downside, it is harder to understand how these results were created. Especially with the developing usage of sophisticated methods like imitation learning (Schmid et al., 2021). However, the integration of this research showed, how such methods could be applied.

5.5 Limitations

Although each study's limitations were stated individually in the publications, some shortcomings have to be considered in the broader context of the whole project.

The practical usability of the current development needs to be discussed in the applied environment. Sports scientists always need to question the achievements of new developments. Under the term practical impact debate, this has already been evaluated in several publications in recent times (Carling, 2013; Mackenzie & Cushion, 2013). Accordingly, this dissertation needs to ask whether the developed methods can be applied in real-world sports settings. Especially the use of SIT (study 3, section 4.3 needs to have acceptance in everyday training. While theoretical models and controlled experiments in the laboratory provide valuable insights for the proof of conduct and the planning of a study, the practical application can be hindered by other field-specific factors, such as the dynamic nature of sports environments (Lames, 2023), practical usability (Carling, 2013) and logistical challenges (Linke, 2019) of setting up and maintaining tracking systems during training sessions or competitions.

Another limiting factor can be the level of accuracy required for meaningful analysis. Various metrics might necessitate different degrees of precision. Some require a high level of accuracy to provide valuable insights, for example, when the output data is further derived for advanced metrics (Linke, 2019). New technologies like computer vision generated results can assess sports movements (Fukushima et al., 2024). This dissertation dealt with the application within sprints in short intervals (study 2, section 4.2). The current technologies may not always meet these requirements, particularly when assessing temporal parameters in rapid movements such as in a sprint (Seidl et al., 2017). Additionally, the accuracy of tracked variables may slightly diminish over longer distances, as even small errors can accumulate over time. This is a notable concern for endurance sports or activities where athletes cover extensive distances.

Another limitation is the feasibility of implementing a tracking method in actual competitive settings. Regulatory allowances in tournaments and the practicality of deploying these systems without interfering with the natural flow of the sport are crucial considerations for PA (Lames, 2023). Especially having sensors worn by an athlete might not be allowed in all sports. The acceptance of new technologies in regulated sports environments often requires extensive validation and approval from third parties.

Addressing these limitations is essential for the continued application and integration of tracking and PA technologies in sports. By acknowledging and working to overcome these challenges, the field can advance towards more robust, accurate and practical solutions that enhance our understanding of athletic performance and inform better training and competition strategies.

6 Conclusion and Outlook

6.1 Conclusion

The integration of technology, especially sensor-based equipment like IMUs into sports has proven to be possible and increasingly simple and insightful. The evolution of tracking technologies and analytical methods has reached a point where their incorporation into training, called SIT, can enhance PA and even real-time decision-making.

This development is complemented by the depth of insights these technologies provide. Modern tracking systems and analytical tools offer a level of detail and precision previously unattainable, allowing coaches, athletes and researchers to uncover nuanced aspects of performance and physiology. These insights can lead to more personalized training programs, improved injury prevention strategies and enhanced understanding of athlete performance and recovery.

This dissertation dived through the process of choosing, validating and leveraging an appropriate measurement technique. The start of this process was the proper validation of a measurement system for sports contexts. This showed that LPSs continue to become more accurate but guided the way to the usage of another technology for running diagnostics. Using IMUs, a proper methodology shows to be a valid tool for further diagnostics. Using this technique, in-field PA was conducted. Together with evaluating data streams for different sensors, e.g. GPSs, the usefulness of Sensor Instrumented Training was shown. The concept of SIT contributes to the development of sports informatics. For example, indication for fatigue could be seen in GPS and GCT curves simultaneously.

The simplicity of application and the richness of the data on new technologies will likely further impact the landscape of sports science. This transformation will enable a more data-driven approach to sports, where decisions are formed by comprehensive and reliable data. This will ultimately lead to improved athletic outcomes and a deeper understanding of human performance.

6.2 Outlook

As we look toward the future, the development of measurement systems is poised for continuous advancements. These systems are becoming increasingly sophisticated, offering more accurate, comprehensive and nuanced data. The trajectory of this progress suggests that future measurement technologies will be even more integrated, less intrusive and capable of providing real-time feedback that can be seamlessly incorporated into training and competition.

The acceptance of these advanced measurement systems by elite coaches and athletes is crucial for widespread adoption. As these stakeholders recognize the tangible benefits these technologies can bring to performance enhancement and injury prevention, their integration into elite sports will likely become more prevalent. The key to this acceptance lies in demonstrating the practical value of these systems, ensuring they are user-friendly, and providing clear evidence of their impact on performance outcomes. Integration into everyday life, e.g. with a smartphone app, could be achieved in the near future. Meanwhile, scientific support is an important piece to pave the way for meaningful technological implementation. As new technologies and methodologies continue to penetrate the market, scientists need to focus on the proper usage of these tools. Future research should integrate the information of different sensors, especially in sensor-based running diagnostics, to further develop the current state-of-the-art.

Moreover, there is an increasing trend toward making scientific data more accessible and understandable to the public. As sports science continues to evolve, complex scientific concepts must be connected to their practical applications in sports. This benefits the athletes and coaches by providing them with actionable insights and engages the broader community, fostering a deeper appreciation and understanding of the science behind sports performance.

With these developments in mind, the future of running diagnostics and analysis is bright, and it has the potential to impact how training and competition are analyzed and enhanced. The key will be ensuring that the sports community integrates technologies and communicates their benefits effectively and with a scientific foundation.

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Drone-Based Position Detection in Sports—Validation and Applications

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Radio and video-based electronic performance and tracking systems (EPTS) for position detection are widely used in a variety of sports. In this paper, the authors introduce an innovative approach to video-based tracking that uses a single camera attached to a drone to capture an area of interest from a bird's eye view. This pilot validation study showcases several applications of this novel approach for the analysis of game and racket sports. To this end, the authors compared positional data retrieved from video footage recorded using a drone with positional data obtained from established radio-based systems in three different setups: a tennis match during training with the drone hovering at a height of 27 m, a small-sided soccer game with the drone at a height of 50 m, and an Ultimate Frisbee match with the drone at a height of 85 m. For each type of playing surface, clay (tennis) and grass (soccer and Ultimate), the drone-based system demonstrated acceptable static accuracy with root mean square errors of 0.02 m (clay) and 0.15 m (grass). The total distance measured using the drone-based system showed an absolute difference of 2.78% in Ultimate and 2.36% in soccer, when compared to an established GPS system and an absolute difference of 2.68% in tennis, when compared to a state-of-the-art LPS. The overall ICC value for consistency was 0.998. Further applications of a drone-based EPTS and the collected positional data in the context of performance analysis are discussed. Based on the findings of this pilot validation study, we conclude that drone-based position detection could serve as a promising alternative to existing EPTS but would benefit from further comparisons in dynamic settings and across different sports.

Keywords: drone, video based, position detection, game sport, validation

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1 INTRODUCTION

Metrics generated by the different position detection technologies are already commonplace for fans of elite sports such as soccer, rugby, basketball, and American football (Barbon Junior et al., 2021; Schmid et al., 2021; Blair et al., 2022; Charamis et al., 2022). Currently, video-based systems that use image recognition are popular for live sports broadcasts and rely on several fixed cameras set up around the field of play. However, there are a number of constraints regarding the location of these systems. For example, the cameras must be placed at a sufficient height, which is often only possible in stadia and other well-equipped training facilities (Siegle et al., 2013; Torres-Ronda et al., 2022).

Besides, previous studies have found that video-based electronic performance and tracking systems (EPTS) for outdoor sports share some limitations, like occlusion during corner kicks in soccer (Iwase and Saito, 2004; Qi et al., 2004; Baysal and Duygulu, 2016; Kim et al., 2018), that can only be overcome by human corrections or the use of more cameras, consequently increasing the cost. Another point is associated with the use of fixed cameras versus moving cameras, as this can vary the complexity of the player tracking process (Chen et al., 2013; Hanzra and Rossi, 2013). Although it is possible, in principle, to use moving (tilting, swaying, zooming) cameras, almost all commercial systems work with fixed cameras.

With position detection becoming increasingly popular, many sport clubs have adopted sensor-based EPTS [e.g (Global position system (GPS)/Global Navigation Satellite System (GNSS)- or radio-based systems/local based system (LPS)], since most training facilities are not suitable for the installation of video-based EPTS. Sensor-based systems are also less costly than video-based systems, which would make it possible for amateur or minor league sports to use this technology. It is important to notice that the use of sensor based EPTS in training is not always possible in stadia as pointed by Shergill et al. (2021), that analyzed the quality of the signal during professional football matches and found out that the position of the players affected the quality of the GNSS signal and therefore their performance measurements.

Nevertheless, the diversity of EPTS available on the market poses a challenge for game analysts, as these different sources of data are typically incompatible. Consequently, comparisons of the players' performances between these different systems, is difficult. This issue has been reported in the literature (Varley et al., 2012; Buchheit et al., 2014; Ellens et al., 2021). This incompatibility and the lack of interchangeability between systems creates a need for a single system capable of providing position detection data in both competition and training settings.

It would be a unique and worthwhile advancement for performance analysis if there was an affordable and reliable EPTS for teams and sport associations with small budgets that could collect data independent from setting, different stadia, or training sites. Unmanned aerial vehicles (UAV), commonly known as drones, could be the solution. Drones are widely available in the consumer market and have been used for several different applications so far, such as agriculture, surveillance, cinematography, and in some cases, during sports events to enhance the spectator experience (Ayranci, 2017). In recent years, drone technology for consumers has advanced so much that relatively inexpensive devices with decent flight characteristics are available and from which high-quality video recordings can be made. So, potentially, drones could play an important role in future in performance analysis. Compared to fixed cameras, these devices are portable and versatile, offer an aerial perspective of the playing field, and produce high quality videos that are suitable for broadcasting, position detection, and tactical analysis. With the ability to analyze the playing field with a single camera and without the need to install any equipment, performance analysts could consider using drones as an alternative to the existing video-based and sensor-based position detection technologies.

Regarding the positional data that can be obtained from drone footage, a review of the literature shows that several different methods based on image processing and computer vision have been used to automatically track players in a variety of sports (Cai and Aggarwal, 1996; Araki et al., 2000; Pers and Kovačič, 2000; Needham and Boyle, 2001; Iwase and Saito, 2004; Di Salvo et al., 2006; Figueroa et al., 2006; Barris and Button, 2008; Barros et al., 2011). More recently, new methods based on deep learning approaches, like convolutional neural networks, have improved the recognition and tracking of players in field sports, reducing the need of an operator to correct the tracking of players (Stein et al., 2017; Thomas et al., 2017; Cust et al., 2018; Renò et al., 2018). However, these methods all rely on multiple fixed cameras, and none have yet made use of a single drone camera. Concerning the use of drones in sports, Ferreira et al. (2015) and Karungaru et al. (2019) report that it is possible to detect and track players using a drone, but neither of these studies investigated its use for performance analysis. These studies also failed to validate the accuracy and reliability of the positional data obtained from the drone footage. Consequently, we believe that the current state of the art in computer vision and deep learning allows for tracking players automatically and provide positional data to derive performance indicators based on drone-based video technology (Thomas et al., 2017; Cust et al., 2018; Liang et al., 2019; Lee et al., 2020).

Thus, this study aims to describe a new method for position detection using a drone-based video system. We believe that the recent advancements in computer vision and deep learning can be used to reliably and automatically track players in a variety of sports settings. This study will be the first to provide validation of positional data obtained from drone footage in three different sports: tennis, Ultimate Frisbee, and soccer. This data will also be used to derive relevant performance indicators for each of these sports based on the drone-based video technology.

2 MATERIALS AND METHODS

2.1 Sample

To collect representative, real-world data for tracking and for the validation of our drone-based video tracking system, we acquired three different samples with varying field sizes, field colors, number of players, and levels of expertise in three different sports: tennis, Ultimate Frisbee and soccer. GPS-and LPS-based technologies were used for the validation of our drone-based video tracking system. For tennis, the sample was represented by two 14-year-old male tennis players with eight and 9 years of experience, respectively. For Ultimate Frisbee, the sample data was collected during a trial match (n = 14), including current or former players from the German national team (age: 28.35 ± 2.46 years). For soccer, eight female amateur soccer players (age:20.80 ± 0.83 years) participated in a small-sided game (4 vs 4).

All of the participants voluntarily gave informed consent to participate in the collection of spatiotemporal tracking data via drone technology. The data was anonymized to ensure confidentiality. All procedures performed in the study were in accordance with the Declaration of Helsinki.

FIGURE 1 | Drone perspective from a bird's eye view for tennis (27 m height), Ultimate Frisbee (85 m height) and soccer (50 m height).

2.2 Drones

An unmanned aerial vehicle is an aircraft without any human pilot, crew, or passengers on board. UAVs are a type of an unmanned aircraft system (UAS), which consist of an additional ground-based controller and a system of communication with the UAV (Abhishek et al., 2020). The drone used in this study was a Mavic Air 2 Model (SZ DJI Technology Co., Ltd. DJI) with Obstacle Sensing, Advanced Pilot Assistance 3.0, a fully stabilized 3-axis gimbal and 1/2″ sensor camera. Video frequency was set to 24 Hz with 4K resolution of 3.840 × 2.160 pixels. As the flight duration of this drone is around 34 min, we used a second drone of the same model to replace the first one and to ensure continuous data acquisition in case we exceeded this duration. The chosen height during stationary flight was determined based on the size of the field, weather conditions and was in accordance with the legal regulations for UAV, in our case the German regulations (www.gesetze-im-internet.de/luftvo_2015/). All of these variables were set to optimize the safety of the participants and the quality of the video footage through the unique bird's-eye view perspective.

2.3 Data Acquisition

The data was collected in three different setups: on a tennis court (23.77 m × 8.23 m) with the drone hovering at a height of 27 m, on an Ultimate Frisbee field (97.11 m × 36.25 m) with the drone at a height of 85 m, and on a small-sided soccer field (39 m × 29 m) with the drone at height of 50 m. All three sports were recorded from a bird's eye view with the drone positioned at the center of the court/field, enabling a full view of the field and the players, including the surrounding areas of interest, as shown in **Figure 1**.

Before each data acquisition, eight red cones (Ø = 0.15 m) were placed on the field, four of which were placed at the corners and the other four at the intersection lines (control points). For the Ultimate Frisbee setup, the control points were located where the end lines intersect with the side-lines in the intersections of the end line with the side lines. For the Tennis setup, the control points were located where the service lines intersect with the single side lines. The 2D locations of these cones (real-world coordinates) were measured using the tachymeter Trimble M3 Total Station with the Trimble Access software (Version: 2012.10). This system was used to measure the distance between a fixed point and the measurement device in X, Y, and Z coordinates. A reflective marker was placed according to the cones' 2D center of mass (COM), which identified the target point with 0.002 m of accuracy.

The cones' corresponding projections on the image (image plane coordinates) were digitized using our developed software (section 2.4). Thus, the homographic parameters of the mathematical image-object transformation were calculated, allowing for 2D kinematic analysis. This method for obtaining the transformation from 2D image coordinates to 2D object coordinates was based on 2D homography (Corke, 2017). Subsequently, both X and Y coordinates represent the transformed coordinates relative to the court/field coordinate system with origin in the bottom right of the field/court.

2.4 Tracking Algorithm

Tracking was done using a flexible software interface developed in the Python programming language (Python Software Foundation, https://www.python.org/). **Figure 2** presents the block diagram of the tracking system, in which multiple object tracking was performed (Bewley et al., 2016; Milan et al., 2016). This was conducted with a 2 phase System. A Faster-RCNN object detection neural network was trained to recognize players from a bird's eye view (Ren et al., 2015). Next, we tracked the initial players' bounding boxes with a generic object tracker called Atom (Danelljan et al., 2019), which performs at the top of specific tracking benchmarks such as UAV123 and TrackingNet.

Errors in the tracking process of the bounding boxes were edited manually through a GUI written with QT (www.qt.io).

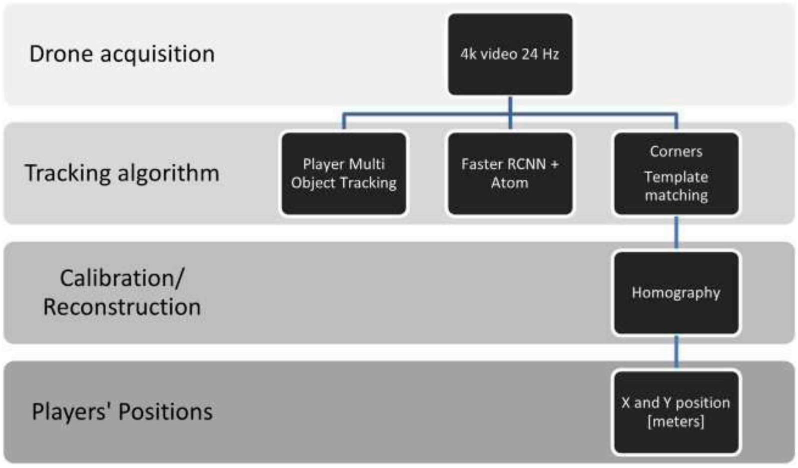

FIGURE 2 | Block diagram showing the main steps of the proposed tracking method using a drone-based video system.

TABLE 1 | Description of the experimental design for tennis, Ultimate Frisbee and soccer, including the number of participants, gender, duration, match type, and tracking devices used.

\Sport	N	Gender	Overall duration (min)	Validation intervals	Exercise type	GPS	LPS	Drone
Tennis	2	Male	29	4 sessions	match	✓	✓	✓
Ultimate Frisbee	14	Mixed	34	3 sessions	match	✓		✓
Soccer	8	Female	5	1session	small-sided game	✓		✓

To transform the player coordinates from frame coordinates to real-world coordinates, we extracted multiple corners of the different game environments using template matching strategies. A personal computer (Intel(R) Core (TM) i7-7700HQ, CPU 2.80GHz, 16 GB RAM, Ubuntu) was used to track the players. All of the coordinates contained the X and Y coordinates of the players, and the corners were saved as a CSV file.

The X and Y positions of the players were defined as the center point of the bounding box enclosing the respective player's outline. Following the tracking procedure, the X and Y positions of the players were reconstructed based on the four corner points extracted for calibration in MATLAB (R2020b, The MathWorks Inc., Natick, MA, United States) using 2D homography (Corke, 2017). Due to slight movements of the drone, the calibration was performed frame by frame to reduce errors.

2.5 Validation

To validate the drone-based video EPTS system developed in this work, two different tests were conducted. First, a static validation was performed using specific known and measured points on the court/field that were measured with the gold standard (tachymeter). Secondly, we conducted a dynamic validation. Ideally, this type of validation is conducted using 3D kinematic analysis like Vicon or Qualisys (Luteberget and Gilgien, 2020), but this is challenging and costly to do in field settings (Linke et al., 2018) and actually cannot be done in large environments like an Ultimate Frisbee field. The alternative is an approximation, which involves comparing the measurements the drone-based video system with other systems that have been reported in the literature (Frencken et al., 2010; Randers et al., 2010; Ogris et al., 2012; Varley et al., 2012; Buchheit et al., 2014; Ellens et al., 2021). In this case, we used a GPS system and a LPS system, described in **Table 1**.

All participants in this study were equipped with at least one transponder for the GPS system (GPSports Sports Performance Indicator (SPI) Pro X, Canberra, Australia). For tennis, an additional transponder was attached for the LPS system (KINEXON Precision Technologies, Munich, Germany). The transponders were placed on the upper thoracic spine between the scapulae.

The GPS transponders were activated 15 min prior to data collection to allow for the acquisition of satellite signals, as only GPS signals that meet the internal quality thresholds established by the manufacturer are recorded (Shergill et al., 2021). The LPS transponders were activated at the same time to reduce contact between the investigators and the athletes in accordance with the COVID-19 guidelines at the time. Just before the start of a match, the drone was positioned above the center of the court/field and set to remain in a stationary position (see **Figure 1**).

2.5.1 Static Validation

For the static validation measurements, the real-world coordinates of four cones on the field/pitch (Ø = 0.15 m) were measured with a tachymeter, which served as the gold standard. For the sake of comparison, 5 minutes of video were acquired at frequency of 24 Hz, just before the data collection session to compare the drone measurements with the tachymeter measurements on the tennis court and on the Ultimate Frisbee field.

Previous studies used a limited number of timepoints for one position to estimate the static measurement, for example by fixing a transponder to the ground for 2 minutes or by measuring the court/field manually before data acquisition (Lara et al., 2018; Linke et al., 2018).

2.5.2 Dynamic Validation

Raw XY-positions from each of the EPTS were exported using the respective software (see **Figure 2**). The raw speed data was synchronized for speed using cross correlation. Which allowed for the calculation of the deviation between the GPS system and the drone system for each point in time and for each setting. Data from the systems was sampled at different frequencies: 15 Hz (GPS), 20 Hz (LPS) and 24 Hz (drone). All of the remaining data analysis steps were executed in MATLAB (R2020b, The MathWorks Inc., Natick, MA, United States). The data from the LPS system and the drone system was down-sampled to 15 Hz using a linear interpolation of the initial values. All positional data was filtered using a fourth-order Butterworth low pass frequency filter (Linke et al., 2018).

The dynamic validation was performed with two kinds of analysis. First, the cumulative distance measured by the drone system was compared to the distance from the LPS system for tennis and from the GPS system for all sports. Secondly, the distance covered across different speed zones was also compared: stationary walking (0–3.9 km/h), jogging (4.0–7.9 km/h), and quick running (above 8 km/h), mostly because the sample hardly reached speeds above 14 km/h. These speed zones were adapted from Krustrup and Mohr (2015).

Speed and acceleration data from the drone and LPS systems were derived from filtered positional data. The GPS system assesses speed data by the rate of change (Doppler) in the satellites' electromagnetic signal frequency (Schutz and Herren, 2000). Therefore, the manufacturer's speed variable was used and served as the basis to calculate acceleration.

2.6 Statistical Analysis

The accuracy of the static XY-position data was estimated by means of the root mean square error (RMSE) as seen in .

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)}{n}} \quad (1)$$

where y_i are the observations, x_i predicted values of a variable, and n the number of observations available for analysis.

Descriptive statistics are provided as means, standard deviations (SD) and coefficient of variation (CV). A Shapiro-Wilk test was used to test the normality of the data. In cases where the data failed the normality test, non-parametric test procedures were used to analyze the data (Wilcoxon signed-rank test).

TABLE 2 | RMSE values for the four control points used to evaluate the static accuracy during the calibration procedure on the tennis court and on the Ultimate Frisbee field. Means and standard deviations are shown for both settings.

Control points	RMSE values (tennis)	RMSE values (Ultimate frisbee)
Number 1	0.04 m	0.20 m
Number 2	0.01 m	0.16 m
Number 3	0.04 m	0.11 m
Number 4	0.02 m	0.13 m
Mean ± sd	0.02 ± 0.01 m	0.15 ± 0.03 m

To evaluate the performance of drone tracking compared to GPS and LPS systems in the three different sports contexts (tennis, Ultimate Frisbee, and soccer), a Bland-Altman plot was drawn to assess the level of systematic difference between measurements of the total distance covered by the players. Pearson's correlations coefficients were classified as (small effect<0.3; medium <0.5; large >0.5). Reliability of total distance covered was assessed calculating intra-class correlation coefficients (ICC). ICC coefficients were classified according to Koo and Li (2016) into poor (ICC ≤0.5), moderate (ICC ≤0.75), good (ICC ≤0.9), and excellent (ICC >0.9). Statistical analyses were conducted in MATLAB R2020b (The MathWorks, Massachusetts, United States) and SPSS (v27.0.1.0).

3 RESULTS

3.1 Static Validation

Table 2 shows the RMSE of the distances between the observed and expected positions on the court/field for the four control points used in the tennis match and in the Ultimate Frisbee match. It is important to reiterate that the four control points were placed in specific positions based on the different court/field sizes for tennis and Ultimate Frisbee.

The mean RMSE for a static position on the tennis court was 0.02 m, 0.08% of the court's length and 0.24% of the court's width. For the Ultimate Frisbee field, the mean RMSE for a static position on the field was 0.15 m, 0.15% of the court's length and 0.41% of the court's width. The maximum RMSEs found in static positions on the tennis court and the Ultimate Frisbee field for a 5-min testing interval was 0.04 and 0.20 m, respectively.

3.2 Dynamic Validation

The regression analysis for the total distance between the drone and the GPS/LPS systems showed a significant linear regression ($p < 0.05$) for all three sports. For tennis, the R^2 value was 0.980 with a RMSE of 21.8 m, RMSE% of 5.78% for GPS, with an ICC value for consistency of 0.974 and the ICC for absolute agreement of 0.923 ($p < 0.001$); for LPS, the R^2 value was 0.999 with a RMSE of 5.1 m, RMSE% of 1.21%, with an ICC value for consistency of 0.999 and the ICC for absolute agreement of 0.998 ($p < 0.001$). For Ultimate Frisbee, the R^2 value was 0.996 with a RMSE of 10.7 m, RMSE% of 1.01%, with an ICC value for consistency of 0.998 and the ICC for absolute agreement of 0.984 ($p < 0.001$). For soccer, the R^2 value was 0.926 with a RMSE of 12.9 m, RMSE% of 3.11%,

TABLE 3 | Descriptive statistics for the different tracking devices (Drone/GPS/LPS) regarding total distance covered and total distance covered in the three different speeds: stationary walking (0–3.9 km/h), jogging (4.0–7.9 km/h), quick running (above 8.0 km/h) in Tennis, Ultimate Frisbee (UF) and Soccer small-sided game. Means, standard deviations and coefficient of variance are shown for all the settings.

	Device	Tennis			UF			Soccer		
		Mean	±SD	CV%	Mean	±SD	CV%	Mean	±SD	CV%
TOTAL DISTANCE (M)	Drone	430.6	168.6	39.15	1022.2	166.9	16.32	404.2	49.0	12.12
	GPS	377.1	141.0	37.39	1050.9	167.9	15.97	413.5	43.8	10.59
	LPS	420.0	166.2	39.57	—	—	—	—	—	—
DISTANCE IN SPEED 0–3.9 kM/H (M)	Drone	143.5	60.9	42.43	148.6	28.0	18.84	90.5	15.7	17.34
	GPS	205.7	87.7	42.63	143.2	25.3	17.66	85.2	12.9	15.14
	LPS	128.17	57.1	44.55	—	—	—	—	—	—
DISTANCE IN SPEED 4.0–7.9 kM/H (M)	Drone	217.8	104.0	47.75	297.2	54.0	18.16	168.4	35.9	21.31
	GPS	143.4	60.9	42.46	303.3	56.8	18.72	161.4	27.6	17.10
	LPS	220.4	101.3	45.96	—	—	—	—	—	—
DISTANCE IN SPEED >8.0 kM/H (M)	Drone	69.3	31.1	44.87	576.4	180.0	31.22	145.2	47.2	32.50
	GPS	27.9	13.8	49.46	684.37	183.0	26.73	166.9	57.3	34.33
	LPS	71.4	34.6	48.45	—	—	—	—	—	—

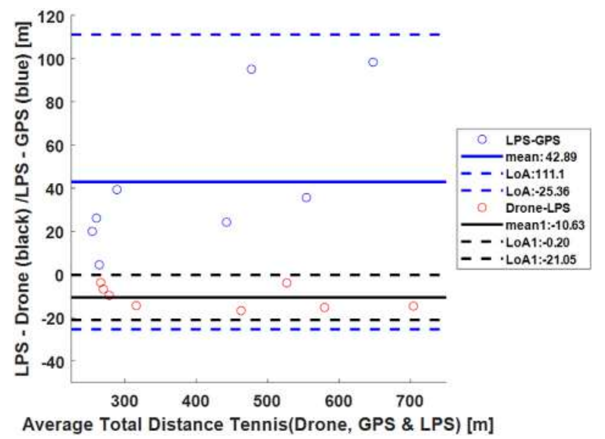

FIGURE 3 | Bland-Altman plot for the total distance covered in a tennis match measured by the drone, GPS, and LPS. Dashed blue lines show the limits of agreement (111.10 m and -25.36 m), and the continuous line shows the mean (42.89 m) between GPS and LPS. Dashed black lines show the limits of agreement (–0.20 m and –21.05 m), and the continuous line shows the mean (–10.63 m) between the drone and LPS.

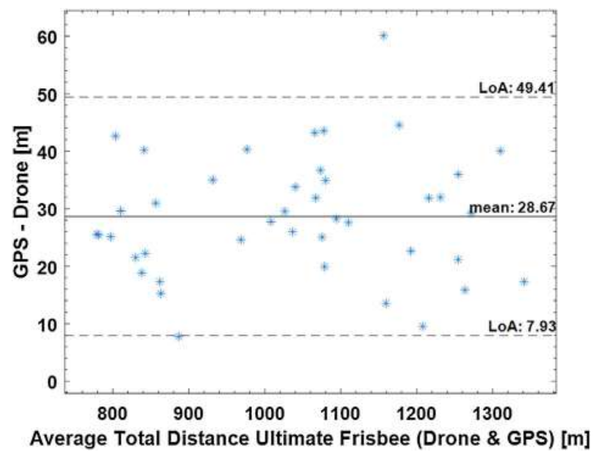

FIGURE 4 | Bland-Altman plot for the total distance covered in an Ultimate Frisbee match measured by the drone and GPS. Dashed lines show the limits of agreement (7.93 and 49.41), and the continuous line shows the mean 28.87 m.

with an ICC value for consistency of 0.956 and the ICC for absolute agreement of 0.942 ($p < 0.001$).

Table 3 shows the descriptive statistics (means, standard deviations anc coefficient of variation) for the different tracking devices (Drone/GPS/LPS) regarding total distance covered and total distance covered in the three different speeds: stationary walking (0–3.9 km/h), jogging (4.0–7.9 km/h), quick running (above 8.0 km/h) in Tennis, Ultimate Frisbee (UF) and soccer small-sided game.

Figures 3–5 show Bland-Altman plots with the mean values between the measurements and the lower and upper limits of agreement for the total distance in all three sports (tennis, Ultimate Frisbee, and soccer).

Regarding the total distance covered, an absolute difference of 13.67% was calculated for tennis, 2.78% for the Ultimate Frisbee, and 2.36% for soccer between the drone and the GPS. The error between GPS and LPS was 9.42% in the tennis match. The total distance covered between the drone and LPS had an absolute difference of 2.68% in the tennis match.

Figures 6, **7** show the deviation in the covered distances in total and at different speeds, as illustrated by box plots. For Ultimate Frisbee and soccer, **Figure 6** shows the measurements from the drone and GPS. For tennis, **Figure 7** shows the measurements from the drone, GPS, and LPS. Since the players in this sample hardly ever reached speeds above 14 km/h, the distances covered in each speed zones were presented as follows: up to 4 km/h, from 4 to 8 km/h and greater than 8 km/h.

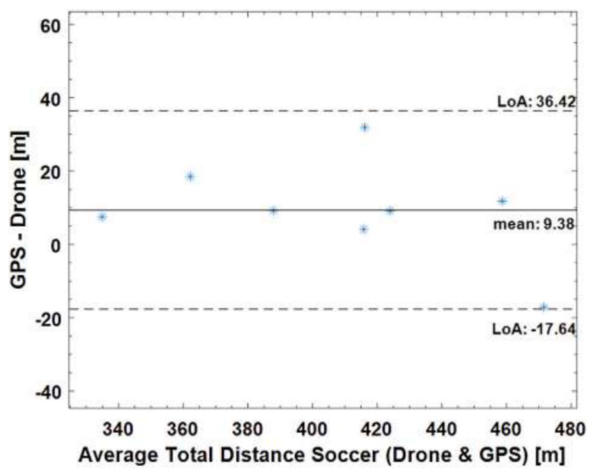

FIGURE 5 | Bland-Altman plot for the total distance covered in a small-sided game soccer match measured by the drone and GPS. Dashed lines show the limits of agreement (36.42 m and −17.64 m), and the continuous line shows the mean (9.39 m).

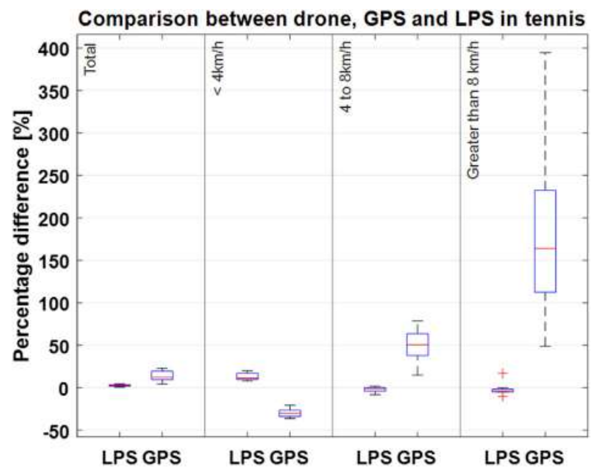

FIGURE 7 | Percentage deviation of the total distance measurements between the drone-based video system and LPS and drone-based video system and GPS in tennis for different speed zones. Boxplots show the respective median (red line); the bottom and top edges of the box indicate the 25th and 75th percentiles (blue box). The whiskers extend to the most extreme data points without considering any outliers ("+" symbol).

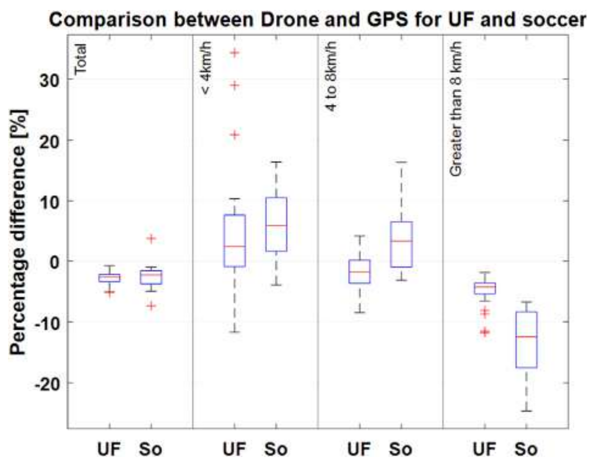

FIGURE 6 | Percentage deviation of the total distance measurements between the drone-based video system and GPS in Ultimate and soccer for different speed zones. Boxplots show the respective median (red line); the bottom and top edges of the box indicate the 25th and 75th percentiles (blue box). The whiskers extend to the most extreme data points without considering any outliers ("+" symbol). UF (Ultimate Frisbee), So (soccer small-sided game).

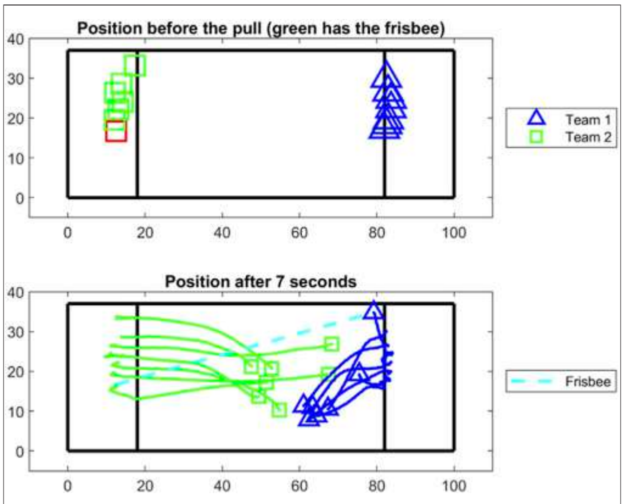

FIGURE 8 | Tracking data recorded with a drone from an Ultimate Frisbee game during the pull and 7 s afterwards. Team 2 (red square) has the frisbee (upper field). Frisbee was not tracked; blue dashed line represents the vector from starting to end position of the passe.

3.3 Exemplary Results in Sports

Figures 8–**10** show exemplary results in the three different sports that can be obtained from a drone-based video EPTS system. **Figure 8** shows the typical movements of players (n = 14) during the pull in an Ultimate Frisbee game, showing that the drone system can deliver not only X and Y positions of the players, but also allows for new insights about tactical displacement using the bird's eye view. **Figure 9** illustrates the X and Y positions of tennis players on the court during a match. **Figure 10** is a direct application of tracking data for game analysis in small-sided soccer games based on heatmaps.

4 DISCUSSION

This study is the first to demonstrate the application of a drone-based video system for the performance analysis of three different sports: tennis, Ultimate Frisbee, and soccer. The results not only

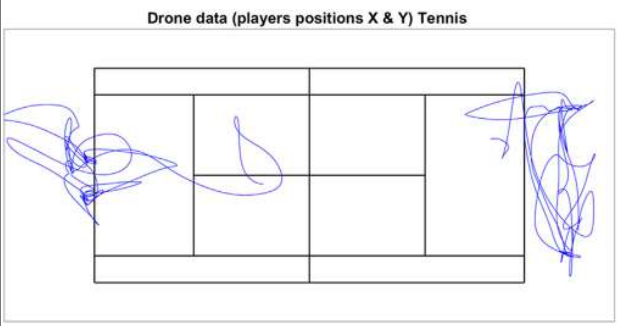

FIGURE 9 | Example of X and Y positions obtained by the drone system for two players during 1-min of gameplay in a tennis match.

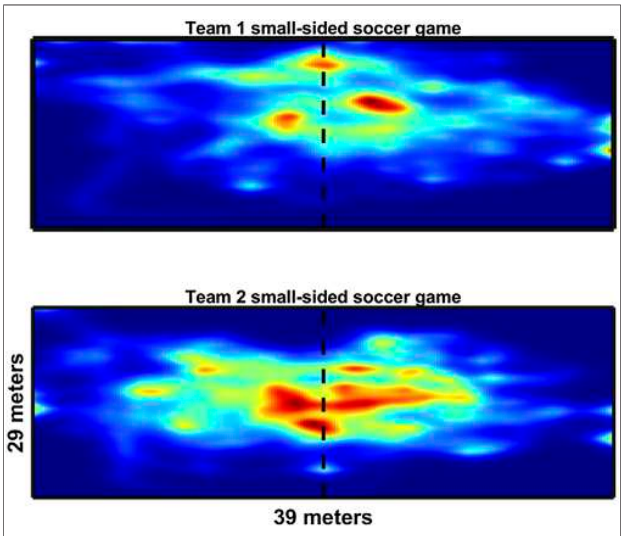

FIGURE 10 | Heatmap representation of the two teams (4 vs 4) during 5 min of gameplay in a small-sided soccer game.

show the system's ability to detect and track players from a bird's eye view (Ferreira et al., 2015; Karungaru et al., 2019), but also to collect and generate position detection data. Furthermore, the results from this study are validated against some of the existing position detection technologies (GPS and LPS) that are currently used in performance analysis.

The mean measurement error found for the static validation was less than 0.41% of the size of the court/field for all three sport settings. The maximum difference found between the known and measured positions on the tennis court and on the Ultimate Frisbee field was 0.04 and 0.20 m, respectively. These values are lower than the ones reported by Alcock et al. (2009), who reported mean errors of 1.5% of the width and 2.5% of the length of a soccer field. The results from the static validation support the accuracy of the drone-based video system for the measurement of static positions on the court/field when compared to the gold standard (the tachymeter). This improved accuracy may be explained by the fact that every frame from the drone footage is calibrated individually since the drone is subjected to small movements during flight.

For the dynamic validation, the measurements of the total distance covered, and the distances covered in different speed zones were compared between the drone system and commercial GPS and LPS systems. The total distance covered measured by the drone had a high correlation with both the GPS and LPS systems, with Pearson correlation coefficients of 0.96 and 0.99, respectively. It is important to clarify that correlation, in this case, does not mean that all of the systems came to the same measurement, but that the systems are related to each other. A better way to evaluate the agreement between the different methods might be a regression analysis. In this way, we would need to determine a formula that best predicts the magnitude of a value obtained from the drone as it relates to another measuring device (GPS or LPS).

Regression analysis shows a R^2 value higher than 0.90, and ICC results showed excellent consistency and absolute agreement in the measurement of the total distance covered. Buchheit et al. (2014) report small differences (5.4%) between GPS and optical tracking systems in relation to total distance covered. In this study, the differences in the total distance covered between the drone and GPS systems are around 3% for Ultimate Frisbee and soccer small-sided game.

However, at this time, there is no gold standard used for dynamic validation of drone-based position detection. The authors chose to present Bland–Altman plots that illustrate some qualitative data, such as the mean bias (how much does the drone deviate from the measurements obtained by the GPS and/or LPS) and the confidence intervals, that may be used to explain some of the systematic and random deviations observed between the different tracking technologies in this study.

The limits of agreement in the Bland-Altmann plot for total distances are 49.41 and 7.99 m for Ultimate Frisbee (drone vs GPS; see Figure 4), 36.52 m and −17.64 m for soccer (drone vs GPS; see Figure 5), 15.74 m and −122 m for tennis (drone vs GPS) and −0.26 m and −21 m for tennis (drone vs LPS; see **Figure 6**). The limits of agreement for the drone vs LPS in tennis look better compared to the results for GPS, as the size of the field may have hindered the precision of the GPS measurements.

Overall, there was excellent agreement in the measured distances covered in different speed zones during the tennis match between the drone and LPS systems. However, there were some noteworthy differences between these two systems at higher speeds (above 8 km/h), which suggests there might have been a systematic error during data collection. For validation purposes, it would be ideal to compare the drone system to an accepted gold standard as the reference system to confirm the accuracy of instantaneous position, speed, and acceleration values. This type of validation should be conducted in the near future for the drone-based video system, especially using regression analysis to compare the results against other EPTS or gold standards like Vicon or Qualisys (Luteberget and Gilgien, 2020).

Based on the findings of this study, the application of a drone-based video system resulted in more accurate static positions and dynamic trajectories (with less deviation) compared to LPS- and

GPS-based systems. This finding is in line with previous studies that compared traditional video-based systems with GPS-based systems (Buchheit et al., 2014; Linke et al., 2018). While it appears that video-based systems generate more accurate and representative results for multi-player tracking compared to sensor-based systems, the process still requires supervision by an experienced operator, as the player trajectories can be unpredictable. Nevertheless, the advantages of a drone-based video system also include video footage from a bird's eye view, which allows for a unique perspective for tactical analysis of both one's own team and the opposing team. The drone's main advantage is its versatility, as it can be used in training or during competitions without the need to install any additional equipment (traditional video-based systems) or attach any devices to the players (sensor-based systems). A drone-based video system also provides a different vantage point than traditional video-based systems, as the drone can fly above the court/field and be maneuvered to remain in a stationary position. Lastly, drones are accessible and less costly than other EPTS, facilitating the ability to use position detection methods for performance analysis at all levels.

It is worth mentioning that the current work presents some limitations regarding its validation at higher speeds, greater than 8 km/h, given that the study sample did not reach such speeds. Nevertheless, the results found in this study are of sufficient validity for Ultimate Frisbee, tennis, and small-sided games in soccer, where other authors have also reported that higher speeds are rarely reached (Linke et al., 2018; Linke et al., 2020).

5 CONCLUSION

To the best of our knowledge, this is the first study to demonstrate and validate the use of drones for performance analysis, as well as present examples of their application in several different game sports (tennis, Ultimate Frisbee, and soccer). The drone-based video system not only detects and tracks players' positions and trajectories, but also provides performance analysis metrics in competition and training settings. The results were validated against known position detection technologies on the market (GPS and LPS). By implementing a drone-based video system, coaches and performance analysts will be able to visualize and quantify the X and Y positions of all players on the court/field. Furthermore, the drone footage will allow for conclusions about the physical demands and tactical behaviors observed in training and in competition across a variety of game sports. Future research can build upon the findings of this work by further testing the drone-based video system in different sport contexts and environments, such as indoor use. In the meantime, this study has shown that drone-based video position detection is both feasible and reliable; this technology has the potential to enhance performance analysis in sports and facilitate access to position detection methods.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

Ethical approval was not provided for this study on human participants because The study was conducted according to the guidelines of the Declaration of Helsinki.Informed Consent Statement: Written informed consent was obtained from all subjects involved in the study. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Simulating Defensive Trajectories in American Football for Predicting League Average Defensive Movements

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American football is an appealing field of research for the use of information technology. While much effort is made to analyze the offensive team in recent years, reasoning about defensive behavior is an emergent topic. As defensive performance and positioning largely contribute to the overall success of the whole team, this study introduces a method to simulate defensive trajectories. The simulation is evaluated by comparing the movements in individual plays to a simulated league average behavior. A data-driven ghosting approach is proposed. Deep neural networks are trained with a multi-agent imitation learning approach, using the tracking data of players of a whole National Football League (NFL) regular season. To evaluate the quality of the predicted movements, a formation-based pass completion probability model is introduced. With the implementation of a learnable order invariant model, based on insights of molecular dynamical machine learning, the accuracy of the model is increased to 81%. The trained pass completion probability model is used to evaluate the ghosted trajectories and serves as a metric to compare the true trajectory to the ghosted ones. Additionally, the study evaluates the ghosting approach with respect to different optimization methods and dataset augmentation. It is shown that a multi-agent imitation learning approach trained with a dataset aggregation method outperforms baseline approaches on the dataset. This network and evaluation scheme presents a new method for teams, sports analysts, and sports scientists to evaluate defensive plays in American football and lays the foundation for more sophisticated data-driven simulation methods.

Keywords: deep learning, Imitation learning, reinforcement learning, NFL analytics, data analytics, ghosting

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1. INTRODUCTION

American football is a widely used sport for the statistical evaluation of the performances of teams. Performance indicators for play-by-play data such as expected points added (EPA[1]), the defense-adjusted value over average (DVOA[2]), and defensive passing and rushing yards help to evaluate defensive plays (Cohea and Payton, 2011). Tracking data is also incorporated to evaluate

[1]https://www.espn.com/nfl/story/_/id/8379024/nfl\discretionary-explaining\discretionary-expected\discretionary-points\discretionary-metric.
[2]https://www.footballoutsiders.com/info/methods#DVOA

single plays or specific game situations (Yurko et al., 2019). As demonstrated by recent Superbowl winners, defensive effectiveness has a major impact on winning. An emergent example for the acknowledgment of this fact is coach Paul Bryants' famous mantra:

> Defense wins championships. Foxworth (2018)

Improving defensive behavior is, therefore, a major predictor for winning championships. Of the last eight Superbowl winners, four were ranked first or second in overall defensive rating in the league. In contrast to the offensive ratings, where just one team was ranked first or second. Hence, coaches' decisions on providing strategies for offense are important. However, defense is a key element for winning and statistics prove that[3]. It is cumbersome to imagine all possible defensive formations applicable for a specific offense. Furthermore, it is hard to determine which defender contributed to a specific defensive play, as defensive outcomes are commonly evaluated as a team achievement. With the emergence of tracking data, it is possible to cluster and classify specific contributions of defensive players, which helps to choose the right player in the corresponding play.

In 2013, the NBA team "Toronto Raptors" introduced a ghosting method to model the defensive behavior of opposing teams. These "ghosts" are synthesizing simulated trajectories of the movements of defensive players on the court. After 6 years of research, they developed a rule-based algorithm to simulate defensive behavior (Lowe, 2013). Unfortunately, this algorithm is not publicly available. This ghosting model computes more aggressive trajectories than observed during any NBA game, and only the most elite defenders (LeBron James in 2013 accounted for that) could mimic the behavior of the ghosts. Hence, the model seems unsuitable for imitating true defensive behavior. In recent years, research in artificial intelligence has leveraged methods to simulate human behavior by mimicking past motions and, therefore, better capture the movements of humans compared to a rule-based programming approach (Hussein et al., 2017). As offensive behavior implies interaction with highly unknown variables such as how the quarterback reacts (including creativity), passes or a scheduled game plan for the specific play, defensive behavior is mostly reactive and could, therefore, be modeled by imitation learning.

Modeling defensive behavior by simulating possible running trajectories of defensive players, knowing the behavior of the offense can be a notable tool. This could be used for setting up tactics beforehand or for the usage in retro-perspective analysis. Furthermore, this method can provide offensive and defensive coaches a tool to adapt their decision for the play strategy.

The presented ghosting model is capable of generating movement trajectories of the defensive teams *via* imitation learning, from the time the ball is snapped until the quarterback throws a pass forward. The model is evaluated using the expected pass completion probability at the moment the quarterback throws the pass forward.

[3]https://www.si.com/nfl/talkoffame/nfl/scoring-defense-the-key-stat-for-super-bowl-contention

The proposed model provides support for the decision-making of defensive coaches and helps with the evaluation of defensive strategies. It can be incorporated with media or fan applications or be used for extensive match analysis.

2. RELATED WORK

The availability of tracking data in American football led to an increased amount of projects about evaluation and application engineering. The most commonly used tools in the area of team performance analytics are advanced statistical methods as well as machine learning and artificial intelligence. This chapter is divided into three parts, statistical methods, neural networks, and imitation learning.

Statistical methods have flourished in the past several years, and expanded the highly competitive landscape of sports analysis. Fernandez and Bornn (2018) modeled pitch control with a parametric approach to model influence areas of specific players with Gaussian functions and add the influence of each player to a team influence model based on the spatial coordinates on the field. Dutta et al. (2019) investigated defensive player behavior by classifying the behavior of defensive backs on two different coverage schemes, man coverage and zone coverage, using Gaussian mixture models to capture the state in an unsupervised manner.

Offensive player routes were analyzed with *neural networks* by recognizing and classifying running routes into different categories from wide out routes and backfield routes to compare the number of routes ran by the offense and the probability of targeting a receiver in that route (Team, 2019). Mehrasa et al. (2017) reduced player trajectories with one-dimensional convolutional neural networks for play recognition and team classification in basketball and ice hockey. The authors conclude, that franchise player or starting lineups contribute heavily to the team classification and identification using tracking data. Burke (2019) used deep neural networks to analyze the decision-making of quarterbacks and compute the pass completion probabilities of the quarterback with respect to the position of receivers and the closest defenders. Deshpande and Evans (2020) picked up this idea and extend the model in a more sophisticated way, by incorporating hypothetical pass probabilities in a Bayesian non parametric catch probability model. Most of the features of models regarding hypothetical passes are unobserved and, therefore, impute observable inputs.

Imitation learning yields multiple areas of operation in sport. Seidl et al. (2017) proposed a sketching tool for basketball play-by-play analysis, where they also use imitation learning to synthesize NBA defense. Coordinated multi-agent imitation learning was first proposed by Le et al. (2017) and was validated to be superior to an unstructured solution of a predator-prey problem, called the pursuit domain and on a soccer domain, where the results also showed a smaller loss in the coordinated case with respect to unstructured behavior. The training of the ghosted soccer players was done with Long Short Term Memory (LSTM) layers, while the Pursuit Domain was modeled with a random forest. A main finding of the study is the benefit of the

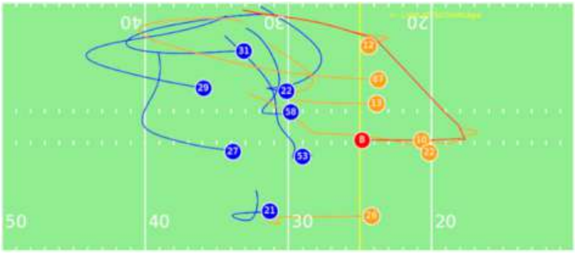

FIGURE 1 | Motivational Play: Eli Manning (10) throws a pass short right to Cody Latimer (12) for 8 yards before stopped by a tackle. The the trajectories of offensive teams are displayed in orange, the trajectories of defensive teams are displayed in blue, and the ball trajectory in red. The line of scrimmage is labeled and displayed in yellow.

alternating training of the model Hochreiter and Schmidhuber (1997) and the cascading training process of the LSTM layers for the problem.

The recently proposed methods and the extensive work by the NFL to make advanced statistics publicly available is the motivation to build a ghosting model for the defensive player trajectories of American football. Imitation learning is used to predict the trajectories of defensive players. Subsequently, these predicted positions are evaluated by comparison with the actual positions using a pass completion probability model.

3. METHODS

In this study, a method to simulate individual and collective defensive behavior of American football players from the time of ball snap until the quarterback throws the pass forward is developed. A big aim of cornerbacks and safeties is trying to intercept passes or prevent offensive receivers from running the ball after the catch. Other defenders (e.g., linebacker, defensive end) try to rush and tackle the quarterback, so the pass cannot even be thrown. To date, to the best of our knowledge, no model accounts for the different team strategies or the contribution of individual defensive players to the outcome of the play.

The proposed ghosting model takes advantage of a comprehensive representation of tracking data. Individual defensive players are modeled with the positional information of the offensive team. As ghosted trajectories do not behave like the true running trajectory, a learned pass completion probability model, similar to previous study (Burke, 2019; Deshpande and Evans, 2020) is proposed to evaluate the true running trajectories with the synthesized trajectories.

3.1. Data

In December 2020, the NFL released a free-to-use, new NFL player and ball tracking dataset for the NFL Big Data Bowl 2021 challenge (NFL Big Data Bowl, 2020). The dataset includes game data of 17 weeks of the 2019 regular season of the NFL. Each game contains play-by-play positional information about defensive and offensive players and football, as well as meta-information about the play as illustrated in **Figure 1**. Positional information is provided for different numbers of players, ranging from 10 players to 21 players. These players are tracked by a radio-frequency-based system (RFID). The sensors were implemented in both of the shoulder pads of the player, to capture the position of the player as well as the upper body orientation at a rate of 10 Hz. Compared to current optical tracking systems used in basketball, hockey, and soccer, RFID-based tracking in American football is error resistant, and it is possible to measure accurate positions and orientation, even with visual indentations. The manufacturer states an accuracy of 6 inches ($\approx$ 15.24 cm). However, to the best knowledge of authors, no validation study evaluating the accuracy is published yet of the system. The recording starts when the offense is set, meaning that the motion of offense and the reaction of the defense before the ball are snapped, are also captured in the data. For each tracked player and ball, every time frame contains its x and y position on the field within $0m \leq x \leq 120m$ and $0m \leq y \leq 53.3m$. The speed and orientation of the upper body of each player are saved to individual vectors. Offensive players also have an attribute for the running routes (e.g., Go, Hitch, and Crossing). For every player, different time frames are marked with the respective events, i.e., when the ball is snapped, the quarterback throws a pass, the pass is received, or the first contact with the defender.

3.2. Pass Completion Model

Pass completion can be modeled in various ways. The NFL introduced a model to evaluate pass completion probabilities of specific players based on 10 features corresponding to every receiver (Team, 2018). With this method, it is difficult to simultaneously evaluate the positions all players', as every single route is computed and player-to-player comparison is conducted. Consequently, a single evaluation metric cannot be generated without engineered adjustments. To circumvent this issue, the pass is captured as a binary problem for the entire team in this study. This simplification helps to capture the completion probability and combines the probabilities of player-to-player single routes analysis in a model where the different routes are automatically combined in an end-to-end approach. In the model, y captures whether the pass was caught, given the specific formation and speed of the players, neglecting the targeted player. The following formulas illustrate that this issue can be considered a binary classification problem with a completion probability:

$$P(y = 1|\mathbf{X}) = \frac{1}{1 + e^{-f(\mathbf{X})}} \tag{1}$$

where $\mathbf{X}$ is the feature vector containing the positional information of all players and is defined according to **Figure 2**, and $f(\mathbf{X})$ is to be optimized by a logistic regression

$$\log\left(\frac{P(y = 1|\mathbf{X})}{1 - P(y = 1|\mathbf{X})}\right) = f(\mathbf{X}) \tag{2}$$

As a universal function approximator of $f(\mathbf{X})$, feed-forward neural networks with different architectures are used, which are optimized by a grid search and are compared to a gradient

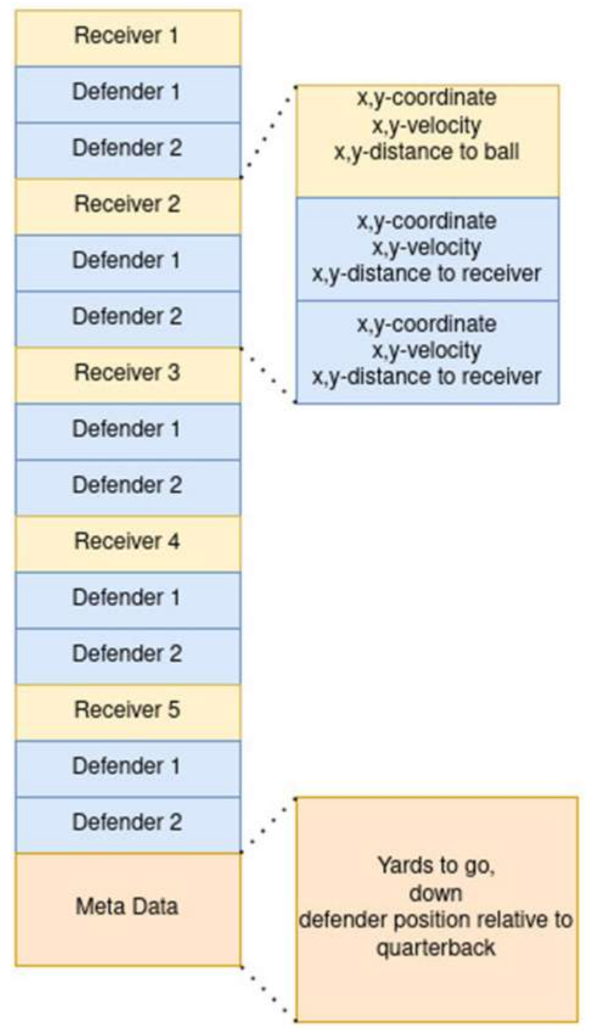

FIGURE 2 | Feature Vector of the pass completion model.

boosted tree model, likewise with optimized hyperparameters by a grid search. Additionally, the problem can also be viewed as multi-class classification, yet as interception probability is low and is linked to large noise, as discussed by Burke (2019) and Deshpande and Evans (2020), it is possible to neglect the special classes in this application and further classify the pass outcome as positive or negative.

The neural network was trained with the ADAM optimizer (Kingma and Ba, 2014), while learning rate and architecture were selected with a grid search resulting in the architecture of three fully-connected layers with batch normalization. The first two layers were of size 64 with an additional dropout layer, while the last layer is a fully-connected layer with 32 neurons. The batch size was kept at 1,024 samples per batch and the learning rate was chosen to be 2e-3. The gradient boosted tree hyperparameter search for the architecture resulted in a maximum depth of 10 and 60 leaves. The learning rate is 0.03. The models were trained with 7-fold stratified cross-validation. Furthermore, a focal loss was used to account for class imbalances, yet, this did not yield better results and was not used/chosen following the law of Occam's razor.

3.2.1. Feature Vector and Training Data

The training, validation, and test data consists of all passes with seven tracked defenders and six tracked offensive players, either complete or incomplete/intercepted from the NFL Season 2019. The training and validation data consists of the first 14 weeks of the NFL regular season, while the test data was taken from the last 3 weeks of the regular season. Overall, 17,346 passes were conducted. After filtering to the specific conditions, 9,199 passes were left. The whole training/test dataset was split 70/30% to accurately train the model and minimize overfitting.

The feature vector was created with respect to the available data from the later proposed ghosting model. As the ghosting model will synthesize the trajectories from the event of ball snap to the moment when the quarterback is throwing the ball, the latest possible time step to determine the pass receiving probability, the event of the forward pass, is used. Besides this information, each of the five receivers is assigned with the relative and absolute position of the two closest defenders as proposed by Burke (2019). The feature vector is ordered as shown in **Figure 2**. The quarterback was handled as a separate feature collection, as the distance to itself is irrelevant. Furthermore, a relative position on the field regarding the yard line and the down and yards until the next down starts was added.

The training set was augmented to make the receiver input order invariant by randomly changing the input receiver position in the feature vector. Furthermore, the play was normalized to always face in one direction and the line of scrimmage is the original orientation regarding the *x*-axis. This can be done, as the play itself should be rotation invariant, and the outcome should not depend on which direction the quarterback throws the pass.

3.3. Ghosting/Deep Imitation Learning

In Le et al. (2017) presented a ghosting model for soccer teams, learned from a season of professional soccer data *via* deep imitation learning. This model was able to capture team behavior in response to different attacking scenarios. In addition to useful insights for team comparisons, the trajectories also produced seemingly trivial outputs upon visual inspection in the first few seconds. However, it is precisely these few seconds in American football that provide insight into defensive behavior, which is why the deep imitation learning approach is transferred to American football and the focus is exactly on these first seconds, because they are essential to the defensive behavior before the pass takes place.

3.3.1. Data and Feature Vector

In this part of the study, the NFL Next Gen Dataset of the 2019 Season is used and the games are filtered for plays with

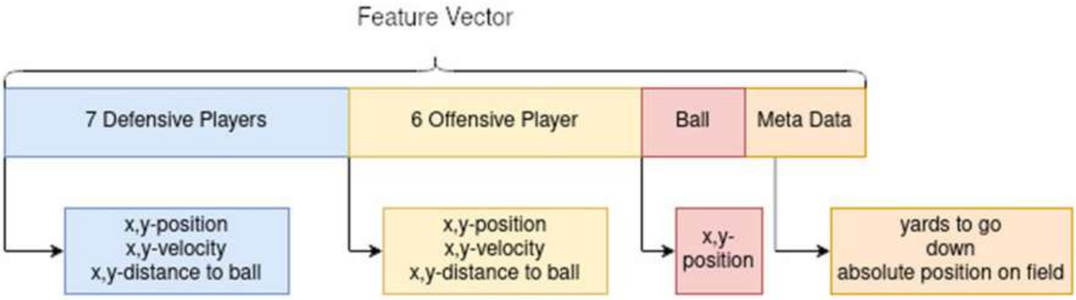

FIGURE 3 | Feature vector ghosting model.

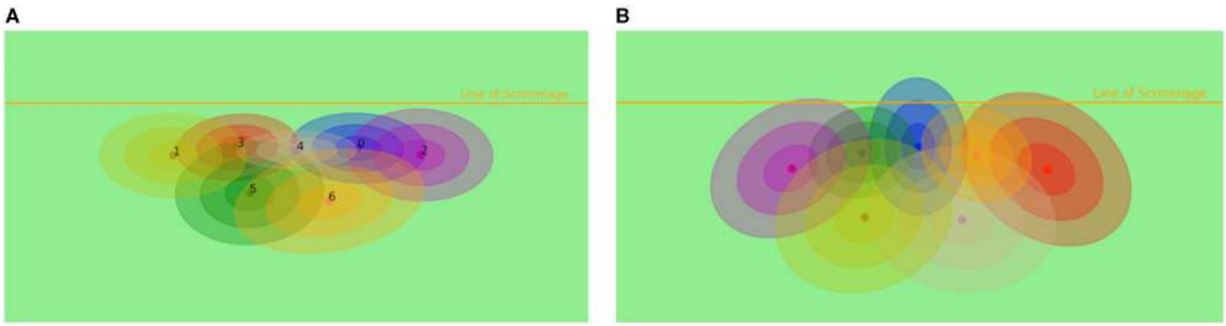

FIGURE 4 | (A) Assignment of specific roles in formations with Gaussian mixture models to the corresponding feature vector. **(B)** Assignment of roles with a learned Hidden Markov model with Gaussian emission functions for different roles to the specific model according to running positions in the coordinated multi-agent approach.

seven defensive and six offensive players and, therefore, 14 trajectories with the ball. Moreover, the vector contains meta-data regarding yards to go until the next down, number of downs, and absolute distance until touchdown. This results in the same number of training sequences as for the completion probability model, all plays are filtered, where there was no forward pass, the quarterback was not sacked and did not perform a handoff. The average sequence has a duration of 3.6 s.

The feature vector of the model is ordered first by the defensive team, then by the offensive team, followed by the ball position and the meta-data, which includes yards to go, number of downs and the absolute position on the field, where the play takes place. The position of players is again normalized so that the line of scrimmage determines the x-axis, and the play takes place in the negative y-direction from the perspective of the offensive team. This is displayed in **Figure 3**. As there is no formation information in the NFL NextGen dataset, a consistent representation of the position of players and positional behavior in the feature vector needs to be guaranteed. To achieve consistency, the tactical role of each player was assigned independent of their named position. Accordingly, an unsupervised role alignment algorithm (Gaussian mixture models) was chosen. The idea of inferring to a specific formation was developed and discussed by Bialkowski et al. (2016). The roles get assigned with a Hungarian algorithm, where a Gaussian mixture model is trained on starting positions and assigns the initial roles according to it. The model is illustrated in **Figure 4A**. This improves the structure of the learning problem, as defensive backs can switch positions and safeties can act as defensive ends. Moreover, cornerbacks and safeties are not bound to be on the left or right side of the field, so assigning positions in a fixed value might disrupt the network and make the learning problem impossible.

3.3.2. Training With Imitation Learning

Imitation is the ability to recognize and reproduce others actions[4]. Hence, imitation learning is learning and developing new skills from observing these skills performed by another actor or oracle. The agents in multi-agent imitation learning contribute individually to a specific goal and need to collaborate.

This multi-agent imitation learning problem arises from two factors, first multiple agents need to learn simultaneously, and the role assignment of the learned agents dependent on the action of the corresponding model, which is in regard again dependant on the assigned role. To overcome this interdependence, Le et al. (2017) proposed an alternating optimization approach, by first optimizing for the imitation task, with a fixed role assignment, next fixing the policies and retrain the assignment model. This

[4]https://en.wikipedia.org/wiki/Imitation

approach is repeated until no further improvement takes place on the validation set.

The assignment model, also called the structured model by Le et al. (2017), is learned *via* an estimation maximization algorithm on a Hidden Markov model with Gaussian emissions, and training was conducted on the same data as the other parts of the algorithm, despite velocity, distance to quarterback and ball position were not used to cluster the trajectories. The results are displayed in **Figure 4B**.

When learning variable-length sequences, recurrent neural networks are suited well for this job. LSTM layers are preferably used to model sequences of this kind and are eminently used when long-term dependencies are playing roles in current predictions. The individual trajectories are modeled with a two-layer LSTM with 128 neurons each. In training, the sequences were split into a length of 25 and an overlap of 10. Later, role-based model learning is compared to static model learning.

The models are trained in three phases according to Le et al. (2017): pretraining, single policy training, and joint policy training. When pretraining, the models are trained with a least-square learning approach without interaction of the single model itself or with other models. This means the model predicts the next timestep of the players, given perfect information and correction of the miss-predictions in training. This method does not resemble realistic trajectories, but initializes models parameters well for the following tasks. In the next step, the policies predict multiple timesteps, with imperfect information of their position, yet all other players have perfect information. This process of predicting multiple timesteps into the future is called rollout. The error of the imperfect information prediction is used to update the model again, and it helps to recover the model from ill predictions. This results in stable position predictions of the policy and enables the model to recover from prediction mistakes and eventually simulates test time during training first introduced by Ross et al. (2011) under the terms of no-regret online learning and present it under the term DAgger (Dataset Aggregation method). In the last step, all ghost models are trained together by predicting the respective next position on the field. Therefore, every model updates the corresponding training data input by imputing the predicted role positions and, therefore, simulating the complete defensive behavior. Empirically, this generates more stable trajectories. The joint training seems to make the model more robust against perturbations in general.

4. RESULTS

4.1. Pass Completion Probability

The pass completion probability is used to validate the proposed ghosting model and, therefore, needs to be appropriately calibrated. As the baseline for the classification problem, a naive classifier of assigning every pass as a catch is used. The result of this method is comparable to the mean pass completion rate in the NFL for the test set data and accounts for 64.8%. First experiments of the pass completion probability model yield disillusioning results, when using ordered data as described by Lucey et al. (2014), as the highest accuracy of the best model is <5% better than the naive classifier.

TABLE 1 | Table comparing the accuracy of pass completion prediction and the correlating miss-classification rate.

Model and data	Accuracy	Miss-classification
Neural Network, ordered Data	69.5%	30.5%
Neural network, order-invariant data	81.6%	18.4%
Gradient boosted tree, order data	66.9%	33.1%
Gradient boosted tree, order-invariant data	76.2%	23.8%

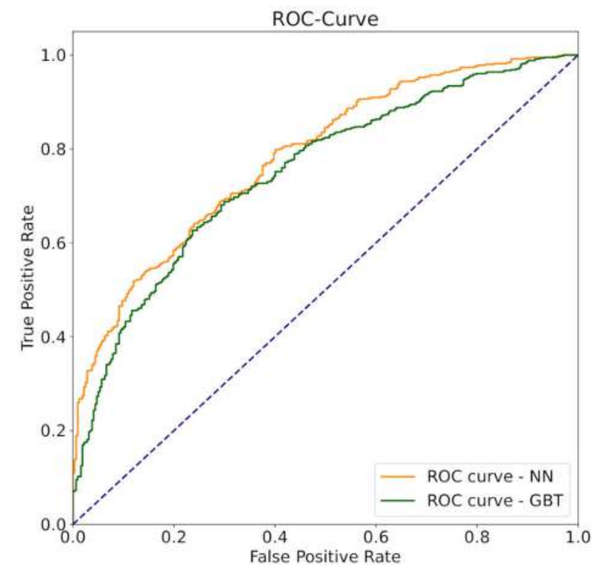

FIGURE 5 | The ROC curve of the pass completion probability model. The AUROC is 0.746 for the neural network and 0.730 for the gradient boosted tree. The dashed blue line, represents the baseline of a random sample, the orange line, the ROC curve of the neural network, and the green line represents the ROC curve of the gradient boosted tree.

In other fields like quantum mechanical force prediction with black box estimators, order invariant learning is important. To achieve this, the atoms are either ordered by distance (Behler and Parrinello, 2007) or the invariance is learned by random permutations (Bapst et al., 2020). When applying random permutations to the order of the receivers, the accuracy of both models, neural networks and gradient boosted trees increases. The neural network outperforms the gradient boosted tree by around 5% in-accuracy (**Table 1**). In **Figure 5**, the Receiver operation characteristics (ROC) curve for the final classification models, with Area under ROC (AUROC) scores of 0.746 and 0.73 respectively, are displayed. The curve shows how well the signal is separated from the noise and returns another evaluation metric for binary classification problems. According to Hosmer and Lemeshow (2000), an acceptable value for the discrimination ability of binary classification is defined between 0.7 < AUROC < 0.8. Rice and Harris (2005) are arguing that AUROC > 0.714 can be classified as good and AUROC > 0.639 as acceptable. Hence, the used classification models are suitable for evaluating the ghosting model. For the following evaluation, the neural

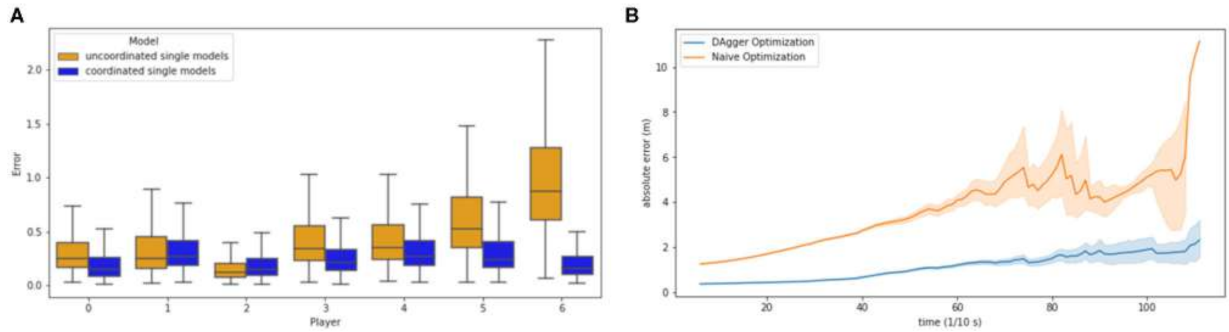

FIGURE 6 | (A) Model error for different roles according to specific models. Blue is the coordinated single model. Yellow is the uncoordinated single model. **(B)** Average rolled-out error throughout play, until the quarterback throws a pass. The blue line indicates the rolled-out error under DAgger optimization. The orange line indicates the rolled-out error without DAgger optimization.

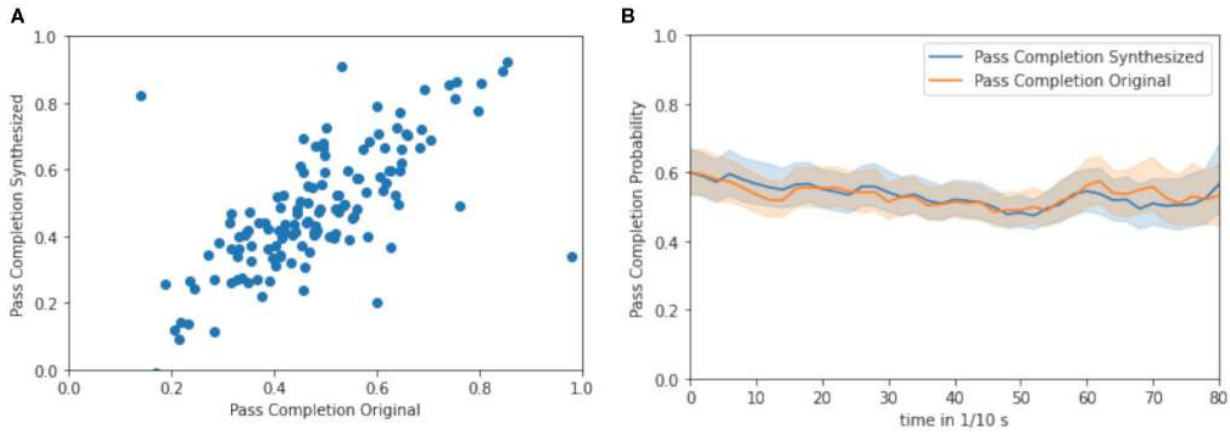

FIGURE 7 | (A) Pass completion probability for synthesized trajectories and true trajectories at the time when the quarterback throws the forward pass (R: 0.545) **(B)** Average pass completion over time between synthesized (blue) and true trajectories (orange) of defensive players.

network approach was chosen due to the higher AUROC and accuracy score.

4.2. Ghosting

For ghosting models to have value, they should conscientiously represent true behavior. In the first step, the exemplary results of the model are qualitatively evaluated, and examples of different behavior produced by the ghosting model are discussed. Finally, the models are checked in terms of prediction accuracy and precision. This means that the true (x,y) position of the players is compared with the predicted (x,y) position.

As discussed by Le et al. (2017), the task of the same player can vary throughout a play. By validating this hypothesis, a coordination model and a team-based model without coordination were trained. The coordination model alternately updates, also called cross-update, the chosen policy with the hidden Markov model, displayed in **Figure 4B**, while the team-based model assigns the feature vector, and hence the formation, with a Gaussian mixture model, displayed in **Figure 4A**.

In **Figure 6A**, the impact on a role-based coordination model, in comparison to a static association of roles can be seen. The error for almost every role of the coordinated model is better than the error of the static model. Especially the error of players 5 and 6 are larger than for the coordinated model.

Figure 6B displays the cascading errors (MAE per timestep) occurring due to the rollout of the trajectories. In this study the rollout approach with the described DAgger algorithm to simulate test time is compared to the naive single-agent learning approach. While the naive optimization model error is drifting very strongly with up to 10 m, the DAgger optimization error remains in an acceptable range of about 2 m. DAgger is especially valuable in this approach, as there is no access to an omniscient oracle and, therefore, needs an approximation for deviations in the given trajectories.

As true running trajectories and simulated trajectories may differ, an impact measurement *via* a “third party,” the trained pass completion probability model is conducted. In **Figure 7A**, the pass completion probability at the time of the thrown pass in the test set is visible for the respective ghosted trajectories and

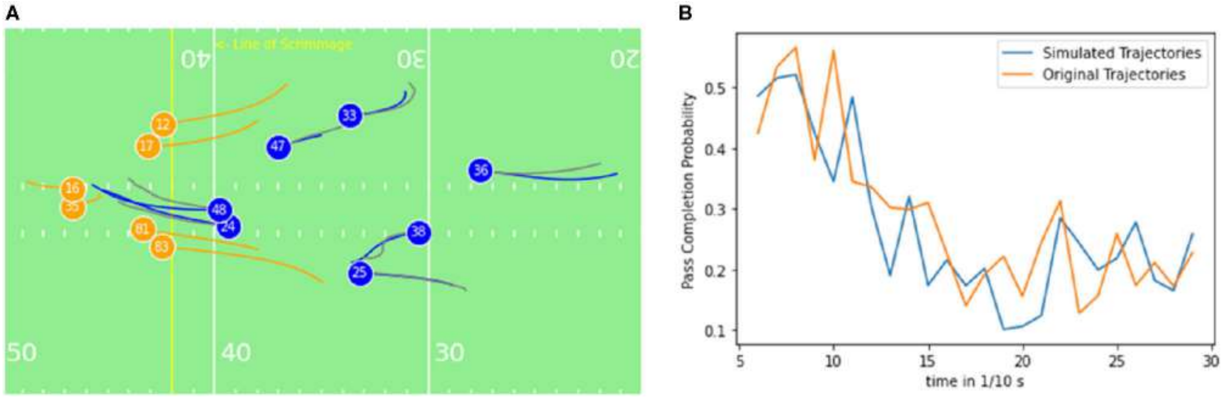

FIGURE 8 | (A) Exemplary short play (≈ 3s): The Quarterback (16) throws a short pass to a receiver (12) on the left side of the field. Offensive players are illustrated in blue, defenders orange and ghosted trajectories in gray color. The initial position of the players is represented by the player shirt number. **(B)** Pass completion probability over the course of the play for the ghost/simulated trajectories and true/original movements.

real trajectories. The R-value is 0.545, which indicates the close positive relationship of the pass completion probability of ghosts to the pass completion probability of the observed defenders. **Figure 7B** displays the average pass completion probability for the synthesized trajectories and the true trajectories throughout the plays in the test set. Although the ghosts run different trajectories during the different plays, in the test set, the average pass completion rate of the ghost is similar to the true pass completion rate, which the ghosts should mimic in the end. With the incorporation of positions of all receivers and defenders, the model is capable of the individual interpretation of the current defensive formation without taking the decision-making of quarterback into account.

5. DISCUSSION

5.1. Pass Completion Probability

The calculation of the pass completion probability for every player, as proposed by Team (2018), is based primarily on the positioning of players, their closest defenders, or separation from the sideline. Sophisticated models like this are very suitable for analyzing quarterback decision-making and even whole plays in-depth but are too complex to assess team performance. In this approach, the total completion probability is used to compare the ghosting model with the actual running routes. Burke (2019) uses a two-step pass completion probability by first selecting the receiving player and calculating the pass completion probability afterwards. This is a very detailed approach to investigate the decision-making of the quarterback but does not cover defensive team behavior. Hence, the distribution of the targeted player and, therefore, the pass completion probability may change. This approach could be extended by Deshpande and Evans (2020) and the suggested hypothetical pass completion probability, where they investigate if the proper player was chosen for the pass. In the current approach, the decision-making of the quarterback is bypassed, and a pass completion probability by the positions of the receivers and the defenders is computed. This enables the approach to give concise information about the current value of specific opposing positions on the field without biasing the model by a designed combination of pass completion probabilities for every player. Nevertheless, the model accounts for applied pressure on the quarterback by incorporating the kinematic parameters and metadata of defenders, so that indirectly, the model can account for a poorly thrown pass due to the movement of nearby players of the defending team.

5.2. Ghosting Model

The objective of the ghosting model is to synthesize realistic defensive behavior. Especially, it should be intrinsically learned to have a team meta behavior, by following a coordinated strategy. In the following section, two examples are investigated and discussed with respect to the evaluation metric.

Figures 8A, **9A** illustrate examples of the observed offensive (blue) and defensive (orange) trajectories for a short and a long play. Parallel to the tracked movement trajectories, the predicted/ghosted movement paths of the defensive players (gray) for the same period are displayed.

In **Figure 8A**, the true running trajectories are compared with the generated ones, which are interchangeably referred to as ghost trajectories or ghosts in this study. In the figure can be seen, that the ghosts behave similarly to the true players except that the ghosts pressuring the quarterback to decide to run in parallel and the players both tried to tackle the quarterback. The pass was thrown after 3 s. The pass completion probability for the original trajectory and the simulated trajectory, displayed in **Figure 8B** has the same tendencies, which is closely related to similar positions. Although the model is returning similar tendencies, high noise in the signal relates to a non-perfect pass completion model. Steerability of the ghosting model is included regarding yards to go, the number of downs, and position on the field regarding the distance to the end zone. When changing these variables, no distinguishably different behavior of the ghosted players compared to the initial ghosting outcome can

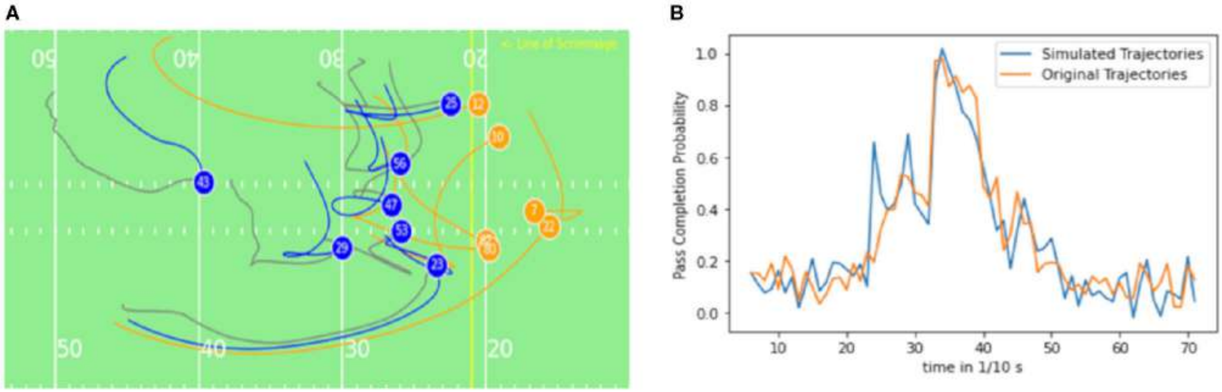

FIGURE 9 | (A) Exemplary long play (≈ 7.2 s): The Quarterback (7) throws a pass to a receiver (12) on the right side of the field. Offensive players are illustrated in blue, defenders orange and ghosted trajectories in gray color. **(B)** Pass completion probability over the course of the play for the ghost/simulated trajectories and true/original movements.

be observed. This indicates a low influence of those variables in the ghosting model for the dataset.

Figure 9A illustrates the behavior of true and ghosted trajectories throughout 7.2 s before the quarterback pass. The ghosted trajectories differ significantly from the actual running trajectories. This is a result of the much larger prediction horizon of the play. The policies/ghosts have significantly more decisions to make and different collaborative behaviors can emerge. After a few seconds, variabilities at the Safety positions (players 43 and 29) can be observed (**Figure 9A**). The running path of defender number 43 closes some space to the offensive receiver (number 12), the same pattern can be observed for defender number 29. In this study, the ghosts move more backwards and the defender number 29 is closing more to the receiver 12. The collaborating models run a different strategy than the actual players, yet the pass completion probability is similar according to (**Figure 9B**). As the model takes the defensive behavior of all teams of the NFL into account, the prediction is an average defensive behavior of all teams. Extensive data of specific- teams and players can help to develop team-specific defensive models according to Seidl et al. (2017).

By comparing the coordinated and uncoordinated models in **Figure 6A**, it can be seen that both safeties have a much larger error than in the coordinated model. This indicates that the safeties are running the most varying strategies and are interchangeable in position (left and right), which yields to the conclusion that the team model cannot capture the strategic changes that are a result of communication between safeties and the reaction to the offensive trajectories. Also, the middle linebacker position (number 4) has a much larger error in the uncoordinated model. These positions seem to have the most different tasks in different strategies, while the cornerbacks (number 1 and 2) and outer linebackers (number 0 and 3) appear to have a more pre determined strategy in the observed formations. Yee et al. (2014) argue that the safety is the most versatile position. Furthermore, **Figure 4B** displays larger covariances in the hidden Gaussian emissions for the running routes that can be observed for the specific players. Hence, compared to the superior coordinated model, the uncoordinated model helps to understand the influence of global strategy and how it differs across single players.

Respectively, looking into the time evaluation of the pass completion model in **Figure 7B**, it can be stated that the average pass completion probability is close to the average pass completion probability over the entire period. This indicates that the model is not distinguishing between the timestamp of the trajectory and cannot infer the time when the pass is thrown up to 8 s. Notably, the average pass completion probability of the model over the period for the ghosting model and the original running trajectories is indistinguishable, therefore, the ghosting model infers a similar strategy to the original data and can be used to simulate short and long trajectories before the pass is thrown.

6. CONCLUSION AND FUTURE WORK

To guarantee the stated accuracy of the predicted positions and make this model helpful for practitioners, the validity of the tracking system needs to be further evaluated. Noteworthy, the sport-specific context turned out to be a challenge for different tracking methods (Hoppe et al., 2018; Linke et al., 2018). Although systems with comparable technology showed promising results in recent validation studies (Blauberger et al., 2021), future research needs to be conducted in the validation of the NFL tracking system.

Deep imitation learning can be mutually adapted to many kinds of team sports with sufficient tracking data at hand. The current study demonstrates that smart feature engineering and reinforcement learning approaches improve the quality of the ghosted trajectories. Investigating a formation with the overall pass completion probability can establish the comparability to run trajectories without comparing the exact position of the players and allowing deviations. However, this lacks the evaluation of the single-player pass completion probability. Upcoming study could include analysis of single player pass completion probability and the variation in those compared to the ghosting models. Furthermore, individualization of players could be included by adding meta-features for every player and, therefore, provide the possibility to compare the performance of individual players in specific plays.

Another drawback of the proposed method is the necessity of a deterministic feature vector. This leads to a massive loss in training data, as it is necessary to determine and adapt to the number of players on the field. In the case, this resulted in a loss of more than 50% of training data for the whole NFL regular season in 2019. With the emergence of graph neural networks and the ongoing research in spatio-temporal graph neural networks (Zhou et al., 2018), this drawback might be resolvable in the near future. Although, the focus of the analysis was kept to pre-throw trajectories for defensive players, the algorithm can be extended to longer trajectories, e.g., movements after the catch. With a sophisticated annotation tool for American football plays, this method could be used to incorporate the versatility of the coverage scheme of defenders. This was not possible with the included data from the NFL dataset 2019 but might be addressed with the work of Dutta et al. (2019). Furthermore, ghosting can be used in the back-end of real-time player sketching. The possible benefit for coaches is also proposed for other sports, like a basketball by Seidl et al. (2017). NFL coaches and analysts can compare their defensive team performance to the league average performance, conduct a hypothetical analysis for specific plays, determine miss behaving defenders, or progress to completely automatic game analysis.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

MS designed the experiment and wrote the software. MS and PB wrote the manuscript was written. ML and PB supported the development of the research design, assisted in the interpretation of the data, and reviewed the manuscript. All authors contributed to the article and approved the submitted version.

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