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Optimizing Haptic Human-Robot Collaboration Considering Human Perception and Idiosyncrasies

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Abstract

Robots are increasingly being introduced to former human-dominated areas with the intention to solve prevailing economic and social challenges. The interaction of humans and robots aims to overcome emerging demands of flexible production, demographic change, and improvement of life in general. The introduction of robots was followed by remarkable production benefits – as long as humans stay out of their reach. However, the ideal picture of perfectly operating robots elegantly solving everyday tasks has not yet been achieved. This casts doubt on the idea of completely replacing human workers with robots, in particular because complementary collaboration may result in better task performance than either could possibly deliver alone. A promising form of complementary collaboration is haptic Human-Robot Collaboration (hHRC), where a human and a robot work jointly in the same place, at the same time, with a common goal, and with direct haptic contact.

Previous research on hHRC developed and applied algorithms based on information acquired online during the interaction. Although these approaches effectively stabilized the system, they are susceptible to delays and can adversely affect usability. Humans heavily rely on visual stimuli that are available prior and during haptic interaction with their environment. In this context, this thesis models individual manipulation behavior of different sized objects as well as mass perception and provides methods for objective and subjective evaluation. As a design basis, it establishes the perception-related assistance strategy framework (PRAS) to provide engineers and researchers with a basis for designing hHRC that enables high usability and acceptance of the robotic system.

This thesis introduces human-centered assistance applications as a novel paradigm of design, evaluation, and application of physical assisting devices (Section 2). By applying psychophysical methods, a human mass perception model was developed (Section 3) and the influence of visual object size cues on manipulation behavior with special interest in the speed-accuracy trade-off was investigated (Sections 6 and 7). Objective (Sections 4 and 7) and subjective (Section 5) assessment methods of hHRC were developed and evaluated.

The results indicate that object size and movement type greatly influence manipulation behavior with potential influence on stability and usability. The compensatory approach within the PRAS framework, where sequentially larger objects are displayed heavier than previous smaller ones, revealed equivalent task performance in comparison to a priori fixed and static strategies. This makes it possible to stabilize initially higher interaction forces of larger objects without affecting task performance. On this basis, it is recommended that perception-related assistance strategies are applied to novel hHRC. Further research should analyze the effect of other perception-related information, such as material and shape, as well as contextual factors and their influence on long-term use. Furthermore, the validity of the results for other, similar devices such as exoskeletons or personal robots need to be confirmed.

Zusammenfassung

Roboter werden zunehmend in ehemals von Menschen dominierten Umgebungen eingeführt, um aktuelle wirtschaftliche und soziale Herausforderungen, wie flexible Produktion, demografischen Wandel oder die Verbesserung des Lebens im Allgemeinen zu bewältigen. Dies bringt erhebliche Vorteile mit sich – solange der Mensch außerhalb ihrer Reichweite bleibt. Gleichzeitig wurde das Idealbild perfekt funktionierender Roboter, die Alltagssituationen elegant lösen, noch nicht erreicht. Mithilfe komplementärer Zusammenarbeit können Aufgaben noch besser gelöst werden, als es Roboter oder Mensch allein vermögen. Ein vielversprechender Ansatz liegt in der haptischen Mensch-Roboter-Kollaboration, bei der Mensch und Roboter gemeinsam am selben Ort, zur selben Zeit, mit einem gemeinsamen Ziel und direktem haptischen Kontakt arbeiten.

Frühere Forschungsarbeiten, welche auf während der Interaktion gewonnenen Informationen basieren, bewirken eine effektive Stabilisierung des Systems und ermöglichen prinzipiell die haptische Interaktion. Sie sind jedoch anfällig auf Latenzen und können die Gebrauchstauglichkeit des Systems beeinträchtigen. Ein großer Teil der physischen Interaktion des Menschen mit seiner Umwelt wird von visuellen Reizen beeinflusst, die vor und während der haptischen Interaktion zur Verfügung stehen. Daher wurde in dieser Arbeit das Manipulationsverhalten eines Individuums bei unterschiedlich großen Objekten untersucht, ein Modell zur Massenwahrnehmung aufgestellt sowie Methoden zur objektiven sowie subjektiven Bewertung eingeführt. Ein Konzept zur Unterstützung des Menschen basierend auf seinen Wahrnehmungseigenschaften (PRAS) wurde vorgestellt, um Ingenieuren und Forschern eine mögliche Gestaltungsgrundlage zu bieten. Übergeordnetes Ziel war es, haptische Mensch-Roboter-Kollaboration ergonomisch zu optimieren, um Gebrauchstauglichkeit und Akzeptanz zu verbessern.

Human-centered assistance applications werden als neue Perspektive auf das Design, die Evaluation und die Anwendung physikalischer Assistenzgeräte vorgestellt (Abschnitt 2). Mit psychophysikalischen Methoden wurde ein Modell menschlicher Wahrnehmung von Trägheitsmassen aufgestellt (Abschnitt 3) und der Einfluss visueller Objektgrößen auf das Manipulationsverhalten untersucht (Abschnitte 6 und 7). Es wurden sowohl objektive (Abschnitte 4 und 7) als auch subjektive (Abschnitt 5) Bewertungsmethoden entwickelt und evaluiert.

Die Ergebnisse zeigen, dass Objektgröße und Bewegungsart das Manipulationsverhalten sowie Stabilität und Gebrauchstauglichkeit stark beeinflussen. Der kompensatorische PRAS-Ansatz, bei dem sequentiell größere Objekte schwerer als vorherige kleinere Objekte dargestellt werden, zeigte eine zu a priori festgelegten und statischen Strategien äquivalente Aufgabenleistung. Dieses Ergebnis ist besonders relevant, da es die Möglichkeit bietet, zunächst höhere Interaktionskräfte induziert durch größere Objekte zu stabilisieren, ohne die Aufgabenleistung zu beeinträchtigen. Auf dieser Grundlage wird empfohlen, objektbezogene Assistenzstrategien in zukünftigen haptischen Mensch-Roboter-Kollaboration anzuwenden. Zukünftige Forschung sollte weitere Kontextfaktoren, deren Einfluss auf lange Sicht und den Ergebnistransfer auf andere Assistenzsysteme wie Exoskelette und Personal Robots untersuchen.

Contents

Nomenclature

Acronyms

CNS	Central Nervous System
Cobot	Collaborating robot
COFOR	Common Frame of Reference
DOF	Degree of Freedom
EMG	Electromyography
FA	Function Allocation
GTO	Golgi tendon organ
hHRC	Haptic Human-Robot Collaboration
HCAA	Human Centered Assistance Applications
HCI	Human-Computer Interaction
HMS	Human-Machine System
HRI	Human-Robot Interaction
IAD	Intelligent Assist Device
IEEE	Institute of Electrical and Electronics Engineers
JND	Just Noticeable Difference
LME	Linear Mixed Effects Model
LoA	Level of Automation
LoHA	Level of Haptic Authority
LoHS	Level of Haptic Support
LoRA	Level of Robot Autonomy
MABA–MABA	Men Are Better At – Machines Are Better At
MS	Muscle spindle
MWI	Material-Weight Illusion
NA	No Assistance
OL	Over Load
PRAS	Perception-related Assistance Strategies
PEST	Parameter Estimation by Sequential Testing
pHRI	Physical Human-Robot Interaction
PARS	Power Assist Robot System
QUEAD	Questionnaire for the Evaluation of Physical Assistive Devices
RL	Reference Level
RQ	Research Question
ShMM	Shared Mental Model
SMI	Size-Mass Illusion
SWI	Size-Weight Illusion
TAM	Technology Acceptance Model

TCP	Tool Center Point
UTAUT	Unified Theory of Acceptance and Use of Technology
UX	User Experience
wMSDs	Work-Related Musculoskeletal Disorders

Measures

100-point scale	Metric strain scale from 0 (no strain) till 100 (maximum strain)
COL	Collisions [-]
DF	Degree of fulfilment [mm]
ERROR	Compiled errors [-]
F	Force [N]
FR	Force rate [N/s]
PPL	Path positioning length [mm]
SDLP	Standard deviation lateral position [mm]
TTC	Time to task completion [s]

Statistics

AIC	Akaike Information Criterion
BIC	Bayes Information Criterion
BF	Bayes Factor
CI	Confidence Interval
d	Cohen's d (effect size)
F	F-test statistic
M	Mean
Md	Median
p	Probability of test statistic if null-hypothesis is assumed
P(Y)	Probability of a variable Y
r	Pearson's correlation
SD	Standard deviation
t	t-test statistic
α	Significance Level (.05) or Cronbach's alpha
η_p^2	Partial eta square (effect size)
ε	Error term
χ^2	Chi-squared

Subscripts

(the following subscripts specify the below reported measures, where $(\cdot)$ can be any of the mentioned variables)

$(\cdot)_0$	start
$(\cdot)_1$	actual
$(\cdot)_{1stpeak}$	first local maximum
$(\cdot)_B$	basic isometric maximum force
$(\cdot)_{Br}$	reduced capacity limit
$(\cdot)_d$	travel distance multiplier
$(\cdot)_{estimated}$	from prior knowledge estimated characteristic
$(\cdot)_f$	task frequency multiplier
$(\cdot)_{fast}$	fast-imprecise movement
$(\cdot)_{IAD}$	caused by the intelligent assist device
$(\cdot)_{kin}$	kinesthetically perceived
$(\cdot)_{mean}$	mean average
$(\cdot)_{object}$	perception-related
$(\cdot)_{precise}$	slow-precise movement
$(\cdot)_t$	admittance target
$(\cdot)_{true}$	true value
$(\cdot)_{visual}$	visually perceived

Symbols

c	damping
d	distance
f	frequency
F	force
k	Stiffness
k	Weber Fraction
m	mass
s	object size
t	time
x	position
$\dot{x}$	velocity
$\ddot{x}$	acceleration
Δ	delta, difference
ρ	material

1 Introduction

"The true delight is in the finding out rather than in the knowing."
~Isaac Asimov

HUMAN-ROBOT INTERACTION is nowadays growing stronger in relevance than ever and progressively merges into many areas of work and life. By utilizing the strength and potential of each partner, novel interaction concepts will be able to solve current social and industrial challenges (Bauer, Wollherr, & Buss, 2008; Bortot, 2014; Khatib, Yokoi, Brock, Chang, & Casal, 1999). Many domains such as rehabilitation, prosthetics, health care, surgery, space, military, agriculture, education, household, industry, and physical work in general are involved in these endeavors (Bicchi, Peshkin, & Colgate, 2008; Sheridan, 2016). The close complementary haptic collaboration between humans and robots is a promising approach to reduce fatigue and stress and increase human capabilities in terms of force, speed, and precision (De Santis, Siciliano, De Luca, & Bicchi, 2008). By using robotic capabilities like power assist, inertia masking, and virtual guidance (Peshkin & Colgate, 1999; Wannasuphoprasit, Akella, Peshkin, & Colgate, 1998) in haptic collaboration with the human high fidelity sensory system, it is possible to compensate weaknesses of each partner by strengths of the other (De Santis et al., 2008; Khatib et al., 1999). Caused by an ongoing demographic change (Frieling, Buch, & Wieselhuber, 2006; Verbeek et al., 2012), increased diverse human capabilities and characteristics will require human-centered approaches (Christ & Beckerle, 2016; Schmidtler, Knott, Hölzel, & Bengler, 2015; Yan, Cempini, Oddo, & Vitiello, 2015) to ensure optimal usability, evolve acceptance, and enable health-preserving applications.

No societal group is more heterogeneous than elderly, where there are 90-year-old marathon runners and people who are already dependent on care with pensionable age (Rinkenauer, 2008). Rinkenauer (2008) concludes that the remaining motoric capabilities mainly influence the type of activities and independence older people are able to. Until now, there is no way to stop aging, but it will eventually be possible to assist humans in their daily life and work to prevent work-related musculoskeletal disorders (wMSDs), and support people to stay active and individual. Consequently, it will be possible to reduce individual effects of aging and get a hang of actively working against age-related degeneration (Louis, Brisswalter, Morio, Barla, & Temprado, 2012; Robinson, MacDonald, & Broadbent, 2014; Voelcker-Rehage, 2006). Declining sensorimotor capabilities with age (Adamo, Martin, & Brown, 2007; Frontera et al., 2000; Salthouse, 2009), accompanied by a higher life expectancy (born in Germany, 2017, boys will in average become 90 and girls 93 years old; DESTATIS, 2017), and higher risk for physical diseases with age (Knieps & Pfaff, 2015) create the need for health-preserving measures. Especially wMSDs, which cause over 25 % of all incapacities to work and form the largest problem in current working conditions (Knieps & Pfaff, 2015) must be addressed. These facts increasingly gain in significance since people are staying longer in their work life. For example, between 2000 and 2016, the working population in Germany, has seen a steady increase of workers within the age of 50+ years (average increase of 3.3 %, cum. 6,499,000 M; DESTATIS, 2017a). Besides elderly, people with disabilities in general would benefit from new robotic solutions to stay active, independent, and individual (Argall, 2015; Beckerle et al., 2017; Biddiss & Chau, 2007).

The call for individuality and flexibility is apparent in many areas of work and life. One relevant example is the so-called mass customization of services and products (Fogliatto, Da Silveira, & Borenstein, 2012). People want to be individual and buy individualized products. Therefore, the state-of-the-art production method is changing extensively. Ever since Unimate, the first industrial robot, introduced by the US car manufacturer General Motors in 1961, the main goal has been a precise and efficient large-scale production of one and the same part over and over. This worked perfectly fine for mass production. But the high productivity in combination with changing demands created a new problem: increased stock-holding costs. Originating in Japan in the 90s, lean production with just-in-time manufacturing (Kanban), an on-demand production was introduced. The increasing performance of processors and computers, the internet, and digitalization made it possible to actually reduce stock-holding (Bauernhansl, Hompel, & Vogel-Heuser, 2014; Reinhart, 2017), but simultaneously created a pitfall for many companies that deployed classical hard-coded industrial robots (Lotter, Deuse, & Lotter, 2016). Many of the admittedly impressive video clips of futuristic smart factories, which are shown right now, can still produce only a single product (Slepov, 2016). Changes in the product often cause cost and time intensive re-programming and re-configuration. Additionally, a bottleneck in form of too few robot experts that actually are capable of programming and using these robots became apparent (Herbst, 2015). Car manufactures are traditionally pioneers for new production systems and often are keen to implement ergonomics and human factors. As one of the first, they have begun to take robots out of their cages and formed complementary hybrid systems consisting of humans and robots to actually improve daily work and production efficiency (Lotter & Wiendahl, 2006; Matthias & Ding, 2013; Wischmann, 2015). Also other branches increasingly realize that the optimal solution consists of *man with machine*, instead of full automation, to meet the challenges of complexity and uncertainty (Bengler, Zimmermann, Bortot, Kienle, & Damböck, 2012; Gögele, 2017; Hancock, 2017; Khatib et al., 1999; Klein, Woods, Bradshaw, Hoffman, & Feltovich, 2004; Schmidtler et al., 2015). A spatially close and direct physical interaction of human and robots is facilitated by current and new standards (DIN EN ISO 10218-1, 2012; DIN EN ISO 10218-2, 2012; ISO TS 15066, 2016), a rapid progression of novel robotic systems (Bauer et al., 2008; M. Goodrich & Schultz, 2007; Krüger, Lien, & Verl, 2009), as well as by governmental funding and media.

> “Once confined to the pages of futuristic dystopian fictions, the field of robotics promises to be the most profoundly disruptive technological shift since the industrial revolution.”

says Dan Shewan (2017) from *The Guardian*.

Robots are given enormous potential which is also apparent in recorded and predicted robot sales. With an average increase of 13 % in worldwide annual supply of industrial robots in the years from 2017–2019, an estimated number of 2.6 M robots will be deployed by 2019 (Gemma, Verl, & Litzenberger, 2016; IFR, 2016a). Additionally, an increase to about 333,000 service robots for professional and 42 M units for personal and domestic use is projected until 2019 (Haegele, Park, & Litzenberger, 2016; IFR, 2016b). The increase in domestic assistants is also backed by subjective data from surveys, in which respondents expressed their desire for robotic help in the household, for elderly and handicapped people, and help to make life easier in general (Dautenhahn et al., 2005; Khan, 1998; Ray, Mondada, & Siegwart, 2008). Although, companies such as Rethink Robotics (Baxter and Sawyer), Universal Robots (UR-series), KUKA (LBR iiwa), ABB (YuMi), and many more popularized the idea of cooperating and collaborating robots in company presentations and media. Still they are only a niche market. Only 5 % of the 290,000 sold industrial robots per year are capable of interacting with the human (Robotenomics, 2016). According to IFR (2016a) and Christensen et al. (2016) this will change drastically soon and Human-Robot Collaboration will have a breakthrough within the next few years (50 % collaborative robots, 16 % traditional industrial robots growth rate per year).

1.1 Haptic Human-Robot Collaboration

This subsection provides relevant **definitions** and **classifications** of Human-Robot Interaction and haptics to form a common foundation of the field of haptic Human-Robot Collaboration and its application within this thesis for each reader. **Rationales** that affirm the high potential of haptic Human-Robot Collaboration are motivated and followed by a **retrospect** at the origin and ongoing design of intelligent assist devices.

1.1.1 Definitions and classification

Human-Robot Interaction (HRI) and, especially its subcategories, are not consistently defined in the literature (Bortot, 2014; Helms, 2006; Henrich, Fischer, Gecks, & Kuhn, 2008; Spillner, 2014; Thiemermann, 2005). Also, there is no commonly accepted taxonomy for HRI (Bauer et al., 2008; M. Goodrich & Schultz, 2007; Onnasch, Maier, & Jürgensohn, 2016; Scholtz, 2002b; Thrun, 2004; Yanco & Drury, 2004, 2002; Zeller, 2005). Standards such as the DIN EN ISO 10218-1 (2012), DIN EN ISO 10218-2 (2012), DIN EN ISO 8373 (2012), and ISO TS 15066, 2016) very accurately define working spaces and conditions, especially in terms of safety, but they lack a detailed definition of the interaction of human and robot in its manifold manifestations. Since the following paragraphs are very dense and reading can be a bit exhausting, I strongly recommend to consult the overview in Fig. 1 to find your way through this introduction.

In order to make the detailed perspective of this thesis on HRI more comprehensible, a generic definition of interaction is given here:

Interaction: "A *relationship* between two or more systems, people, or groups that results in *mutual* or *reciprocal influence*" (VandenBos, 2015, p. 549) [emphasis added].

Mutual or reciprocal influence is characterized by a bilateral flow of information. It is defined as communication between human and robot:

Communication: "The *transmission of information*, which may be by *verbal* or *nonverbal* means" (VandenBos, 2015, p. 215) [emphasis added].

This communication can be *explicit*, evoked deliberately by each interacting partner, or *implicit*, implied by the nature of human or robot behavior and the underlying task characteristics. Humans and robots are able to express themselves and receive information aurally (e.g., voice), visually (e.g., gesture), and haptically (e.g., touch or manipulate) receive information. If this exchange of information is based on common goals, common plans, and an allocation of functions (see Section 1.1.2), a *Common Frame of Reference* (COFOR, see Section 1.2.3) is created (Hoc, 2001). Since, the two partners within an HRI will inevitably interfere with each other, it is crucial to define the way they are approaching their goal together.

Interference is defined as the positive or negative effects of one partner on the goals of the other. They either promote the achievement or maintenance of someone's goals (*positive interference*), or threaten them (*negative interference*; Castelfranchi, 1998).
Since the initial motivation for the combination of humans and robots is based on the idea to use skills of each partner to eliminate weaknesses of the other, a common goal is mandatory for cooperative actions. Therefore, the definition of cooperation underlying this thesis reads as follows:

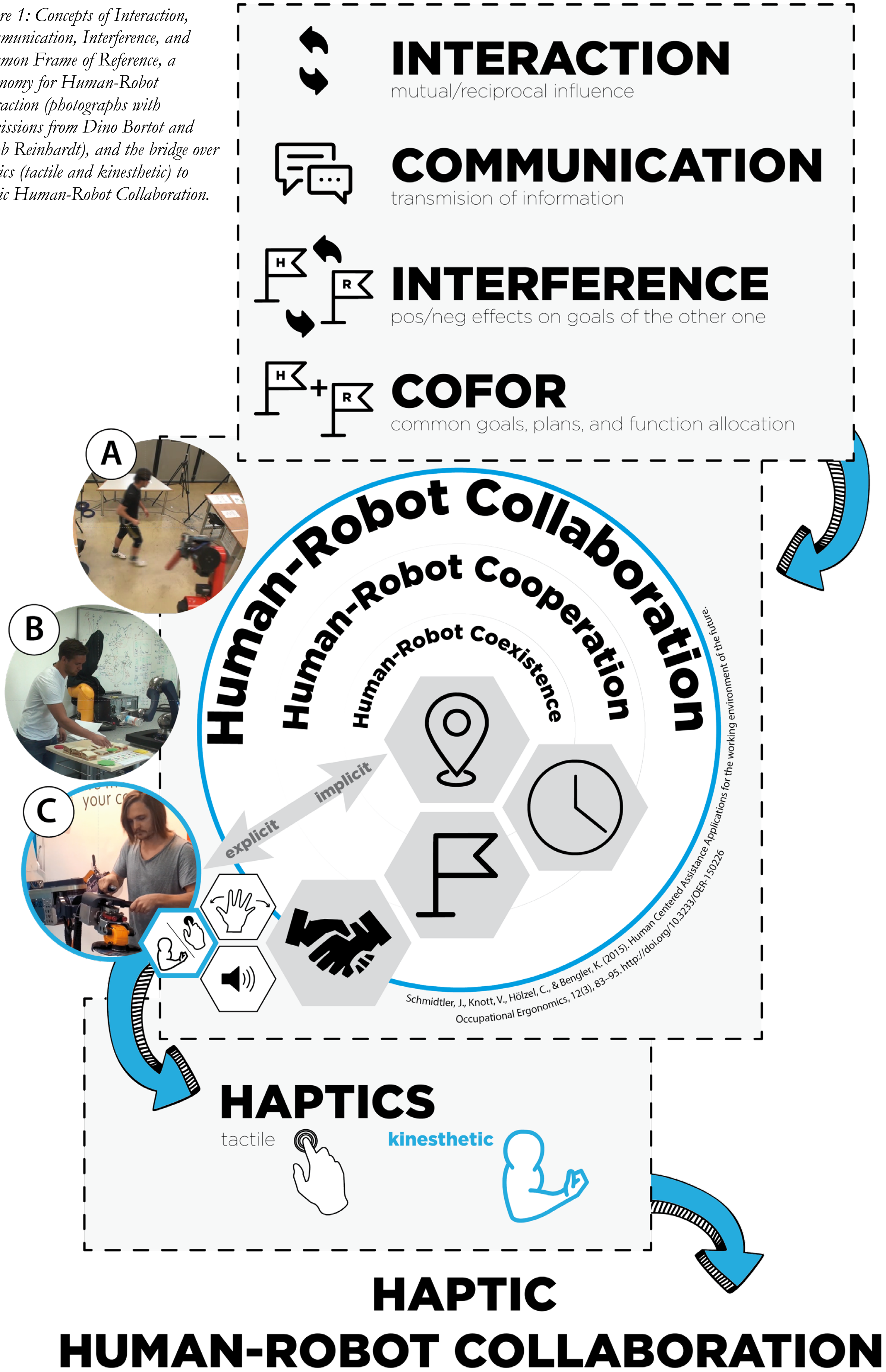
Cooperation: "A process whereby two or more individuals *work together* toward the attainment of a *mutual goal* or *complementary goals*" (VandenBos, 2015, p. 251) [emphasis added], "[…] accomplished by the *division of labor* among participants, as an activity where each person is responsible for a portion of the problem solving […]" (Roschelle & Teasley, 1995, p. 70) [emphasis added] and *a priori fixed* distribution of roles at the beginning of a task (Dillenbourg, Baker, Blaye, & O'Malley, 1996; Jarrasse, Sanguineti, & Burdet, 2013).

At this juncture, this work partially disagrees with the definition of cooperation of Hoc (2001, p. 515). While his two minimal conditions for cooperation are accepted: (1) "Each one strives towards goals and can interfere with the other on goals, resources, procedures, etc. (2) Each one tries to manage the interference to facilitate the individual activities and/or the common task when it exists.", his auxiliary "[…] it does not suppose the generation of a *common goal* or *common plan*" (Hoc, 2001, p. 515) [emphasis added] has to be declined with the strong reference to this work's understanding of *mutual* and *complementary goals* within an HRI. An effective HRI can only take place if there are at least short-term goals of human and robot that are congruent and as a consequence both partners have a COFOR. If the interaction between two entities is getting closer the term collaboration in its following definition will be used:

Collaboration: "An interpersonal *relationship* in which the parties show cooperation and *sensitivity* to the others' *needs*" (VandenBos, 2015, p. 209) [emphasis added], "[…] mutual engagement in *a coordinated effort* to *solve the problem together*" (Roschelle & Teasley, 1995, p. 70) [emphasis added], and *no a priori*, but spontaneous role distribution during the task (Dillenbourg et al., 1996; Jarrasse et al., 2013; Sebanz & Knoblich, 2009).

This thesis follows the classification of HRI as an umbrella term (Fig. 1), consisting of *Human-Robot Coexistence*, *Cooperation*, and *Collaboration* introduced by the author (Schmidtler et al., 2015; also see Section 2.). It is mainly influenced by the classifications of Bortot (2014), as well as by the taxonomy of Yanco and Drury (2004).

Figure 1: Concepts of Interaction, Communication, Interference, and Common Frame of Reference, a taxonomy for Human-Robot Interaction (photographs with permissions from Dino Bortot and Jakob Reinhardt), and the bridge over haptics (tactile and kinesthetic) to haptic Human-Robot Collaboration.



Human-Robot Coexistence: Human and robot are present in the *same space* at the *same time*. For example, an industrial robot without a safety fence acting besides a human worker, a delivery robot passing by a human pedestrian or a vacuum cleaner robot cleaning the floor next to oneself. Within these contexts, only short-term interference occurs and no close interaction takes place. Avoidance is often the main theme of this interaction (Onnasch et al., 2016). Fig. 1, A shows a worker occasionally passing by a moving robot without serious interference (Bortot, Born, & Bengler, 2013).

Human-Robot Cooperation: Human and robot are present in the *same space* at the *same time* and work with a *common goal*. For example, tasks where both partners contribute with subtasks to achieve a shared superior goal. Both partners are adding value to the shared task, interferences getting longer and more intense. Usually this includes a dynamic prioritization of own short-term and more global long-term goals (Klein et al., 2004). Fig. 1, B shows a person making sandwiches and a robot is adding the dressing. This creates interference, which is solved by both partners (Reinhardt, Pereira, Beckert, & Bengler, 2017).

Human-Robot Collaboration: Human and robot are present in the *same space* at the *same time*, work with a *common goal* in *close complementary joint action*. Explicit communication via gesture, voice, or haptic contact takes place, e.g., to summon a mobile robot by speech command, wave at a robot with your hand, or manipulate a robot by grabbing and moving it. Fig. 1, C shows the author actively collaborating with a power assisting robot via haptic interaction.

This definition implies a smooth transition from implicit communication (coexistence and cooperation) to explicit communication (cooperation and collaboration). It is crucial to understand that classifying a specific interaction of human and robot within this taxonomy is not a once-and-for-all decision, but rather a continuously shift between the defined design spaces according to the environmental and task-specific requirements. This thesis will mainly deal with the close complementary haptic collaboration of human and robot and therefore applies the following definition of haptics:

Haptics: "Haptics describes the sense of *touch* and *movement* and the (mechanical) interactions involving these" (Hatzfeld & Kern, 2014, p. 3) [emphasis added].

The haptic system enables us to interact with our environment, virtual or real, by means of mechanical, sensory, motor, and cognitive abilities (Jandura & Srinivasan, 1994). Its interaction can be classified in *motor control* (see Section 1.2.1) and *perception* (see Section 1.3.1; Kirkpatrick & Douglas, 2002). Based on the physiological taxonomy of haptic perception provided by the DIN EN ISO 9241-910 (2011), a classification in *touch* – tactile perception (mechanical, thermal, electrical, and chemical stimulation) – and *movement* – kinesthetic perception (physical force, body orientation, limb alignment, and joint position) – is reasonable. This thesis will focus on mechanical stimuli and therefore defines tactile and kinesthetic as follows:

Tactile: "[…] perception based on sensory receptors located in the *human skin*." [cutaneous receptors] (Hatzfeld & Kern, 2014, p. 12) [emphasis added].

Kinesthetic: "[…] perception of the operational state of the human locomotor system, particularly *joint position*, *limb alignment*, *body orientation*, and *muscle tension*." [receptors in muscles, tendons and joints, see Section 1.2.1] (Hatzfeld & Kern, 2014, p. 12) [emphasis added].

The term kinesthetic is often only used for the perception of properties of the limbs, while *proprioception* refers more general to perception of the whole body (Hatzfeld & Kern, 2014; Loomis & Lederman, 1986). Since this differentiation has only a minor technical influence this thesis will use the two terms indiscriminately. Referring to the abovementioned haptic collaboration of a human and a power assisting robot (Fig. 1, C) active kinesthetic interaction outlines the main field of research within this thesis.

Haptic Human-Robot Collaboration (hHRC)
therefore describes

“

robotic systems that are supposed to **interact directly** with humans, **assist** them in performing **physical tasks**, enhance motor training and rehabilitation, and even interact socially such as when shaking hands or dancing

”

(Karniel, Peer, Donchin, Mussa-Ivaldi, & Loeb, 2012, p. 193) [emphasis added].

It is a subgroup of physical Human-Robot Interaction pHRI (De Santis et al., 2008) and characterized by an intentionally kinesthetic collaboration of human and robot (Bicchi et al., 2008) to perform physical tasks together (Groten, 2011; Reed, Peshkin, Hartmann, Edward Colgate, & Patton, 2005). The combination of high adaptability and sensitivity of humans with the power and inexhaustibility of robots to reduce human stress and fatigue at constant or increasing task performance is the main motivator for hHRC (Cherubini, Passama, Crosnier, Lasnier, & Fraisse, 2016; Heyer, 2010). Haptic collaboration can be categorized into two distinct classes, joint object manipulation and haptic collaboration without an object (e.g., programming by demonstration) (Burghart, Yigit, & Kerpa, 2002). This thesis will concentrate on the first category with focus on moving heavy and bulky objects. Examples for hHRC applications, where human strength is amplified and augmented, are Cobots (collaborating robots; Akella et al., 1999; Peshkin & Colgate, 1999) IADs (intelligent assist devices; Colgate, Peshkin, & Klostermeyer, 2003), PARS (power assist robot systems; Rahman & Ikeura, 2012a), and exoskeletons (Kazerooni, 2008). Section 1.1.3 provides a more detailed view on applications, benchmarks, and the considered use case.

Goodrich and Schultz (2007) assume in their survey of HRI-related challenges and key themes that haptics is treated separately from HRI, because haptics exhibits a longer tradition. Ongoing research within the last two decades clearly disagrees with this perspective. Especially the IEEE Transactions on Haptics, which is managed by the Robotics & Automation Society, ACM's Transactions on Human-Robot Interaction, and many frequently cited authors share the view of this thesis (Campeau-Lecours et al., 2017; Campeau-Lecours, Otis, & Gosselin, 2016; Cherubini et al., 2016; Colgate et al., 2003; Dimeas & Aspragathos, 2016; Feth, Groten, Peer, & Buss, 2011; Groten, Feth, Klatzky, & Peer, 2013; Ikeura & Inooka, 1995a; Lawitzky, Mörtl, & Hirche, 2010; Mörtl et al., 2012; Peshkin et al., 2001; Peshkin & Colgate, 1999; S. M. M. Rahman & Ikeura, 2012a;

Reed, 2012; Reed & Peshkin, 2008). Since there is some controversy in the community about HRI being merely a chimera and full automation or even fully autonomous robots should be the goal, the next chapter will give a view on function allocation and the inevitable dynamic shifting between the addressed categories of HRI.

1.1.2 Seven rationales for complementary haptic collaboration

Since the distinct separation of humans and robots is diminishing, the initially static allocation of only manual or fully automated tasks will be reconsidered (Bengler et al., 2012). The approach of function allocation (FA) within human-robot systems is the logical consequence of a long tradition to assign and modify the degree of automation in human-machine systems (HMS). The decision which functions or tasks are allocated to the human or the robot constitutes one of the most essential human factors research question (de Winter & Dodou, 2014; Hancock & Scallen, 1996; Price, 1985). In order to address this question this thesis defines

seven rationales for complementary haptic collaboration

(see Table 1)

to provide an answer to a fictional roboticist's question:

> “Why do we bother the human with Human-Robot Interaction anyway? Would not full automation be the right way to go?”

The first theoretical framework was based on elementary functions and an allocation of each one by an efficiency *comparison* between human and machine (Fitts, 1951; Hoc, 2000). The today well-known Fitts' MABA–MABA list ("Men Are Better At – Machines Are Better At") consists of eleven statements about whether the human or the machine will fulfill a specific function better. Within the MABA–MABA list the different information processing and actuating capabilities are compared and all functions that are performed better by either human or machine should be done by the human/be automated. The main statement in this sixty years old static FA theory is that humans outperform machines in detection, perception, judgement, induction, improvisation, and long-term memory, whilst the machine is superior in functions such as speed, power, computation, replication, simultaneous operations, and short-term memory. Although, de Winter and Dodou (2014) show that the MABA-MABA list still fulfills basic scientific theories such as plausibility, explanatory and descriptive adequacy, interpretability, simplicity, and generalizability, it is deemed as outdated, static, and insufficient by many researchers (Bye, Hollnagel, & Brendeford, 1999; Hancock & Scallen, 1996). A survey conducted by de Winter and Hancock (2015) shows, current and future machines are considered to surpass humans with respect to detection, perception, and long-term memory but remain only a supporting actor regarding judgment, induction, and improvisation.

Kidd (1992) pointed out that human skills will always be required in robotic systems. According to him, designers should apply robotic technology to support and enhance these skills instead of a heedless substitution. He adds that human-centered design has been mostly ignored in robotics at this time and suggests investigations beyond technological issues with a careful consideration of FA between human and robot. Also de Winter and Dodou (2014, p.7–8) point out that Fitts' report did already address pressing topics such as "reclaiming control when automation fails", "the phenomenon of skill degradation [… and] that automation changes the nature of work", "different levels of automation", and "the importance of keeping the human involved". Ever since the notorious *Ironies of Automation* article (Bainbridge, 1983), a steady discussion about automation, autonomy, and human involvement is lively. In order to understand the double-edged discussion one has to see that automation nor autonomy is an all-or-nothing phenomenon (Beer, Fisk, & Rogers, 2014; de Winter & Dodou, 2014). It can take place at different levels and stages with different degrees of autonomy (Endsley & Kaber, 1999; Parasuraman, Sheridan, & Wickens, 2000). Since a robot's degree of autonomy also sets the scene what a robot can perform and the level at which an interaction can take place, HRI cannot be thoroughly conceived without taking this fact into account (Thrun, 2004). This thesis therefore applies the following definitions:

Automation: "Device or system that accomplishes (partially or fully) a function that was previously, or conceivably could be, carried out (partially or fully) by a human operator." (Parasuraman & Riley, 1997; Parasuraman, Sheridan, & Wickens, 2000, p. 287)

Autonomy: "The extent to which a robot can sense its environment, plan based on that environment, and act upon that environment with the intent of reaching some task-specific goal (either given to or created by the robot) without external control" (Beer, Fisk, & Rogers, 2014, p. 77), and Christensen et al. (2016, p. 14) add, "[…] while conforming to a set of rules or laws that define or constrain its behavior." E.g., an autonomous lawnmower will mow your garden, avoiding ditches and fences and maintaining safety of itself and its environment (including humans and pets).

Rationale 1

Infinite number of possibilities cannot be automated.

The crux is the infinite number of explicit execution rules that would (but cannot) be defined for every possible goal and situation (Christensen et al., 2016). Robots are moving from the laboratory to more heterogeneous, more dynamic, and more complex areas such as homes and workplaces, where reliability will be lower and not any possible scenario can be accounted for by designed algorithms (Parasuraman & Riley, 1997; Slepov, 2016). It resembles the *black swan theory* introduced by Taleb (2008), a metaphor for surprising events with major effects. "There's a saying in robotics: Anything a human being can do after age five is very easy for a robot […] Learn to play chess, no problem. Learn to walk, no way" (Kolhatkar, 2017).

Rationale 2
Higher LoA require more sophisticated interaction.

The Levels of Automation (LoA) introduced by Sheridan and Verplank (1978) and revised by Endsley and Kaber (1999) are still the foundation to be chosen but are currently in revision especially in the light of HRI. Endsley and Kaber (1999) proposed that functions have to be automated along a continuum of low (fully manual) to high (fully automated) degrees. They introduced the stages *information acquisition*, *information analysis*, *decision and action selection*, and *action implementation*. Bengler et al. (2012) also emphasize a view of fading LoA between autonomy, cooperation, and handling, where today's non-robotic power-enhancing handling devices and completely autonomous robots constitute the possible range with cooperative and collaborative systems in between. Beer et al. (2014) also pointed out that the aforementioned LoA models and taxonomies can only partially inform HRI. In particular, robotic capabilities in both function and physical form (mobility, environmental manipulation, and social interaction) separate them from classical automation. In their article, Beer et al. (2014) emphasize that it is crucial to consider the degree to which a human and robot interact and to what extent each partner can act autonomously. They follow with the statement that two perspectives on autonomy in HRI exist: (1) Higher robot autonomy requires less frequent interaction (Yanco & Drury, 2004) and (2) higher robot autonomy requires higher levels and more sophisticated interaction (M. Goodrich & Schultz, 2007; Thrun, 2004).

Rationale 3
A human-machine system centered perspective supersedes old-established engineering and ergonomic concepts.

Similar to the classical LoA, the *Level of Robot Autonomy* (LoRA) range from teleoperation to fully autonomous systems and influence the way in which humans and robots interact with each other (Beer et al., 2014). Between these two extreme anchor points of fully manual (*human interaction*) and fully autonomous (*human intervention*) lies a continuum of shared control, where a robot's LoRA may vary depending on the environment, task, and interaction over time (Abbink, Mulder, & Boer, 2012; Argall, 2015; Beer et al., 2014; Flemisch et al., 2010; Flemisch, Abbink, Itoh, Pacaux-Lemoine, & Weßel, 2016; Mark Mulder, Abbink, & Carlson, 2015). At this point it is important to see the difference between intervention (e.g., with a pool cleaning robot working in near isolation) and interaction (e.g., with a walking assistance device; Beer et al., 2014). This thesis especially addresses high levels of interaction in medium to low LoRA/LoA ranging from *Action Support*, *Shared Control with Human Initiative* and *Shared Control with Robot Initiative*. As proposed by Hoc, Young, and Blosseville (2009), a shift from a strict LoA perspective to a cooperative perspective will be important: In future dynamic situations, humans nor robots will fully control the course of events within a HRI. They will rather be confronted with interactive situations. The often chosen direction of a machine-centered viewpoint ("too engineering") or in contrast human-centered viewpoint ("too ergonomic") will be superseded by a human-machine system centered design perspective (Hoc, 2013), where functions are allocated and their interference managed in order to perform the overall task of the system.

Rationale 4

A complementary collaboration provides better results than one agent alone could be capable of.

Almost 40 years ago, Wiener and Curry (1980, p. 995) already identified: "[…] the question is no longer whether one or another function can be automated, but, rather, whether it should be." It is no longer about *what a robot can do* but rather *what a robot should do*, and *to which extent* (Beer et al., 2014; Bengler et al., 2012). For the last 60 years in industrial robotic history, the main concept of FA has been *leftover*, where the human only gets to do what the robot is not able to (Nemeth, 2004). The problems arising from this concept are manifold and especially address human factors in areas of acceptance, trust, well-being, and safety. In contrast to the full-automation approach, many researches seek to understand the requirements and basic concepts of joint and shared activity (Abbink et al., 2012; Flemisch et al., 2012, 2016; Klein et al., 2004; Mark Mulder et al., 2015). The synergy of human and robot increases overall performance considerably through the complementary abilities of both partners (Khatib, Yokoi, Brock, Chang, & Casal, 1999). This thesis will mainly rely on the concept of *complementary* FA, where a task or goal is completed more efficient, effective, and safe, and is reached easier with higher satisfaction by a team of interacting partners than by each partner alone (Grote, Ryser, Wäler, Windischer, & Weik, 2000; Jordan, 1963). Static FA does not satisfy Rationale 1 and 3 and adaptation to all possible circumstances because of lack of flexibility (Hoc, 2013). It is replaced by dynamic smoothly shifts of abilities, authority, control, and responsibility (Abbink et al., 2012; Flemisch et al., 2012) between human and robot, where *adaptable* (human is in charge), *adaptive* (machine is in charge), and *shared* (both are in charge) FA methods are conceivable (Inagaki, 2003).

Rationale 5
Humans should and want to stay
active, individual, and in charge.

Beyond the common heuristic of "dirty, dangerous, and demanding" tasks (originating from the Japanese expression 3K: kitanai, kiken, kitsui) novel collaborating robots will incorporate a complementary FA, which in part contains a *flexible allocation by users* (adaptable and humanized). The operator can choose the type and number of functions according to values, needs, and interests. According to Argall (2015) and Biddiss and Chau (2007), users of assistive devices overwhelmingly want to possess maximal control authority. The authors recognized that human operators are often dissatisfied with assistance devices taking over more control than necessary. Again, Fitts (1951, p. 6) already emphasized that "human tasks should provide activity [… and] the role of the human operators […] should be active rather than passive ones." Tying in with the introductory idea that elderly and people with disabilities should be assisted by remaining active, it is essential to consider possible *attitudes* towards robot assistants. Lee and Moray (1992) suggest a model of a user's choice between manual and automated control, based on *trust in automation* and *self-confidence* in the ability to control the system manually. Following the ideal that robots will be able to do everything in the future, humans are supposed to perform fewer and fewer tasks, which is contrary to our actual existence. "The science on longevity and resilience indicates that the drive to stay physically and cognitively active is necessary for health and wellness. The effects of increasingly sedentary lifestyles are already widespread and well-known" (Matarić, 2017, p. 1). Contrarily, robotics provides a way to encourage and assist people to be active and do their own work (Matarić, 2017). A nice example can be found in sports, where electrical bikes physically assist people, by applying physiological feedback, to be active without overloading them (Meyer, Steffan, & Senner, 2014; Meyer, Zhang, & Tomizuka, 2015; Meyer, Zhang, Tomizuka, & Senner, 2015). The concept of *self-efficacy* (Bandura, 1977) is closely related to this fact. It describes the confidence in own abilities to achieve intended outcomes. Possible statements by users could be: "*I really want to do this*; *I'm glad that I'm still able to do this*; *The robot is a great help to achieve my goals*." The later defined *work self-efficacy*, where many empirical studies already have shown higher work related performance (Stajkovic & Luthans, 1998) and improved adaptability to new technology (Hill, Smith, & Mann, 1987), strengthens the message of supporting and not replacing people. Bröhl, Nelles, Brandl, Mertens, and Schlick (2016) already implemented self-efficacy as an anchor variable for personal characteristics, adapted from Karrer, Glaser, Clemens and Bruder (2009), in their technology acceptance model for Human-Robot Cooperation. Also *stereotypes* and *habits* can be pleased by a close collaboration of human and robot (Kolhatkar, 2017). Possible statements by users could be: "*I have always done this; This is how it has to be done*."

Rationale 6

Roles are changing from robotic expert to everyday user and from master-slave scenarios to equal partners.

Scholtz (2002) defines five models for *roles of the human* in HRI: Supervisor (monitoring and controlling; Sheridan & Verplank, 1978), operator (actively controlling), mechanic (programming and adjusting), peer (real coworker), and bystander (not involved). Yanco & Drury (2004, 2002) borrowed this conceptualization and added ten additional categories based on the interaction and robot characteristics, which was picked up and adapted by Onnasch et al. (2016). They leave out the mechanic and define the role of the peer more in detail. They found five distinctive interaction roles, namely: supervisor, operator, collaborator, cooperator, and bystander (human within a Human-Robot Coexistence). Whereas for a long time most humans in proximity to robots have been robotic or control experts, the inexorable increase of robots in every area brings everyday users as the main users into play. The roles, characteristics, and capabilities of the human and the robot in sociotechnical systems are fundamentally shifting right now (e.g., in terms of Industry 4.0 and automated driving; Schmidtler, Körber, et al., 2016). A prime review on role assignment for human-robot joint motor action by Jarrasse et al. (2013) addresses these facts and summarizes promising research in the field of advanced interaction schemes that go beyond common master-slave solutions.

Rationale 7

In case of voluntary physical contact, the human haptic sense has to be utilized in HRI more frequently.

"Because they [current cooperative robots] are allowed near people, they move like yoga instructors, putting you to sleep in the process" (Slepov, 2016). This intriguing quote contains two main messages: 1) Media conveys a distorted picture of the reality (there are no fast, strong, and accurate and at the same time safe robots working close to humans right now) and 2) many promising benefits of robots as of now diminish if they are let out of their cages. Bengler et al. (2012, p. 158) mention the DARPA Grand and Urban Challenge as a clear example "that in many complex situations a human intercept is inevitable in order to resolve the situation." In order to be effectively able to resolve unexpected situations as well as address the Rationales 1–6, this thesis follows the set of four design guidelines proposed by Abbink et al. (2012) by sharing control between human and robot on a **haptic level**, where the human should [adapted from Abbink et al., 2012, p. 21]:

1. always remain in control, but is able to experience or initiate smooth shifts between LoA,
2. receive continuous feedback about robotic boundaries and functionality,
3. continuously interact with the robot, and
4. benefit from increased performance and/or reduced workload.

Promising results have been achieved by many researchers in the field of haptic shared control in areas such as automotive (Abbink, 2006; M. Mulder, Mulder, van Paassen, & Abbink, 2008; Petermeijer & Abbink, 2013), aviation (K. H. Goodrich, Schutte, & Williams, 2008), and robotics (Abbott, Panadda, & Allison, 2007; Jarrasse et al., 2013; Li et al., 2015; Madan, Kucukyilmaz, Sezgin, & Basdogan, 2015; Marayong & Okamura, 2004; Mörtl et al., 2012) and serve as a model for the further work within this thesis.

Table 1.

Seven Rationales for Complementary Haptic Collaboration

1	Infinite number of possibilities cannot be automated
2	Higher LoA require more sophisticated interaction
3	A human-machine system centered perspective supersedes old-established engineering and ergonomic concepts
4	A complementary collaboration provides better results than one agent alone could be capable of
5	Humans should and want to stay active, individual, and in charge
6	Roles are changing from robotic expert to everyday user and from master-slave scenarios to equal partners
7	In case of voluntary physical contact, the human haptic sense has to be utilized in HRI more frequently

1.1.3 Applications and the considered use case

The mentioned haptic contact may happen *occasionally* (hands-off pHRI) and therefore unwillingly (collision) if normal operation is without physical contact, or on *purpose* (hands-on pHRI or hHRC) if the human is actually supposed to exchange forces in joint action with the robot (Bicchi et al., 2008) to overcome human physical limits (De Santis et al., 2008). Gartner's Hype Cycle (2016), the IFR (Haegele et al., 2016), the IEEE (2017), and many companies and research groups recognized the societal needs for the *support of motor functionality* (assistive robots, mobility aids, physical rehabilitation and training) and *human augmentation* (collaborative assembly, logistics, surgery, construction, and entertainment). This thesis will especially address human strength amplification as a part of human augmentation within industrial and work settings.

The diverse characteristics of humans (dense sensors, ability to interpret sensory data, flexibility, and problem solving skills) and robots (power, high speed, accuracy, and repeatability) led to a new generation of hHRC systems called *intelligent assist devices* (IADs; Bicchi et al., 2008; Tan, 2003). They are intended for co-manipulation of payloads, human strength amplification, and guidance via virtual surfaces (Colgate et al., 2003; Robotic-Industries-Association, 2002). Ralph Mosher's (1967) famous *Handyman to Hardiman* concepts (see Fig. 2, A) at General Electric in the late 1960s marked the basis for many developments and current research in the field of human power augmentation (Bicchi et al., 2008; Tan, 2003). A further initiative of General Motors in the 1990s, led to two main developments by two groups: The *Human Extender* at the University of California Berkley within the group of Homayoon Kazerooni (Kazerooni, 1990, 1993, 1996) and *Cobots* at Northwestern University within the groups of J. Edward Colgate and Michael A. Peshkin (Akella et al., 1999; Peshkin et al., 2001; Peshkin & Colgate, 1999, 2000; Wannasuphoprasit, 1999; Wannasuphoprasit et al., 1998). At the same time, the Ford Motor Company cooperated with Fanuc Robotics on these topics. Fanuc's gantry-type system already used six powered admittance-controlled axes, was able to sense human inputs via force measuring handles, and already could implement virtual walls in a funnel shape that assisted the assembly motion (see Fig. 2, B; Bicchi et al., 2008). Around the same time the Toyota Motor Company worked on a similar concept called Skill-Assist (see Fig. 2, C). The novel and distinctive feature was the dynamic behavior according to the manipulation type. The DB preferred for moving payloads over long distances is mainly inertial, while the DB for precise positioning is more viscous (Yamada, Konosu, Morizono, & Umetani, 1999). With these findings Yamada and colleagues were able to significantly reduce operator force and time to task completion, while improving subjective ratings. However, it has to be noted that there is no statement about the number of participants and the actual experimental apparatus was not a functioning 6-DOF Skill-Assist prototype but a simpler 1-DOF system consisting of a linear actuator and a vertical force measuring handle.

IADs in industrial applications are mainly distinguishable via cable vs. rigid structures. Kazerooni's group developed a servo-controlled lift assist (cable balancer) marketed by Gorbel, Inc. under the name G-Force (see Fig. 2, D), which uses a sliding handle to sense up/down movements. Colgate and Peshkin's spin-off Cobotics, Inc. (later acquired by Stanley Works, Inc.) developed the iLift (vertical lift assistance) and iTrolley (horizontal movement of the overhead crane; see Fig. 2, E). Its key innovation was a cable angle sensor that detects small deviations of the cable from its vertical alignment and translates these signals in speed and direction. Data showed that initial starting forces were only modestly reduced since iTrolley only accelerates the support structure, not the suspended payload, but stopping forces could tremendously be reduced less overshooting of the overhead crane due to inertia. At this point, the abovementioned definition of hands-on was split into *hands-on handles* (operator manipulates via designated handles placed at the IAD) and *hands-on payload* (operator manipulates via the object itself, held by the IAD; Bicchi et al., 2008; Robotic-Industries-Association, 2002). This key distinction in contrast to remote controlled systems, applies a direct haptic manipulability of the object together with the robot and therefore provides the human with immediate feedback about the object, the robot, and the task (see Fig. 3).

These cable based systems are in contrast to Cobots – collaborative robots, named by Colgate's and Peshkin's former post-doctoral fellow Brent Gillespie (Morris, 2016). Cobots are especially capable of reducing stress and fatigue stemming from inertia. Via power amplification, virtual surfaces, and a rigid structure inertia can be masked[i]. Especially starting and stopping heavy payloads is possible without overloading the human operator. Cobots are able to divide control between human and robot and create possibilities of *free mode* (the human guides alone, the robot takes off parts of inertial and gravitational masses), *path mode* (the human initializes movement, but the robot steers along a defined three-dimensional path), and *surface mode* (constraining virtual surfaces either resist human inputs or drag the system to certain areas like a gravitational field). Especially path and surface mode are additionally able to simulate different behaviors like friction and active guidance and provide Cobots with higher LoRA than the former mentioned IADs. A more detailed description of the capabilities and advantages of Cobots can be found in Schmidtler, Harbauer, and Bengler (2014). Another approach, which can be counted to Cobots are *Power Assist Robot Systems* (PARS). PARS apply classical industrial robots (e.g., companies such as Comau, ATOUN Fig. 2 F, and RB3D Fig. 2. G) with force measuring and control systems to sense human force inputs and provide typical robotic capabilities like guidance and repeatability (Helms, 2006; S. M. M. Rahman & Ikeura, 2012a).

A third alternative in contrast to cable and rigid structures is provided by the less stationary approach of body-worn human extenders (Kazerooni, 1993, 1996) that amplify human force and reach. Nowadays revitalized and broadly known as *exoskeletons*, many sophisticated concepts within the industrial, domestic, and rehabilitation area are being developed right now and promise great results within the next few years (Kazerooni, 2005, 2008; Knott & Bengler, 2017).

[i] Inertia masking, i.e., reducing [adjusting] the starting, stopping, and turning forces (Colgate et al., 2003)

Following the 50-year-long tradition of human power amplification using robotics, the question arises why these systems have not found their way to daily work and life. The functionality to accomplish the desired tasks is mostly given, but many systems still demonstrate limited usability and acceptability not only due to technical limitations but also due to insufficient knowledge about the human (Campeau-Lecours et al., 2016; S. M. M. Rahman & Ikeura, 2012a; Yan et al., 2015). Especially high demanding heterogeneous work professions such as craftsmanship, e.g., carpentry and meat-processing (Matthieu et al., 2014; Paxman, Liu, Wu, & Dissanayake, 2006), construction, e.g., prefabricated houses or road construction (Bock, Linner, & Ike, 2012), logistics, e.g., furniture hauling and airports (Bonkenburt, 2016), forestry, and landscape gardening (Knight, 2015) will need new solutions to prevent wMSDs and assist men and women to carry, manipulate, and operate heavy labor.

Bicchi, Peshkin, and Colgate (2008) follow up that especially the assembly area in the automotive industry, where heavy and bulky parts such as engine blocks and interior parts are manipulated, has not yet been considered by the introduction of robotics. This fact has to be seen especially in the

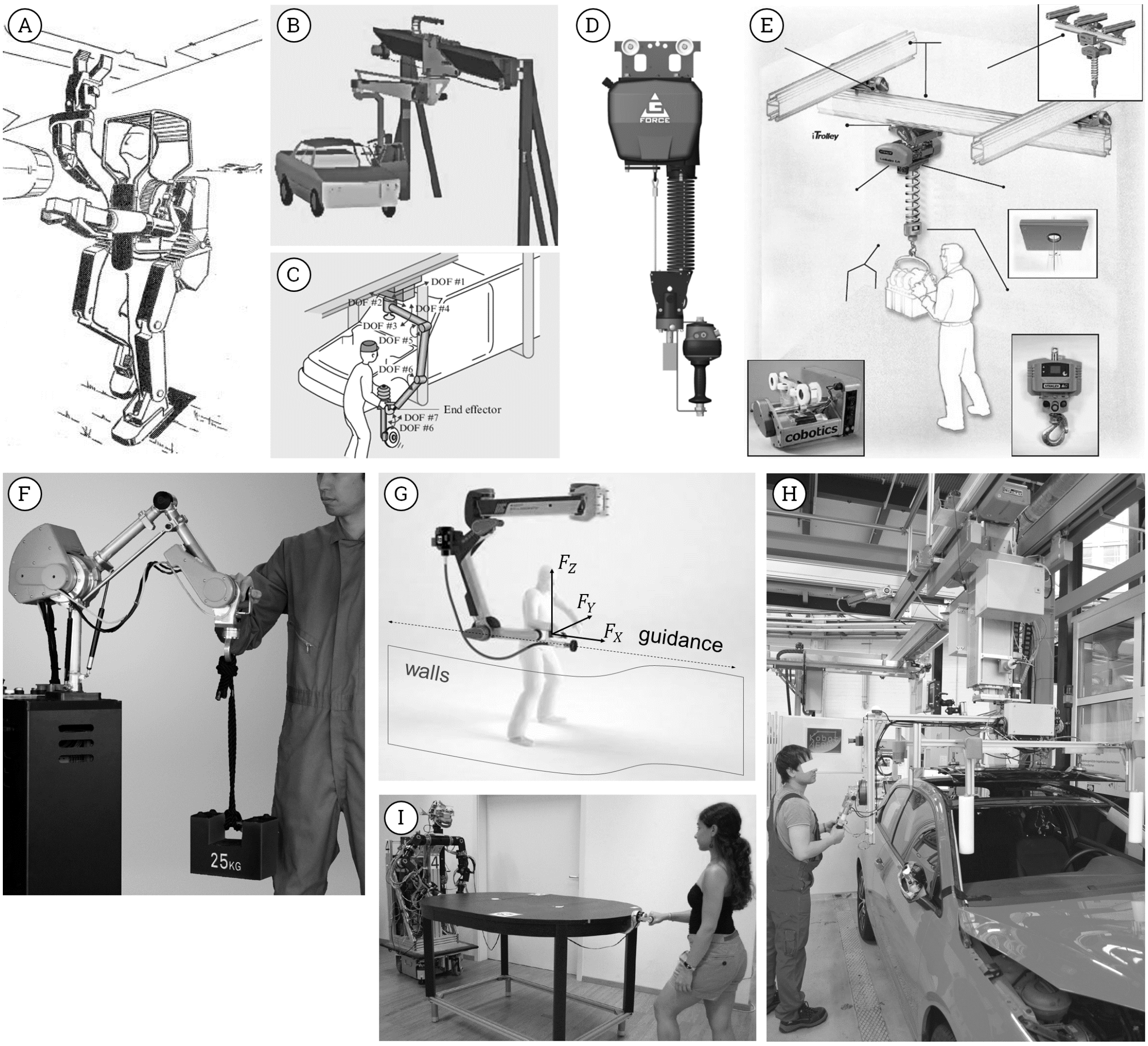


Figure 2: Historic and representative LAD applications. A: Hardiman (Mosher, 1967); B: Fanuc (Bicchi et al., 2008), C: Toyota Skill-Assist (Yamada et al., 1999)*; D: Gorbel Inc. G-Force (Gorbel, 2017); E: Stanley iLift and iTrolley (Stanley, 2005); F: ATUON VIWA (ATOUN, 2017); G: RB3D 7A15 [adapted] (RB3D, 2017); H: KobotAERGO (Surdilovic, 2017); I: Humanoid robot (Mörtl et al., 2012).*

light that robotics was more or less invented for the automotive industry and has a major history in this industry. However, surprisingly, no extensive transition of knowledge and hardware from one to another work sector has happened yet. Only few and large companies, such as GM, Ford, and BMW, tried to implement robotics for human augmentation in the assembly area but did not reach a point after single and specialized solutions. In particular, the high manipulation frequency of diverse sized and weighted objects within the final assembly of automobiles represents an outstanding example for the topics of investigation. Therefore, this thesis explicitly addresses the gain of new knowledge about the human operator in terms of human perception (Section 3, 6 and 7), idiosyncrasies (Section 5, 6 and 7), and optimized collaborative performance (Section 4, 5, and 7) in the automotive assembly.

1.2 Control Loop in Collaborative Object Manipulation

Designing a robot [machine] is in fact designing a Human-Robot [machine] System, using a multidisciplinary approach (Hoc, 2013). Hence, the first task is to understand each agent's capabilities and needs to eventually design an effective, efficient, and satisfying collaborative system. This chapter will give a brief overview about **human motor control**, relevant **robot control** paradigms for haptic interaction, and the consequential **human factors related implications** of hHRC. A short description and depicted control loop (Fig. 7) of an exemplary hHRC provides a common ground for the reader.

Fig. 3 depicts an exemplary automotive assembly operation. A human worker grabs the handles of a Cobot (hands-on controls) or directly the object (hands-on payload, as depicted) and the

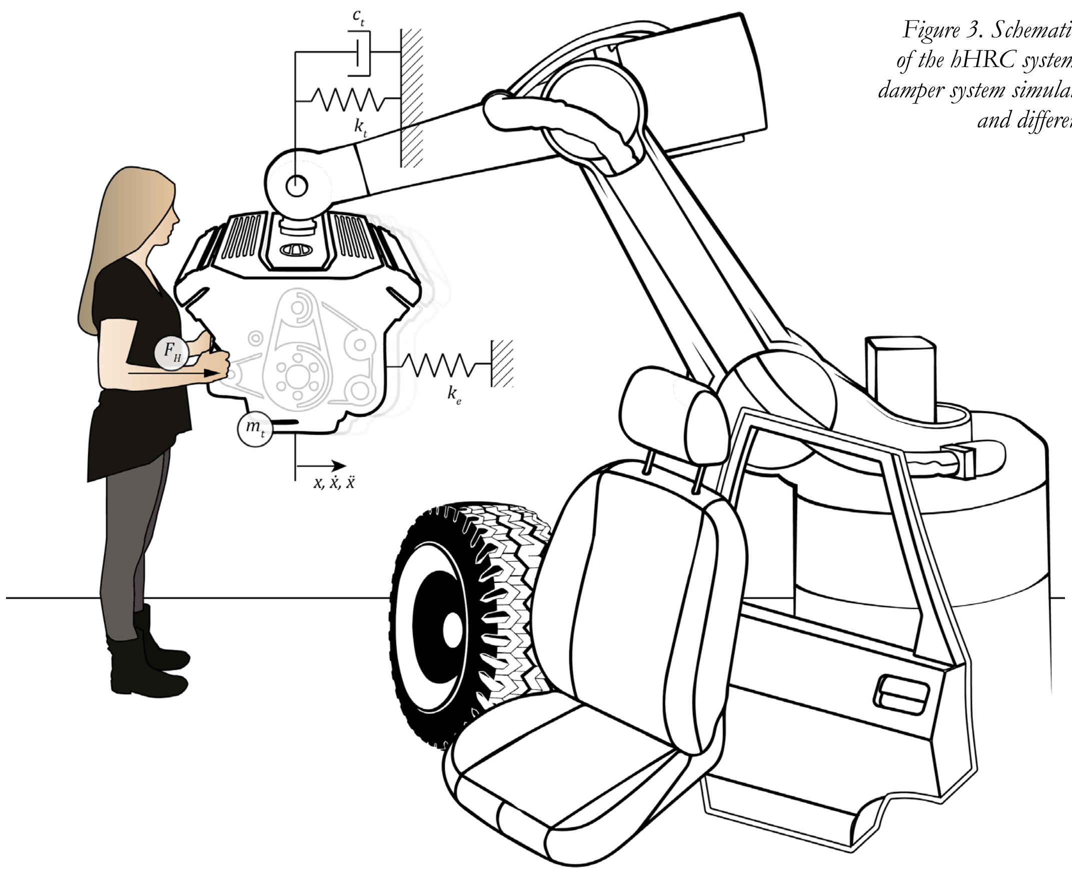


Figure 3. Schematic representation of the hHRC system. Spring-mass-damper system simulated by the robot and different sized objects.

applied forces and torques are measured via a force-torque sensor (*robot-sense*). Over his/her hands the human operator will get haptic information from the Cobot (*human-sense*). Since hHRC explicitly addresses haptic interaction, the human visual system will not be explained in detail, but is relevant to visually perceive the environment, the Cobot and the handled payload[ii]. The goal-oriented task execution is based on an initial externally (by the company) and internally (by the worker) set of goals, incorporating to bring the part to its designation and finally assemble it at the considered location at the car body. Accounting for the speed-accuracy trade-off (Marayong & Okamura, 2004; Schmidtler, Körber, & Bengler, 2016), the visuomotor task can be divided into *fast-imprecise bringing* and *slow-precise positioning* of an object, which will be summarized by *manipulation types*. Addressing the need for symmetric force-penetration of and interaction with the human musculoskeletal system to prevent one-sided strain (e.g., industrial high repetitive task) and to provide safe and diverse manipulability (e.g., rotations will be easier to execute), only *bimanual planar manipulations* (push and pull in free space[iii]) were considered.

1.2.1 Human motor control

Motor control is hard, and it is not surprising that robots trying to control their motions fully autonomously fail in sometimes hilarious manner (e.g., falling of live stages or failing in the easiest pick and place tasks). Humans are able to control their motions due to many years of permanent training, failing, and learning. At first glance, simple activities such as touching the tip of our nose with the index finger is insanely hard for infants. It takes an incredibly long time to actually learn to control our movements, but as Chase (2016) points out we can professionalize it so far that people actually pay millions for other people that only slightly do certain things better than average (e.g., 225 M € for a single club transfer of soccer star Neymar). Besides our fascination of motor control, we also invest more neural resources to the problem of limb movement than we do to almost anything else (Burdet, Franklin, & Milner, 2013; Rosenbaum, 2010). One of the reasons why humans are able to control their movements so elegantly and seemingly without effort is because we compensate delays. These delays, originating in the process of perceiving, planning, and reacting accordingly, are compensated by learning and recalling. Humans build internal models about their movements and resulting changes in their environment via learning and continuously update these models during a lifespan and as a consequence of injuries, fatigue, failures, and similar (*error-based learning*, Diedrichsen, White, Newman, & Lally, 2010). As we pick up a new object we build a new model, based on experienced errors in previous scenarios, adapt to future movements, and therefore are generally able to perform dexterous motor controls like lifting objects (Flanagan, Bowman, & Johansson, 2006), goal-directed grasping (Johansson & Cole, 1992), and grip force modulation (Flanagan & Wing, 1997). Fig. 4 depicts the involved *feedforward control* pathway enabling humans to anticipate and therefore preplan future movements. Hence, it is possible for humans to move around and physically manipulate their surrounding environment in complex, but efficient and adaptable ways.

[ii] Vision passively senses and feeds in the feedback-loop, haptics is additionally able to actively react.
[iii] Free space (controlled movements) is the opposing boundary to rigid constraints (controlled contact forces) of a continuum of mechanical impedance (Casadio, Pressman, & Mussa-Ivaldi, 2015).

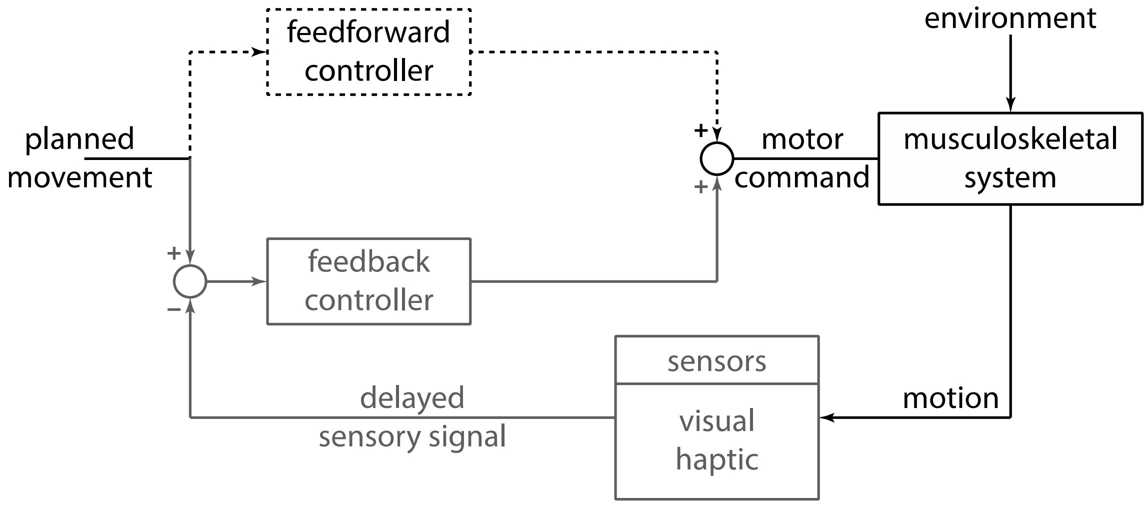


Figure 4. Schematic of feedforward (dotted) and feedback (gray) control pathways in human motor control. Solid lines represent involvement of both control pathway types. Adapted from Burdet et al. (2013, p. 6).

A "man is not a machine, at least not a machine like the machines man make" (Jordan, 1963, p. 9). This sentence has to be rethought since nowadays humans very often serve as a role model for novel robotic concepts; vice versa the robot serves to understand human motor control (Burdet et al., 2013). For instance, Abbink (2006) compares the essentials of the human motor control system with those of a robot, which consists of linkages (skeleton), actuators (muscles), a sensor system (proprioceptors), and a controller (the central nervous system, CNS) that is connected to the actuators via wires (nerves). Adopting this concept, the dominating areas of human motor control within hHRC will briefly be described and depicted in Fig. 5. For a thorough review on human motor control, please also consider the work of Burdet, Franklin, and Milner (2013) as well as Rosenbaum (2010).

The **CNS** (consisting of the brain, brainstem, and spinal cord) receives and integrates feedback from the proprioceptors with feedback from visual sensors (and others such as auditory) and plans movements via feed-forward control (see Fig. 4). Afferent[iv] and efferent neural signals travelling along nerves via electrochemical processes are the couriers of the bilateral information flow. They are prone to transport time delays, because of the traveled distance (besides other factors). Output neurons sending signals directly to muscles are primarily located in the spinal cord (*lower motoneurons*). *Interneurons*, located in the spinal cord, and neurons in the brainstem and brain (*upper motoneurons*) additionally provide synaptic input. The **motor cortex** was the first area which evidently has been localized in the brain. In 1870, Fritsch and Hitzig, two German physiologists, applied voltage to the motor cortex of dogs and observed muscle twitches immediately after applying the electrical stimuli (Rosenbaum, 2010). Two Canadian neurosurgeons, Penfield and Rasmussen (1950), did seal the deal on human brain function when they treated epilepsy by cutting nerve tracts in the brain. By means of repeating stimulations of different areas, they observed muscle responses and as a consequence developed a *motor map*, today well-known as *motoric homunculus* (Fig. 5).

[iv] Towards (afferent) or away from (efferent) the CNS

With the help of **proprioceptors**, including the vestibular system, joint sensors, skin receptors, muscle spindles (MS), and Golgi Tendon Organs (GTOs), it is possible for humans to be aware of their body orientation and movements even with closed eyes (*feedback control*, Fig. 4). Convincing examples of why this sense of perception is so important for our movement control can be found in the story of I. W. –"the man who lost his body" (due to an illness Ian Waterman lost almost his entire proprioceptive sense; McNeill, Quaeghebeur, & Duncan, 2010) or after excessive use of narcotics (e.g., tumbling walk because of intoxication).

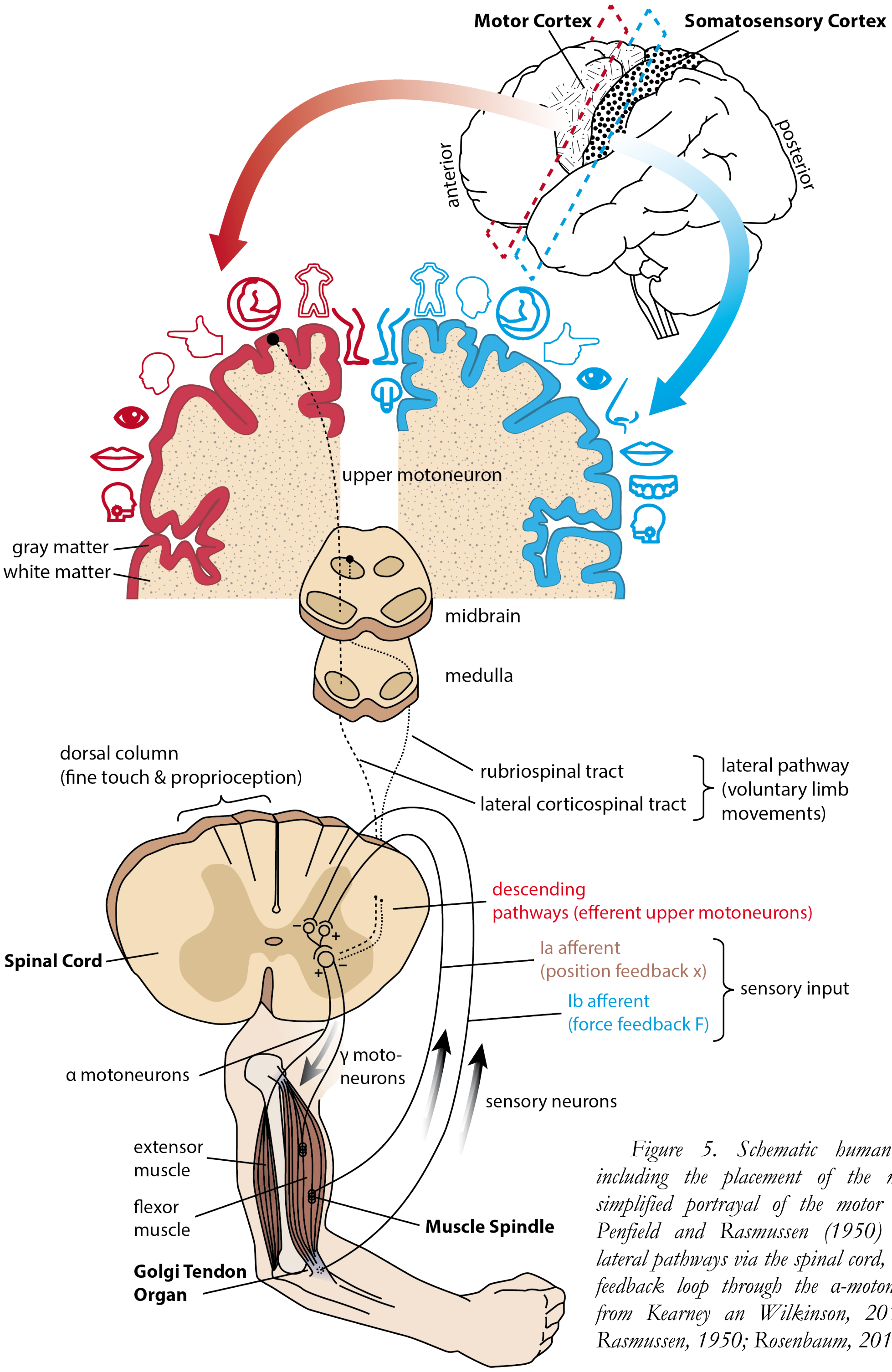


Figure 5. Schematic human motor control including the placement of the motor cortex, a simplified portrayal of the motor homunculi after Penfield and Rasmussen (1950) the determining lateral pathways via the spinal cord, and spinal reflex feedback loop through the a-motoneurons (adapted from Kearney an Wilkinson, 2017; Penfield an Rasmussen, 1950; Rosenbaum, 2010).

Information about orientation and acceleration of the head is provided by the vestibular system located in the middle ear. Within the scope of this thesis, its feedback can be neglected, since the occurring accelerations are small in the considered cases. Sensory endings in the joints (joint or capsule sensors) are able to assess joint angles. According to Rosenbaum (2010), there is no consent in the literature at the moment, if these sensors adapt very slowly (therefore provide only static limb position) or rather quickly (therefore provide mainly information at extreme joint angles). Receptors in the skin (also tactile or cutaneous receptors) sense deformations of the skin surface and are able to provide information on touch, pressure, vibrations, temperature, and pain. The two main proprioceptors within this thesis are MS (position and velocity feedback) and GTOs (force feedback). Like the former receptors, MS and GTOs send information to higher levels of the CNS, but also directly back to the α-motoneuron. This forms a fast feedback loop also called spinal reflex. Following the abovementioned transportation time delays and energy-efficiency considerations, it is fairly obvious that spinal reflexes are able to contribute much faster to motor control than commands stemming from the CNS.

Within the human muscle only the *extrafusal fibers* (large-diameter muscle fibers, skeletal muscle) are powerful enough to move and stabilize our limbs (Rosenbaum, 2010). **Muscle spindles** (Fig. 6) are parallel and attached to extrafusal fibers. They contain smaller fibers called *intrafusal fibers*. When the skeletal muscle stretches, the MS also stretches, fires, and sends information back to the CNS (γ-afferent neurons) and the α-motoneuron (afferent neurons Ia and II). Sensitivity of the

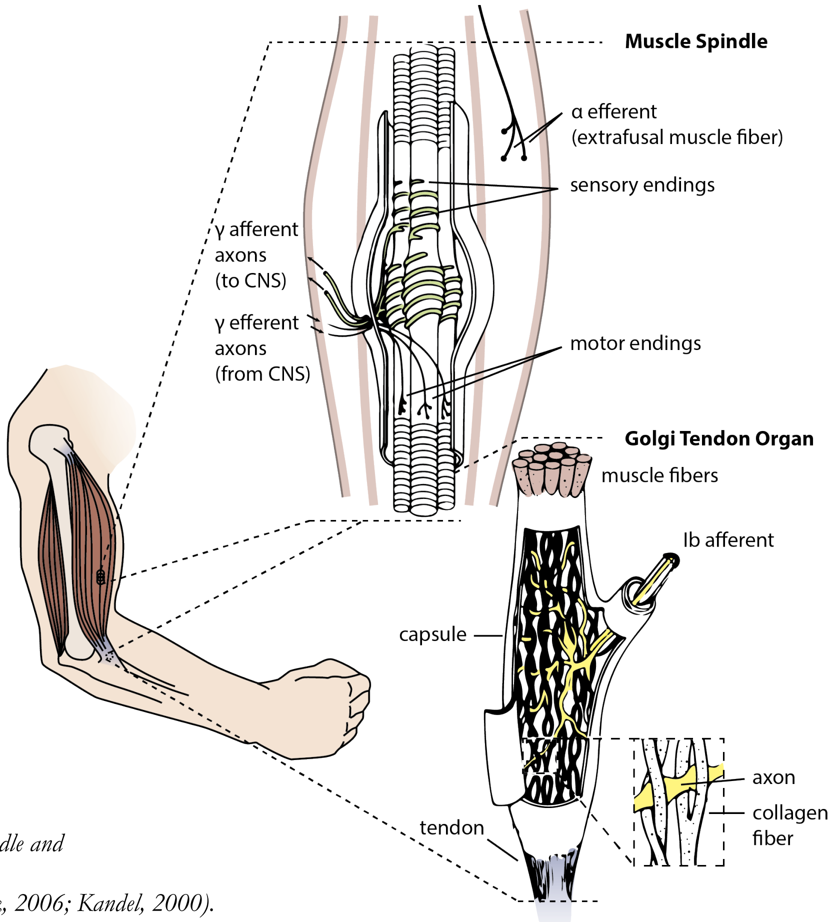


Figure 6. Muscle Spindle and Golgi Tendon Organ (adapted from Abbink, 2006; Kandel, 2000).

afferents is adapted by the CNS through efferent γ-motoneurons (Abbink, 2006). The most important functionality of the MS is a position and velocity feedback loop.

Golgi tendon organs (Fig. 6) are located between the ends of the skeletal muscle and the tendon (the link to other anatomical structures such as bones and skin). They communicate via one afferent Ib neuron, which originates from a mesh of axons and collagen fibers. When the GTO is stretched, the axons are squeezed by the collagen fibers, which causes them to send signals to the CNS. There are no efferent endings, like in MS. The GTOs main functionality is a force feedback loop, which contributes substantially to human motor control. During the interaction with a hHRC system GTOs are expected to play an important role.

1.2.2 Robot control

Currently many industrial robots are position-controlled, which turns out to be inadequate for controlling the interaction of a robot with the environment (De Santis et al., 2008). Compliant behavior is needed to create a natural and intuitive physical or haptic interaction with a human operator. Currently two main control schemes are used in hHRC, known as impedance (input: x, $\dot{x}$, $\ddot{x}$; output: F) and admittance control (input: F; output: x, $\dot{x}$, $\ddot{x}$). Large inertia and significant friction of IADs such as they are apparent in the automotive context, the scope of this thesis, call for admittance control schemes, where a robot is capable of sensing and controlling exchanged forces to collaborate with a human (Lecours & Gosselin, 2013). The human force is measured as an input and the displacement of the robot is the outcome (Hatzfeld & Kern, 2014). No further information is provided by the human in traditional admittance control. These systems are designed analogous to the physical representation of a one-dimensional spring-mass-damper, defined by a *human interaction force* F_H, a *virtual target mass* m_t, a *virtual target damping* c_t, a *virtual target stiffness* k_t, and *friction* μ of the physical structure caused by the IAD mass m_{IAD} and object mass m_{obj} and gravitation g (Fig. 3):

$$F_H = m_t(\ddot{x} - \ddot{x}_0) + c_t(\dot{x} - \dot{x}_0) + k_t(x - x_0) + \left(m_{IAD} + m_{obj}\right) \cdot \mu g. \tag{1}$$

Further, x_0 defines the *starting point* and x, $\dot{x}$, and $\ddot{x}$ are *position*, *velocity*, and *acceleration* of the IAD. For the considerations in this thesis, stiffness k_t and friction μ are neglected, since no contact with any real or virtual surface was object of investigation and as a consequence is considered as constant. Therefore (1) translates into a relationship that, when the admittance parameters (mass m_t and damping c_t) are set to high values, a larger human interaction force F_H is required to move the IAD at a certain velocity and/or acceleration (Lecours, Mayer-St-Onge, & Gosselin, 2012):

$$F_H = m_t(\ddot{x} - \ddot{x}_0) + c_t(\dot{x} - \dot{x}_0). \tag{2}$$

Present control strategies, such as variable admittance control are beginning to incorporate more intelligence using more sophisticated information about *velocity* and *acceleration* (Duchaine & Gosselin, 2007; Ikeura & Inooka, 1995b; Kosuge & Kazamura, 1997; Lecours et al., 2012), *vision* (Agravante, Cherubini, Bussy, Gergondet, & Kheddar, 2014) or *EMG* signals (Grafakos, Dimeas, & Aspragathos, 2016; Peternel, Tsagarakis, & Ajoudani, 2017) to anticipate human intention and model his/her motion behavior.

At this junction, the main concern is that individual operators will have individual prior knowledge and expectations (Section 6 and 7; Schmidtler & Bengler, 2016, 2017), will perceive differently (Section 3 and 5; Schmidtler, Bengler, Dimeas, & Campeau-Lecours, 2017; Schmidtler & Körber, 2017), and therefore will behave very differently (Section 4, 7, and complementary studies; Schmidtler & Bengler, 2017; Schmidtler, Harbauer, & Bengler, 2014; Schmidtler, Körber, & Bengler, 2016; Schmidtler, Petersen, & Bengler, 2016). Additionally, for example, using EMG signals can represent a very complex endeavor, since human muscles and muscle composition are very diverse. This aspect appears in the development of robotic prostheses, which are supposed to execute movements by means of EMG signals (Brantley, Luu, Nakagome, & Contreas-Vidal, 2017). In some cases of hHRC, this method is implemented counterintuitively. For example, higher human grip force of the robotic interface (measured at the forearm) is translated in higher damping of the system (Grafakos et al., 2016). From a roboticist point of view, this clearly helps to stabilize the system, especially in case of unexpected robot behavior (Tran, Liu, Ranasinghe, Carmichael, & Liu, 2015), and avoids pitfalls in terms of very high human impedances. From a human factors point of view, manipulability will be highly affected by high damping and the human operator will very likely try to work against the viscosity applying higher forces. The result will be an iteration of higher damping and higher interaction forces that eventually will lead to low usability and decreasing acceptance of the system. Well working learning algorithms will probably be one way to overcome human diversity but imply the drawback that the controllability and understanding of the robot's internal control processes are widely lost (Gribovskaya, Kheddar, & Billard, 2011). In the wake of one's own conviction, this thesis provides mathematical interaction models in order to provide understandable and comprehensible design recommendations for new hHRC control strategies.

“

Although the concept of industrial *cobots* dates back to 1999, most present-day hybrid human-machine assembly systems are merely weight compensators.

”

say Cherubini et al. (2016, p. 1) in *Robotics and Computer-Integrated Manufacturing*.

As motivated by the initial introduction, IADs were introduced here and there at the beginning of the 2000s, but most current systems are still simply weight compensators (Cherubini et al., 2016; Yao, Weidner, Weidner, & Wulfsberg, 2015). These *passive* systems are able to react on human force inputs in a very natural physical way and provide high safety and stability (Albu-Schäffer, Ott, & Hirzinger, 2007). The downside are sometimes high interaction forces, misunderstandings, and therefore lower usability of these systems (Dimeas & Aspragathos, 2016; Labrecque, Hache, Abdallah, & Gosselin, 2016; Medina, Lorenz, & Hirche, 2017). Present approaches often address robots able to *proactively* perform movements together with a human (Lawitzky et al., 2010). In contrast to passive approaches, proactive robots will not only react to the human input, but also with higher LoRA actively work towards a common goal (Medina, Lorenz, & Hirche, 2015; Medina et al., 2017).

Human behavior models that predict human intention and behavior will very likely lead to higher task performance and less human effort. Jarrassé, Paik, Pasqui, and Morel (2008) applied offline recorded human planar free-motion trajectories to design a human motion predicting hHRC. In a simple point-to-point experiment using a Haption Virtuose manipulator, they recorded less interaction force in the predictive force-feedback condition. These results point in a promising direction but should be taken with caution, as neither sample size nor subjective data are reported.

One of the very few studies involving large-scale kinesthetic collaboration and human full-body motion was conducted by Mörtl et al. (2012). The authors investigated effort sharing strategies, i.e. distribution of voluntary force inputs among the two agents, in a collaborative planar manipulation task applying three different role assignments (static, weighted proactive, and discrete role allocation). With a sample of 18 participants, they could show increasing task performance (time to task completion, effort, amount of disagreement) with adaptive behavior of the robot but inverse subjective impressions (NASA-TLX and questions about collaboration, comfort, pleasure,

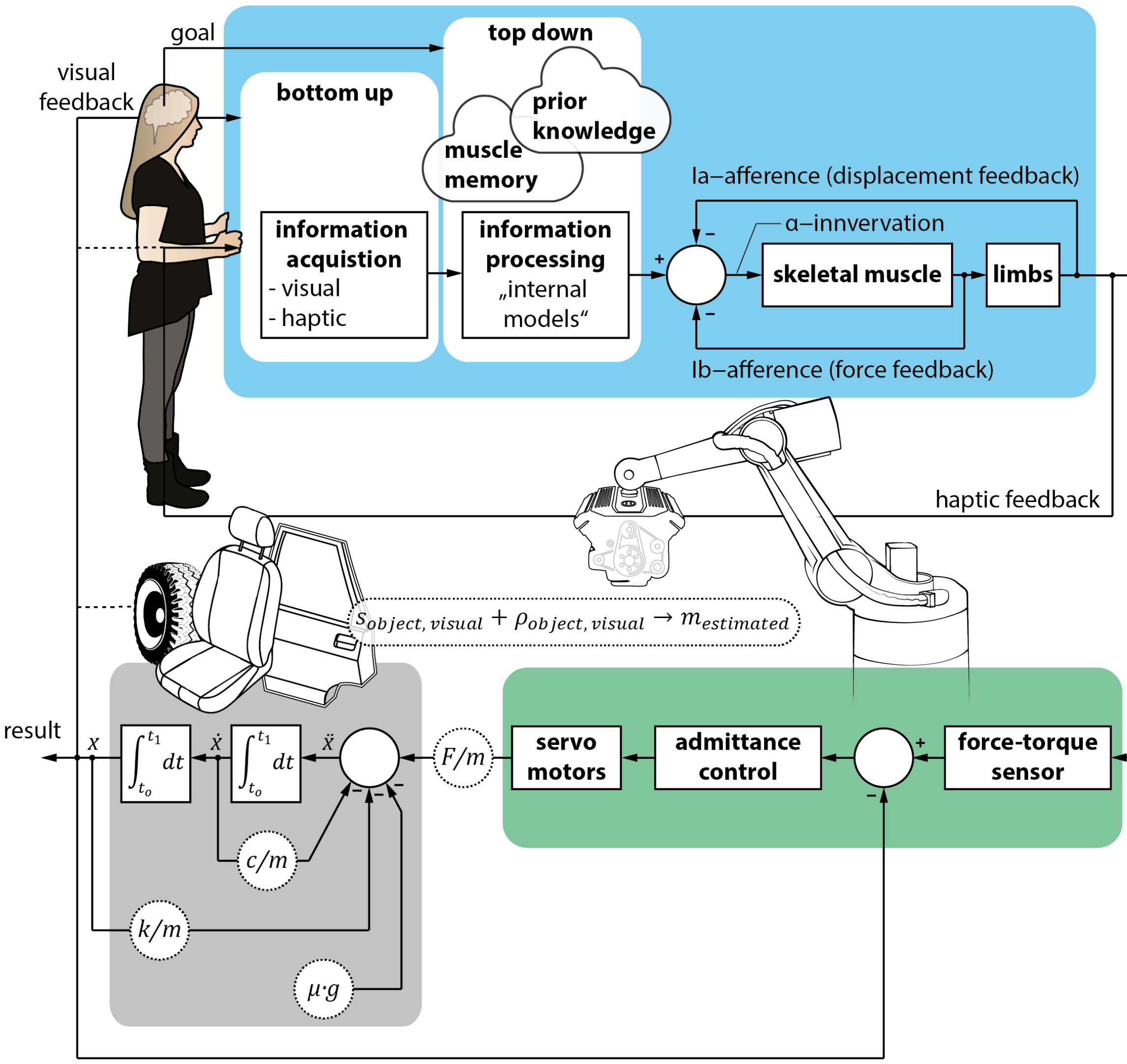


Figure 7. Haptic Human-Robot control loop in collaborative object manipulation. Human (blue), robot (green), and object (grey). Adapted from H. Bubb (personal communication, July 14, 2017).

predictability, trust, and similar). This trade-off reveals clear objective advantages for dynamic robot behavior, but in particular provoke an intensive investigation of subjective criteria in and evaluation of hHRC. It also addresses the ongoing discussion whether static or adaptive behavior is more favorable.

Ranatunga, Cremer, Popa, and Lewis (2015) applied an online adaptive admittance controller to a PR2 robot to investigate varying human intentions, a nominal task model, and different robot dynamics. Although their control strategy was able to adapt to different human subjects and as a consequence achieved better performance in terms of trajectory smoothness, the small sample size (two male participants) and performance measure (only the dimensionless squared jerk) reduce the impact of the results.

Dimeas and Aspragathos (2015) presented a method for variable admittance control combining human-like decision making and adaption by using a Fuzzy Model Reference Learning Controller (neural network to adapt towards minimum jerk). The algorithm measured velocity and force at the human interface and altered the damping of the robot admittance online. Twelve participants performed ten linear point-to-point movements using a KUKA LWR and obvious improvements in terms of required effort and time to task completion were measurable. The authors also reported subjective data which shows that with very small movements (0.2–0.3 m) and, therefore probably lower speeds and forces, more than half of the test persons could not find any difference in the robot control strategy. With a displacement of 0.4 m, all participants were able to perceive a difference and 84 % of them preferred the predictive control system. One of the latest approaches from Nikolaidis, Hsu, and Srinivasa (2017) applies a probabilistic decision process, called Bounded-Memory Adaption Model. This model assumes different collaboration modes in which the human will operate and as a consequence adapts by switching between these modes. The authors call this process *mutual adaptation*, which is in contrast to one-way adaptation of the robot to the human. The high-level interaction and coordination goal to increase team performance while maintaining the human operator's trust in the robot was achieved. However, the evaluation took place in an online survey via Amazon's Mechanical Turk with 69 samples and no real haptic interaction.

Another noteworthy work of Madan, Kucukyilmaz, Sezgin, and Basdogan (2015) dealt with *haptic interaction patterns* developed out of typical human-human collaborative transport of an object. They found three interaction types, namely: 1) work in harmony, 2) cope with conflicts, and 3) remain passive during interaction. They used velocity and power related information to classify these patterns and accomplished an 86 % successful identification classifier.

Parallel to their work many other research groups also picked up the idea to study human-human interaction (*human dyads*) to derive and create human-like hHRC (Corteville, Aertbelien, Bruyninckx, De Schutter, & Van Brussel, 2007; Groten, 2011; Noohi, Zefran, & Patton, 2016; Reed & Peshkin, 2008; Sawers et al., 2017; Surdilovic, Nguyen, & Radojicic, 2011; Yang et al., 2011). The studies repeatedly present increasing task performance (time to task completion, effort) and collaboration (smoothness of movement), but also negative subjective impressions such as the feeling that the second person is a burden or competitor. In order to inform novel control strategies about human internal models in the onset and during an interaction, this thesis especially addresses perception-related cues and inertial mass of the admittance equation (2).

1.2.3 Implications

> “While the system at hand may be operating with perfect reliability and perfect predictability it may still appear opaque to the attendant operator.”

says Hancock (2017, p. 285) in *Ergonomics*.

In the case of impaired usability, typically the system is not faulty, but rather it may appear opaque to the human operator if states of the interaction are not clear (Hancock, 2017). Mode confusion, where the robot’s expectations mismatch human intentions, can lead to unintended interaction forces, safety risks, discomfort, and low usability (Medina et al., 2017). As stated in the previous Section, it is therefore a very promising approach to implement *human intention* and *perception models*, including individual needs and capabilities, in novel hHRC control strategies. The term intention will be used in this thesis based on the following definition and description:

Intention: “1. a *prior conscious* decision to perform a behavior. […] 2. more generally, any directedness in one’s thoughts or behaviors, *whether or not* this involves *conscious* decision making” (VandenBos, 2015, p. 549) [emphasis added]. Within the mentioned interaction modes (see 1.1.1) this involves mutual knowledge and behavior recognition over an implicit or explicit interface (Bengler et al., 2012). The correct acquisition and interpretation of humans’ and robots’ intentions enables the formulation of a *shared mental model* (ShMM) in which both collaborating partners are aware of each other and the predefined goal, which eventually leads to high team performance (Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000).

Shared mental models have a long tradition in HCI, but in the field of HRI they can currently only be found in the social robotics area (e.g., seal-like PARO robot or My Real Baby; Mutlu, Roy, & Šabanović, 2016). De Santis et al. (2008) see the key challenge of ShMM in embodiment, in which people attribute human-like qualities and capabilities to robots because of anthropomorphic mental models. What is more, they continue that indeed mental models may change with experience, but anthropomorphism still is a forced consequence of our nature, especially for non-skilled users in HRI. Therefore, it is understandable that many studies in hHRC are adressing human-like behavior of robots to evoke and promote intention recognition via previously experienced, learned, and expected human-human and human-object interaction. The anticipation of actions and feedback is essential for well-tuned interaction (Hoffman & Breazeal, 2004; Knoblich & Jordan, 2003) and, for this reason, the human has to see the robot as acting intentionally (Sebanz & Knoblich, 2009; van der Wel, Knoblich, & Sebanz, 2011).

Each partner in hHRC depends on the input and feedback of the other to achieve a predefined goal. In hHRC, trust is not exclusively a human attitude. Trust in human instruction, which is a computable measure of trust in human inputs, has to be taken into account at the robotics side (Argall, 2015; Argall & Murphey, 2014). Hence, in order to develop new technologies to perceive human intention, knowledge about capabilities, characteristics, and idiosyncrasies of human operators have to be investigated to acquire knowledge for sensor, actuator, and control design as well (Beckerle et al., 2017). According to Sheridan (2016), the comparison and utilization of operator mental models to a machine's mental model in a specific situation (online or offline) can result in safety and efficiency benefits in human–robot systems.

In order to model human perception in hHRC a classical representation also applied by Wickens, Lee, Liu, and Gordon-Becker (2004) will be used. They propose a perception model that proceeds by three often simultaneous and concurrent processes:

1) *bottom-up* feature analysis or *data-based processing* (e.g. incoming data from haptic and visual analysis of stimuli such as object size and mass, Fig. 3, 6, and 7),

2) *unitization* (division into processible shares), and

3) *top-down* or *knowledge-based processing* (existing knowledge based on expectations that are based on experiences, see Fig. 7). Especially the interaction and potential interference of these perceptual processes are of interest within this thesis. For more details, interested readers can consider Goldstein (2014) and Sections 3, 6, and 7 of this thesis.

How do these perceptual processes influence hHRC?

This thesis attempts to close the gap between engineering and psychological views on hHRC, presented by Hirche (2005) as the fundamental methodical challenge. Basic design goals of haptic systems such as stability, haptic quality (or transparency), and usability (Hatzfeld & Kern, 2014) are often only partially achievable at the same time and therefore cause trade-offs in many cases (also consider Section 1.4). This fact becomes very understandable when looking at how stability is usually achieved by increasing damping c_t (Duchaine & Gosselin, 2008; Duchaine, Mayer St-Onge, Gao, & Gosselin, 2012; Tsumugiwa, Fuchikami, Kamiyoshi, Yokogawa, & Yoshida, 2007) or the ratio of m_t/c_t in the admittance equation (1 and 2) (Campeau-Lecours et al., 2016). Eventually, these adaptations lead to low task performance and increased operator effort (Dimeas & Aspragathos, 2016) which are indicators for low usability and often make for rejection of novel technology. Applying admittance control, haptic communication mainly takes place via parametrization of the mass-damping equation (2). This allows to convey diverse haptic characteristics of virtual walls (e.g., gravitational or potential fields, less and high friction, elasticity and rigidity), adaption to movement types (e.g., high damping for slow-precise and low damping for fast-imprecise motion), to various types of operators (e.g., physical and cognitive capabilities, individual preferences and needs), and different types of objects (e.g., heavier for larger, denser or heavy-looking objects). Especially the last-mentioned adaption has not been addressed by the robotic literature until today and therefore represents one focus of investigation in this thesis. Effective communication via an existing COFOR and an interface design that lets both partners be aware of each other, the task, and the environment at every time will be essential (Chen & Barnes, 2014). General questions and field of research in hHRC such as the gap between perception and action (psychophysics), coadaptation, intuitiveness, and human-likeness (Karniel, Peer, Donchin, Mussa-Ivaldi, & Loeb, 2012), are addressed.

While there is only little to no data for hHRC systems in industrial settings and their acceptance or rejection, surveys in the area of prosthetics are consulted. They point out that (besides bad hardware design) unsatisfactory control is cited as a major influential point (Biddiss & Chau, 2007). For instance Beckerle et al. (2017) provided a notable list of three main design demands for haptically assistive devices, which are adapted to hHRC and applied for the following work:

Control Design
should "fit like a glove".

Control design: Since many assistive machines are still burdensome to operate, hHRC control strategies should "fit like a glove" and as a consequence reduce (or maybe even eliminate) training time which eventually will speed up adoption by the users. Beckerle et al. (2017) currently see two ways to achieve this: A) employ learning methods that incrementally adapt to the operator, situation, and environment (Castellini, Bongers, Nowak, & van der Sluis, 2016) and B) introduce shared autonomy to traditionally human-operated assistive machines (Argall, 2015; Jain et al., 2015). Especially shared autonomy will only be possible if proactive capabilities (see 1.2.2) are enabled. Key challenge within these approaches will be the design of shared control and machine learning algorithms that are predictable for the user and do not override their demands. Also, it has to be taken into account that human abilities and preferences will change over time.

Sensory Feedback
is the basis for successful collaboration.

Sensory Feedback: Appropriate feedback is the basis for successful collaboration. Closing the hHRC control loop (Fig. 7) and overcoming the apparent information flaws as well as adding important information about human stress, fatigue, comfort, and motivation, as well as external variables such as manipulated object characteristics, environment, and movement types will be crucial.

Assessment
methods still are not standardized.

Assessment: Even in rehabilitation (where there is already a great amount of literature on hHRC), but especially in the field of industrial and domestic hHRC, there are still no standards to evaluate physically assisting robotic approaches. Currently, some new approaches are being developed to evaluate hHRC, such as the quantification of physical strain and strain reduction in industrial hHRC applications (Knott, 2017; Knott, Wiest, & Bengler, 2016) and approaches that go beyond the purely subjective evaluation of usability applying objective efficiency, effort, and performance measurements. Groten (2011) provides an extensive list on quantitative experiments on haptic collaboration.

1.3 Perception-Related Assistance Strategy

The biggest illusion we fall victim to is that we think motor control is easy. "We don't even think about motor control, until it goes wrong" (Chase, 2016, 4:09 min). As infants, nine months and older, we learn to preprogram our grip size and hand orientation on the basis of visual information (Rosenbaum, 2010) and begin to update our knowledge about object sizes and weights.

Variations in object properties that are not directly linked to its weight (e.g., size, material, shape, color) can influence perceived heaviness of an object and therefore are considered illusory (Jones, 1986).

Illusions are "the marked and often surprising discrepancy between a physical stimulus [incoming bottom-up data] and its corresponding percept [comparison with top-down knowledge]" (Lederman & Jones, 2011, p. 273).

In a comprehensive review Lederman and Jones (2011) summarize kinesthetic illusions caused by object properties such as *material* (texture, stiffness, temperature), *geometry* (size, shape), and the hybrid attribute *weight* that is influenced by both material and geometric properties. This thesis focusses especially on perceived weight (more precisely: inertial mass, Section 3 and 4) and its interaction with size (Section 6 and 7). Among other potential influencing phenomena such as the Material-Weight Illusion (MWI; Buckingham, Cant, and Goodale, 2009; Buckingham, Ranger, and Goodale, 2011; Ellis and Lederman, 1999) especially the strong and robust Size-Weight Illusion (SWI) is discussed more in detail. Found by the French physician Augustin Charpentier in 1891 (Murray, Ellis, Bandomir, & Ross, 1999), this psychophysical finding describes the illusion (cognitive distortion; Gregory, 1997, 2006) that when lifting two equally weighted, but different sized objects, the smaller is perceived to be heavier. Details on theories, underlying mechanisms, and relevant findings can be found in the publications of Section 6 and 7. The experiments in this thesis extend the previous results to include new forms of manipulation (bimanual horizontal large-scale whole-body movements instead of only small one-handed lifting), distinct manipulation types (fast-imprecise, slow-precise), larger objects (comparable to objects in automotive assembly), and high inertia (from 40 kg to 489 kg). No study could have been found that investigates object size related influences on human perception and motor behavior in the field of hHRC. The group around Ikeura conducted studies close to the topic of object weight perception and its influences on hHRC in the years between 2008 and 2012, but also with the limitations mentioned (S. M. M. Rahman & Ikeura, 2012a, 2012b; S. M. M. Rahman, Ikeura, Nobe, & Sawai, 2008; S. M. M. Rahman, Ikeura, Shinsuke, Hayakawa, & Sawai, 2010). Additionally, the group around Hirche conducted several experiments on the influence of undesired interaction wrenches biasing human intention recognition (Mörtl et al., 2012) and estimation of object dynamics in hHRC (Cehajic, Dohmann, & Hirche, 2017), which tie in with the line of argumentation of this thesis.

Why is it important to consider object characteristics in the control strategy of hHRC?

Imagine you are at a party and the host offers you a drink. The cup looks like a traditional Bavarian beer mug made of glass, but by touching and lifting it, you realize that it is made out of plastic, only glass-looking, and apparently weighting way less than you expected. Your internal feed-forward model (top-down, based on prior knowledge, see Fig. 4 and 7) anticipated a heavy object and therefore preprogrammed your initial forces. After moving the object this sensorimotor prediction is updated via your internal feedback loop (bottom-up, new incoming visual and somatosensory data, see Fig. 4 and 7) and you are uncertain for a short moment. If the cup is opaque, this surprising effect is even greater, since you are not aware about what and how much is in the cup. Transferring this example to hHRC, analog issues can arise. The human operator will be able to visually (if hands-on payload is available, even haptically) perceive the object to be manipulated, but s/he will be unaware of the provided robotic admittance parameters (equation 1 and 2) to a certain extent. This visual (and/or haptic) stimulus will address existing (prior) knowledge about a particular object characteristic (e.g., light or heavy) which in turn can lead to accidental misuse by applying inadequate forces. Consequences can be that the operator applies to little force and the IAD will not or only move very slow, which eventually can lead to usability and acceptance issues, or the operator applies to high forces and the IAD gets unstable because of unexpected accelerations and safety issues will arise. These facts will be present not only in future assembly lines (mass customization will require flexible and versatile applicable hHRC solutions), but especially in daily life with high variability of objects and tasks. Especially in the initially motivated case of assisting elderly who exhibit slower reaction times (Salthouse, 2009) and decreased sensorimotor sensitivity (Adamo et al., 2007) the described issues could even intensify.

“

> The workers do not think of themselves as using a machine: they just think of themselves as moving the engine.

”

Norman (2009, p. 87) about Cobots in his book *The Design of Future Things*.

This fact will greatly impair the acceptance and adoption of physically assisting devices.

An elegant robot control should account for these potential misunderstandings in an intuitive manner by applying object-dependent changes to the admittance parameters in contrast to rather static ones. By exploiting these advantages, the above-mentioned insufficient exchange of information in classical hHRC can be eliminated and a more natural and transparent collaboration can take place. These types of control updates will be called *perception-related assistance strategies* (PRAS). They are based on an estimation of user intent which, as stated before, will be fundamental for robotic systems sharing control with and physically assist humans (Section 1.2). Figure 8 depicts the proposed PRAS framework.

The ordinate shows the *level of haptic support* (LoHS), which is a one-dimensional generalization of power assistance and guidance provided by the robotic system. The LoHS is divided into three areas by the boundaries *no assistance* (NA), *overload limit* (OL), and *reference level* (RL) and ranges from passive master-slave to proactive shared control systems. The proposed framework assumes that hHRC always has to be designed below an ergonomically set OL. This limit can be set according to various existing standards and recommendations. This thesis applies the proposed methods and values of DIN EN 1005-3, (2009) and ISO 11228-2 (2007) as well as the values of the assembly specific force atlas (Wakula, Berg, Schaub, & Bruder, 2009). The following three steps are used to define an age-, gender-, and stature-related OL:

A – Basic isometric maximum force value:

The standards provide basic maximum forces F_B for adults in Europe based on muscle-strength force limits. They differentiate between professional (15th percentile) and domestic use (1st percentile). As reference either a 100 % female distribution between 20 and 30 years (DIN EN 1005-3, 2009) or a natural distribution of 59 % female and 41 % male (ISO 11228-2, 2007) are proposed. Relevant for this thesis is a standing position and bimanual push/pull whole-body movements. These requirements result in the following basic maximum force values:

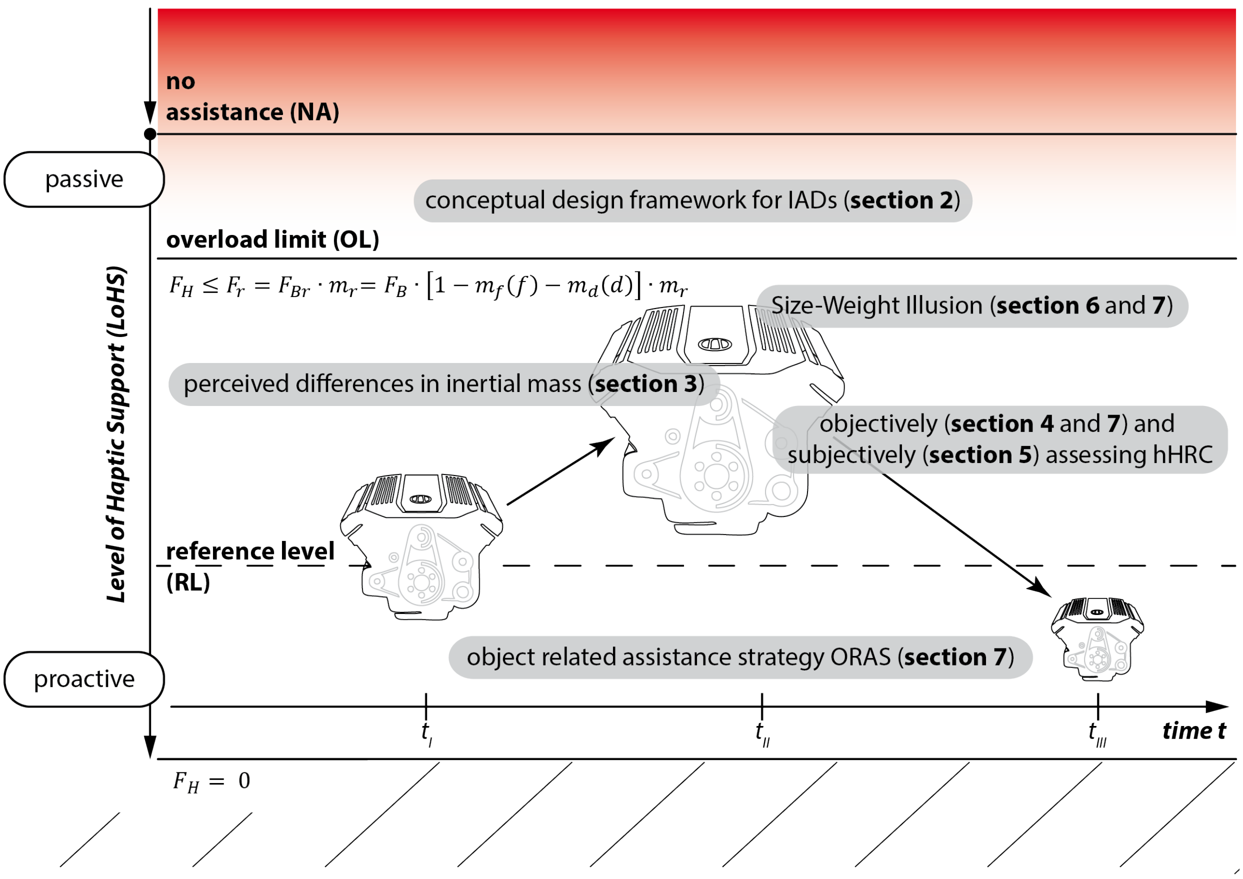


Figure 8. Perception-related assistance strategy (PRAS) framework for haptic Human-Robot Collaboration. Level of Haptic Support (LoHS) describes a continuous scale of robotic power assistance with no assistance at the top and maximum assistance at the bottom.

$F_{B,\,mean,\,push}$ = 228.0 N (SD = 84.4 N), $F_{B,\,mean,\,pull}$ = 161.0 N (SD = 45.7 N). According to the DIN EN 1005-3 (2009) these values are adjusted to professional ($F_{B,\,15.p,\,push}$ = 200 N, $F_{B,\,15.p,\,pull}$ = 145 N) and domestic applications ($F_{B,\,1.p,\,push}$ = 119 N, $F_{B,\,1.p,\,pull}$ = 96 N). Since these values lack of an age- and gender-related differentiation the values of the ISO 11228-2 (2007), summarized in TABLE 2, will be applied.

Table 2. Basic isometric maximum force values for pushing and pulling, separated by age group, application area, and gender distribution. Values are according to the ISO 11228-2 (2007)

		Pushing, $F_{B,\,push}$ [N]		**Pulling**, $F_{B,\,pull}$ [N]	
Age [years]	**Area**	100 % female	59 % female/ 41 % male*	100 % female	59 % female/ 41 % male*
20–49	professional	141	185	113	151
	domestic	83	97	64	76
50–64	professional	133	176	106	142
	domestic	77	97	58	71

* natural distribution (ISO 11228-2, 2007)

B – Adjusted capacity limits:

Frequency and duration of a task highly influence fatigue and as a consequence maximum force. This is accounted for by applying multipliers for operation frequency m_f and traveled distance m_d as well as the differentiation between *initial force* (to set an object in motion and accelerate it) and *sustained force* (to keep an object in motion at more or less constant velocity). Within the scope of this work, frequencies f of one manipulation every 60 seconds (1/min = 0.0167 Hz) are suggested because they correspond to a common cycle time in automotive assembly. This results in a task frequency multiplier m_f = 0.25. Initial forces are considered via a travelled distance d below five meters, which results in a travel distance multiplier of m_f (< 5 m) = 0.23 (female) and 0.3 (male). Sustained forces are taken into account by distances over five meters, which results in values for m_f (5-10 m) = 0.27–0.39 (female) and 0.18–0.26 (male). These factors are multiplied with the basic isometric maximum force F_B to find a reduced capacity limit F_{Br}.

$$F_{Br} = F_B \cdot \left[1 - m_f(f) - m_d(d)\right]. \tag{3}$$

C – Estimated impact and risk score:

The previous steps specifically address maximum capacity limits, which in this framework are in the NA–OL continuum. Since this area and also the area near the lower boarder of OL are not advisable for future hHRC applications, a *risk-sensitive force* F_R has to be taken into account. Multiplying F_{Br} with an additional *risk-sensitive factor* m_r ranging from ≤ 0.5 (advised) to > 0.7 (avoid) in the DIN EN 1005-3 (2009) and 0.85 (upper limit "green zone") to 1.0 (upper limit "yellow zone") in the ISO 11228-2 (2007).

$$F_H \leq F_r = F_{Br} \cdot m_r. \tag{4}$$

At this junction, it is important to understand that these standards mainly apply to identify hazards and estimate as well as evaluate risks. Initially they were not meant to apply for the design of interaction forces with admittance-controlled robots but can serve as a well-founded basis to identify the OL in the proposed PRAS framework.

Significant contributions are also published by Snook and Ciriello (1991) who acquired psychophysically accepted values for different manual handling tasks, including pushing and pulling. Their revised tables are used to identify the initial RL assignment according to manual handling type (push or pull), force type (initial or sustained), gender, handle height, manipulation duration, frequency, and distance (TABLE 3). It has to be mentioned that these (and similar) maximum acceptable forces may not correspond to biomechanical tolerance (Weston, Aurand, Dufour, Knapik, & Marras, 2017).

Table 3. Psychophysical accepted values for bimanual planar pushing and pulling for a frequency $f = 1/min = 0.0167$ Hz, for 90 % of the population (10. percentile) according to the ISO 11228-2 (2007) and Snook and Ciriello (1991)

		Pushing, $F_{H, accepted}$ [N† / kg‡]		**Pulling**, $F_{H, accepted}$ [N† / kg‡]	
		female	male	female	male
force type	**distance** [m]	(h_w = 1.35 m)	(h_w = 1.44 m)	(h_w = 1.35 m)	(h_w = 1.44 m)
initial	2	170 / 17	250 / 25	170 / 17	180 / 18
sustained	2	100 / 10	150 / 15	100 / 10	120 / 12
sustained	8	70 / 7	130 / 13	90 / 9	100 / 10

† ISO 11228-2 (2007); ‡ Snook and Ciriello (1991)

The abscissa of the PRAS framework (Fig. 8) shows the temporal progression (*time t*), here divided into the Sections I, II, and III, in which different sized objects (e.g., medium, large, and small) are manipulated in a hHRC. Below the above elaborated OL this thesis assumes a continuum of possible addmitance configurations for different object characteristics, especially object size. According to prior acquired and learned knowledge about a commonly anticipated relation of size and weight, humans tend to invest higher forces on larger objects compared to smaller ones (Buckingham & MacDonald, 2016; Buckingham, Michelakakis, & Rajendran, 2016; Flanagan & Beltzner, 2000; Flanagan, Bittner, & Johansson, 2008; Schmidtler & Bengler, 2016, 2017). Therefore, the main idea of the PRAS is to adapt the LoHS according to object sizes. Hence, a larger object should, to a certain degree, display higher inertia than a previous manipulated smaller object, in order to be perceived as heavier, whilst a smaller object should be perceived as lighter and change the LoHS to higher levels.

Combined with the argumentation that humans can cause instable behavior of admittance controlled hHRC, an elegant solution to involuntary high or low forces, misunderstandings and resulting stabilities issues (Burdet, Ganesh, Yang, & Albu-Schäffer, 2014; Lecours et al., 2012) could lay in a skillfull application of the PRAS (*chance*, e.g., larger objects are displayed with higher inertia to cope for higher initial interaction forces and therefore increase stability). Still, *challenges* may arise if the combination of differing LoHS and object sizes are inappropriate (e.g., perception of strong mismatches between object size and displayed weight can result in large differences between expected and experienced strain). This inevitably will lead to even increased illusion effects and as a consequence to the rejection of adaptive hHRC (Schmidtler & Bengler, 2016; Schmidtler et al., 2014, 2015). If it should turn out that the users are more attached to a static robot behavior, which in some cases may be easier to learn and anticipate, size cues will still influence conservative admittance controls in form of *nuisance* (e.g., SWI will still be present in the case of static LoHS). In any case, it will be advisable and relevant to consider object size characteristics in novel adaptive hHRC, to reduce sensory noise at the human side and create chances to overcome trade-offs at the robotic side (e.g., stability vs. usability).

Apparently, we are able to perform very well
in motor control and manipulating our environment
because we have learned and professionalized it.
Why should we let a robot rob us these great capabilities?

1.4 Optimization Criteria and Design Goals

One counter-argument to the abovementioned approach could be that people, who obviously are very flexible and adaptable, quickly learn to know the new situation, the robot's settings, and the interaction and then are able to achieve high performance after a certain number of repetitions. This machine-centered view has been followed now for many years in robotics, but as seen in HCI a long time ago, this design approach often leads to a dead end, trade-offs and resignation. For instance, Palm's PDAs were only usable via a certain pen, which as an interaction paradigm worked just fine back then. Apple changed the interaction paradigm in an evolutionary way from using a pen and desktop-fakes to tactile finger interaction with adapted dialogue design, which turned out to be a huge success for professional and personal use. For a long time, most of the developing effort in robotics has been spent in hardware and software functionality and autonomy. In contrast, only little was done to design intuitive HRI interfaces and controls (Yanco, Drury, & Scholtz, 2004). As Bengler et al. (2012) point out, the interface and relationship between worker and robot has to be optimized in a way to be accurate, reliable, efficient, and intuitive through multi-model user interfaces for continuous and resilient communication. According to basic ergonomic and human factors principles it is not desirable to design a system for the simple sake of creation and implementation, just because it is possible (cf., the left-over approach in former automation efforts). The task and function allocation relevant topics of Section 1.1.2 state that future hHRC will need real complementary features in order to provide the benefits they claim. Which means, the robot has to be able to perceive the human operators' skills and needs as well as has to sense the environment and the task-dependent features (e.g., object characteristics, movement types, and context). Future hHRC will only be successful if the systems follow ergonomic and human factors design principles accompanied by basic haptic design goals. In order to address the introduced information exchange challenges between human and robot, dialogue principles of human-machine systems are adapted to hHRC, presented in TABLE 4 (DIN EN ISO 9241-110, 2006)[v]. They serve as the basis for the following optimization criteria of hHRC:

It is possible to formulate optimal solutions for robotic control problems with given total inertia and actuator limits of a mechanism by comparing mechanical and actuation alternatives at their best control performance (De Santis et al., 2008). But what are the main optimization goals of hHRC including the human operator? Hatzfeld and Kern (2014) summarize three basic haptic design goals: stability, haptic quality, and usability. Together with general instructions for haptic

Table 4. Haptic Human-Robot Collaboration dialogue principles, adapted from DIN EN ISO 9241-110 (2006)

Suitability for the task	– Collaborating with the robot should not be more difficult than the task itself. *(If more resources are needed to use the robot than to fulfill the task by oneself, the robot is a burden.)*
Self-descriptiveness	– hHRC should be understood through self-explanatory design without additional instructions. *(The robot conveys most of its information haptically. It has to be designed perceptible and intuitive.)*
Conformity with user expectations	– hHRC should meet expectations and correspond to previous workflows. *(User-, object-, task-, and environment-related factors have to be considered.)*
Error tolerance	– User inputs must not lead to unstable system states or system breakdowns. *(The user will only trust and accept a stable system. Natural human force inputs have to be considered.)*
Controllability	– The user should have control over the interaction, taking into account the user's skills and needs. *(In haptic shared control the human should be able to control and overrule proactive robotic behavior.)*
Suitability for individualization	– The robot should provide adaptation to the characteristics of users, tasks, and environments. *(Besides a system-driven adaption, operator-driven adaptability has to be possible.)*
Suitability for learning	– Feedback and explanations should help the user to form a conceptual understanding of the interactive system. *(If requested, the operator should get information about internal parametrization and control strategy of the robot, e.g., visualizing the LoHS or virtual walls.)*

[v] This part of the ISO 9241 deals with the ergonomic design of interactive systems and describes principles of dialogue design, which are fundamentally independent of a particular dialogue technique. In this thesis they are adapted to and applied in the analysis, design, and evaluation of collaborative robotic systems (see TABLE 4).

inputs, outputs and/or their combination, listed in the DIN EN ISO 9241-920 (2015), they serve as a basis and are adapted to hHRC by adding relevant influencing factors and optimization goals:

1) Ensuring **stability**, which affects safety, task performance, and the interaction itself, while improving haptic transparency is one main requirement for physical interaction. Trade-offs are inevitable and thus have to be designed accordingly. Since **safety** and **dependability** are crucial for any further considerations of interaction they serve as the design basis via an intrinsic passivity of cobots and limited maximum energy in the system (De Santis et al., 2008).
2) Sufficient haptic quality or **transparency** has to be ensured. It is defined as "[…] basic feature [that] qualifies the capacity for a robot to follow human movements without any human-perceptible resistive force." (Jarrassé, Paik, Pasqui, & Morel, 2008, p. 2134). In this thesis, transparency is extended by the dialogue principles of self-descriptiveness, conformity with user expectations, and error tolerance (see. TABLE 4). Additionally, as proposed in the PRAS (1.3), resistive forces provided by the robot are reasonable, if they are willingly applied by the current control strategy, serve communication purposes and/or contribute to usability. Robots that provide appropriate feedback about the current operation may achieve transparency. "However, much consideration is needed in determining how much, when, and what type of feedback is most beneficial for a given task […],"(Beer et al., 2014, p. 89).
3) Enabling high **usability**, which is defined as the extent to which a hHRC can be used by specified users to achieve specified goals with *effectiveness* (accuracy, completeness and lack of negative consequences), *efficiency* (relationship between achieved results and used resources, e.g., time, human effort), and *user satisfaction* (attitudes[vi], emotions[vii], and comfort[viii]) in a specified context of use (DIN EN ISO 9241-11, 2016). Especially usability has to be considered very carefully, because, as De Santis et al. (2008) point out, if collaboration takes place in a working environment, these systems have to be designed even better than for domestic applications in order for them to be accepted. Originally from HCI, some of the classical usability constructs are transferred to hHRC, like Scholtz (2002a) proposed it. Quantitative measurable results can be key features of optimal hHRC. Groten (2011) provides an extensive list of potential usability metrics for hHRC. The publications of Section 4, 6, and 7 especially address usability assessment in hHRC and their method development.
4) Besides anticipative aspects, attitudes also "include the extent to which expectations are met" (DIN EN ISO 9241-11, 2016, p. 10). This affects **trust** (Gibo, Mugge, & Abbink, 2017), **acceptance** (Argall, 2015; Bröhl et al., 2016), and **user experience** (DIN EN ISO 9241-11, 2016). Since these factors will have major influence on the adoption of new technology, it is very advisable to actively shape them.
5) Enable **complementarity**. "The criteria are considered crucial for efficient and safe operating of a work system, as they describe the conditions human operators need in order to develop and optimally use their skills and knowledge" (Grote et al., 2000, p. 271). The same authors

[vi] "[…] beliefs and opinions about the [robot] or the interaction with the [robot]. […] can result from users' experiences of the system or similar systems and from the opinions of other people." (DIN EN ISO 9241-11, 2016, p. 18)
[vii] "[…] how users feel when interacting with the [robot]." (DIN EN ISO 9241-11, 2016, p. 18)
[viii] "Comfort or discomfort is a subjective aspect of satisfaction associated with the physical experience of using the [robot]." (DIN EN ISO 9241-11, 2016, p. 18)

provide empirically tested criteria for the evaluation of the complementarity of human-machine systems such as *process transparency*, *dynamic coupling*, *decision authority*, and *flexibility*. These are similar to the above-mentioned dialogue principles (TABLE 4).

6) Also, the often-desired quality of an **intuitive** interface and communication is supported by the abovementioned criteria. Intuition is defined as „immediate insight or perception, as contrasted with conscious reasoning or reflection" (VandenBos, 2015, p. 561). Translated to the topic of this thesis an intuitive control would imply the PRAS, where larger objects are displayed heavier than smaller once (*coherent modalities*; DIN EN ISO 9241-920, 2015). Whereas an easy to learn approach (as proposed in the dialogue principles, TABLE 4) could imply that the operator will learn that each object is exactly displayed as equally heavy. Section 7 especially addresses these contrary views.
7) With an improved admittance management reduced operator forces are possible reducing **human effort**, **stress**, and **fatigue**, which are basic ergonomic performance criterion (De Santis et al., 2008). For the sake of completeness and because this is obviously one very important innovation driver for hHRC it is mentioned but will not be investigated any further within this thesis[ix].
8) Finally, the worker's **well-being** has to be ensured, given that s/he tends to tire and will be susceptible to mistakes resulting from cognitive lapses or physical fatigue (Bicchi et al., 2008).

1.5 Research Questions and Contributions

Even though current hHRC systems have been developed and are technically ready to use, they still do not meet the greater part of the abovementioned design goals. Especially the trade-off between stability and usability motivated the following research activities. Bengler et al. (2012) emphasize among others two main objectives of research in the field of HRI which are in line with this thesis:

1) Modelling human behavior within cooperative systems to infer user states and intentions, and
2) Definition of metrics and methods to assess cooperation.

The main aim of this thesis is to optimize haptic Human-Robot Collaboration in terms of the design goals (1 – 6) applying an admittance-controlled system with respect to inertial mass m_t and object size cues s_{visual}. The following research questions (RQ) are intended to support this aim considering the given PRAS framework (Fig. 8). Each RQ will refer to different Sections, which are indicated in brackets. Additionally, the intended contribution is listed below.

Psychophysics can help finding the specific and appropriate quantitative values for the PRAS framework to ensure that the individual human operator will be able to perceive the intended information. Additionally, it is important that the assistive device is equipped with appropriate sensors and actors. Knowledge about quantitative values of human perception will facilitate these selections (Feyzabadi et al., 2013; Khabbaz, Goldenberg, & Drake, 2016; Vicentini, Galvan, Botturi, & Fiorini, 2010) and will most likely result in reduced costs. Hence, the first RQ reads:

[ix] For a far-reaching review and a novel global approach applying a standardized cardiopulmonary exercise testing consider the dissertation of Knott (2017).

RQ1: To what extent can a human perceive changes of inertial mass in planar bimanual manipulations? *Contribution*: Human model for the perception of inertial mass differences in bimanual planar manipulations (Section 3).

To achieve the mentioned design goals, knowledge about human intention and behavior while manipulating different sized objects is mandatory. Humans are prone to the SWI in small lifting tasks, but if large-scale whole-body movements using larger objects and higher masses still lead to the illusory effect is not sure yet. Therefore, it is unclear if this human idiosyncrasy will be relevant for novel IADs. The second and third RQ read:

RQ2: To what extent will the parameters object size and inertial mass influence the human motor behavior and performance when using a collaborative robot? *Contribution*: Replication of the SWI for larger objects, higher masses, different movement types, and investigation of potential influencing effects on task performance and acceptance (Section 6 and 7).

RQ3: How should the level of haptic support (LoHS) be designed to allow the user to accept the robot system and effective, efficient, and satisfactory collaboration is ensured? *Contribution*: Review of existing literature and concepts for physical human augmentation in the production and logistic environment (Section 2). Assessment methods for objective and subjective evaluation of hHRC (Section 4, 5, and 7). Recommendations for the optimization of hHRC applying the PRAS framework (Section 4, 5, 6, and 7).

1.6 Thesis Outline

Except for the Introduction (**Chapter 1**) and Discussion (**Chapter 9**), each chapter is based on a publication. They are attached in their original format in the Appendix (A–F).

Chapter 2 describes the concept of Human Centered Assistance Applications (HCAA), a taxonomy for the classification of Human-Robot Interaction in Human-Robot Coexistence, Cooperation, and Collaboration, as well as a closed-loop human-machine system with a formulation of the basic fields of research and goals of design and evaluation approaches within the area of human physical augmentation are provided.

Chapter 3 introduces a model of human inertial mass perception in horizontal bimanual manipulation. It contains the results of several experiments using psychophysical methods to obtain differential thresholds with varying reference stimuli, movement types (precise, imprecise), and directions (sagittal, transversal).

Chapter 4 addresses the quantification of usability of haptic Human-Robot Collaboration. It contains the results of a Human-Human Interaction experiment (Human Dyads) to investigate usability metrics and benefits of two motor control systems working together in large scale movements.

In addition to objective measurements, **Chapter 5** reports on the design and validation of a questionnaire to subjectively assess usability and acceptance of physically assisting devices. The mismatch between visually perceived object size and incoming somatosensory data can cause illusions at the human operator. This so-called Size-Weight-Illusion (SWI) has been known for a very long time but was only shown for very small movements and low masses.

Chapter 6 demonstrates the existence of this illusion in bimanual horizontal large-scale manipulation tasks with high masses and longer distances. Additionally, the different interaction modes (hands-on payload and hands-on control) as well as a control group without vision was implemented. The results are transferred to the domain of haptic Human-Robot Collaboration and a possible control implementation using a Bayes framework is given.

Chapter 7 analyzes the influence of the Size-Weight-Illusion on the usability of novel power assisting devices. A study investigates different control strategies to either cope with the illusion (compensatory, a chance), fix the assistance to a priori static level (static, unwanted nuisance) or to create a mismatch (control group) between expected and perceived inertia. Different movement types according to the speed-accuracy trade-off of human motor tasks (fast-imprecise and slow-precise) have been implemented to address potential different influences within the special use case of automotive assembly.

Chapter 8 summarizes complementary studies conducted and published by the author that are informative for the message of the thesis. Finally, the main results and conclusions including limitations and recommendations are discussed in **Chapter 9**.

2 Human Centered Assistance Applications for the Working Environment of the Future

Schmidtler, J., Knott, V., Hölzel, C., & Bengler, K. (2015). Human Centered Assistance Applications for the working environment of the future. *Occupational Ergonomics*, *12(3)*, 83-95, DOI: 103233/OER-150226.

"Just a machine? That's like saying that you are just an ape."
~Blue Robot (Automata)

Summary [x]

This article provides an overview of previous research and concepts of physical assisting devices in the branch of production and logistics. In the context of current social, technological, and legal changes new technical approaches are introduced and discussed that will support the human worker in an industrial environment. The novel design concept of Human Centered Assistance Applications (HCAA) is proposed, including an overview about three distinctive approaches pursued at the Chair of Ergonomics at the Technical University of Munich: Exoskeletons (Lifting Aid), collaborative robots (Cobot), and orthosis (Assembly Glove).

A novel classification of HRI in the categories *coexistence* (common time and workspace), *cooperation* (common time, workspace, and goal), and *collaboration* (common time, workspace, goal, and contact) is introduced that constitutes the ground for physical assisting devices using robotic features. They are sought to optimize working conditions by applying and adapting collaborative assistance systems in terms of human acceptance and well-being. The fundamental ideas behind it are summarized and are used to revise the classical human-machine system view to create a framework for research, design, and evaluation of HCAA. Insights of fundamental sciences such as cognition and neuroscience (e.g., human haptic perception, haptic illusions, and usability), anthropometrics (e.g., distributions of human body measurements for suitable geometric properties and adaptability), biomechanics (e.g., knowledge about maximum and acceptable human muscle forces and handy force path allocation), and physiology (e.g., EMG, respiratory analysis, and heart rate controller) provide the basis for user-centered designs, research, and testing. The article proposes the application of respiratory analysis, motion tracking, and force measuring as possible tools for the evaluation of HCAAs. These tools furthermore provide the data basis for modelling, simulation, and design recommendations.

The article concludes the HCAA approach by affirming the idea of complementary collaboration using the abilities, flexibility, and knowledge of humans, which still will be the key success factor in future working environments. The holistic HCAA approach presents a promising way to cope with current and future challenges such as demographic change, diverse operators, and changing work contents and demands.

[x] The article was written cooperatively with helpful input from Verena Knott (in chapters 1.3.1 Exoskeleton – Lifting Aid and 2.3.1 Respiratory analysis), Christin Hölzel (in chapters 1.3.3 Orthosis – Assembly Glove and 2.3.2 Force measuring), and Klaus Bengler (overall comments). All remaining parts were written independently by the first author, including the concept of HCAA, the classification of HRI, and the interaction model.

3 Human Perception of Inertial Mass for Joint Human-Robot Object Manipulation

Schmidtler, J. & Körber, M. (2018). Human Perception of Inertial Mass for Joint Human-Robot Object Manipulation. *ACM Transaction on Applied Perception* (TAP), 15(3), 15,
DOI: 10.1145/3182176

"Essentially, all models are wrong, but some are useful."
~George Box & Norman Draper

Summary [xi]

This article empirically investigates human perception of inertial mass discrimination in active planar bimanual manipulations. As previous studies have shown, people prefer inertial dynamic robot behavior for moving payloads over longer distances. Aim of this study was to build a human model to investigate just noticeable differences within the PRAS framework (see 1.3) motivated by the underlying psychophysical studies.

An extensive review of existing literature on force and inertial mass perception summarizes previous results that are later used to formulate a generic Weber Fractions model. Six experiments involving 165 participants were conducted to evaluate the differential threshold (just noticeable difference, JND) and Weber Fraction *k* according to different ranges of inertial mass stimuli (5 – 90 kg m/s²), directional anisotropy (sagittal, transversal), and different movement types (imprecise, precise). Based on these results a human inertial mass perception model was developed by fitting a linear mixed effects models (LME). In contrast to previous studies, dependent errors in the perceptual data from the longitudinal experimental design were considered using LME. Models were compared by applying the Akaike Information Criteria and Bayes Information Criteria (AIC, BIC) as well as chi-squared (χ^2) tests. The novel coefficients of determination R_{LME}^2 (Nakagawa & Schielzeth, 2013) and Ω^2 (Xu, 2003) provide a further easy to read quality criteria. Two models are introduced: First, a linear relationship of JND to fixed effects of reference mass $mass_{ref}$ and movement type *movement.type* as well as a random slope and intercept effects stemming from individual differences based on different masses ($mass_{ref}$ | *subject*) and an error term ε, which contains the remaining and arbitrary effects. Second, an exponential relationship of Weber Fraction *k* and reference stimulus I_{RS}, which is the quotient of $mass_{ref}$ and adapted stimulus $mass_{ref} + \Delta$ mass, including an asymptote parallel to abscissa.

In conclusion, differential thresholds near the perception boundary exponentially increased and resulted in constant behavior for higher stimuli (10 – 30 kg m/s²). This has been found in the acquired data and in previous studies. No effect of directions (sagittal and transversal) in precise motions but a large effect of movement type (precise and imprecise) was found. The models were used to set the inertial mass differences for the following SWI studies as well as to inform the proposed PRAS framework.

[xi] The students Anna Sophia Maier, Lukas Kirn, Thomas Illa, and Christoph Baur supported in conducting the experiments in this article. Moritz Körber assisted the statistical analyses.

4 A Trouble Shared Is a Trouble Halved – Usability Measures for Human-Robot Collaboration

Schmidtler, J., Körber, M., & Bengler, K. (2016). A trouble shared is a trouble halved – Usability Measures for Human-Robot Collaboration. In *Proceedings of the 2016 IEEE International Conference on Systems, Man, and Cybernetics*, 217-222, DOI: 10.1109/SMC.2016.7844244.

"Coming together is a beginning; keeping together is progress; working together is success."
~Henry Ford

Summary [xii]

This article reports on an empirical study evaluating objective usability measures for hHRC in planar manipulation tasks. Relevant haptic human-human collaboration literature is introduced to show that previous experiments have found highly positive effects of a second person in terms of accuracy and efficiency in co-manipulation tasks. It also appears that human dyad literature mainly focused on small one-handed movements. Most of them were table-based rotations or path following tasks. Therefore, the conducted study should provide insight if existing usability measures are applicable for large-scale whole-body manipulations. The resulting research questions are, if adaptive power assistance (less inertia and the second person), cause higher accuracy (less SDLP) and higher efficiency (less TTC) in planar large-scale manipulation tasks.

In order to address these questions, a human dyad experiment was designed, applying two usability measures of interest recorded via Vicon motion tracking and post-processed with MATLAB. The standard deviation lateral position (SDLP), which is a commonly used accuracy measure in the automotive area, was chosen to evaluate effectiveness. The time to task completion (TTC), which is one of the most basic usability measures in many areas such as HCI, was chosen to evaluate efficiency. A within-subject design consisting of the four factors *instruction* (to be fast, to be accurate), *person* (single, dyad), *movement type* (push, parallel), and *weight* (40 kg, 70 kg) was applied. Originally 40 participants (one participant had to be excluded because of data-logging problems) attended the study. The randomized 4 x 2 conditions were tested with a common four-wheeled trolley and an eight-shaped given path which the participants had to follow.

The results show significant differences and strong effects of SDLP as an accuracy therefore effectiveness measure, as well as for TTC as an efficiency measure. Significant effects of the second person, the inertial mass condition, as well as the instruction provide an important knowledge base for further usability evaluation experiments. For this reason, the main purpose of the study – finding robust objective usability criteria – was fulfilled.

Concluding, the study could show that established usability measures of related research fields are applicable for hHRC in large-scale whole-body movements. Additionally, it confirms results of previous studies about potential high benefits of a second motor system with human-like acting and sensing capabilities in collaborative manipulation.

[xii] The experiment reported in this paper was conducted with Asuman Sezgin, who has taken the part of the well-trained second person. Moritz Körber and Klaus Bengler supported the experimental design and writing process.

5 A Questionnaire for the Evaluation of Physical Assistive Devices (QUEAD) – Testing Usability and Acceptance in physical Human-Robot Interaction

Schmidtler, J., Bengler, K., Dimeas, F., & Campeau-Lecours, A. (2017). A Questionnaire for the Evaluation of Physical Assistive Devices (QUEAD) – Testing Usability and Acceptance in physical Human-Robot Interaction. In the *Proceedings of the 2017 IEEE International Conference on Systems, Man, and Cybernetics*, 876-881, DOI: 10.1109/SMC.2017.8122720.

"Many aspects of usability can best be studied by simply asking the users."
~Jakob Nielsen

Summary [xiii]

Since previous results within this thesis showed appropriate measures for objective evaluation, this work should shed light on the subjective evaluation of hHRC. If nothing else, because existing usability questionnaires were designed to evaluate mainly HCI applications and do not meet the requirements of haptic collaboration. Based on increasing efforts in the area of physical assisting devices subjective analyses will become increasingly important to gaze beyond purely technical perspectives. Therefore, based on the *Technology Acceptance Model* (TAM) and its update the *Unified Theory of Acceptance and Use of Technology* (UTAUT) combined with classical usability constructs such as attitudes, emotions, and comfort a questionnaire was developed. The iteratively designed QUEAD was evaluated in two sequential experiments with respect to its reliability and validity.

The first version consisted of 26 items divided into the five scales *Perceived Usefulness* (PU), *Perceived Ease of Use* (PEU), *Comfort* (C), *Attitude* (A), and *Emotions* (E). Nine participants were asked to manipulate a rectangle with a 7-DOF KINOVA JACO robot to fit three differently oriented targets. Besides a classical (CLASSIC) coordinate orientation at JACO's base, a new (NEW) adaptive orientation control relating to the gripper's orientation at the tool center point. The first version showed reliable results (Cronbach's α_{mean} = .80) in both conditions and all scales. The apparently poor criterion validity was very likely a result out of the small sample size.

Based on these results, the second version has been shortened to 16 items, keeping the previous five superior performing scales and high reliability within the scales and the complete questionnaire (Cronbach's α > .80). A KUKA LWR robot equipped with a force-measuring handle and laser pointer was used to solve a planar mace several times. A total of 21 participants took part and filled out the questionnaire after solving the mace five times. Three different modes were applied and tested twice. Again, high reliability was measurable using Cronbach's α and retest correlations. Criterion validity was acceptable and construct validity proved convergence of the scales.

Concluding, the QUEAD in its second version is reliable and valid to subjectively asses hHRC. A manual as well as a pen-and-paper version to use the questionnaire is provided online by the authors.

[xiii] This work was realized in an international collaboration with Dr. Fotios Dimeas (at that time with the University of Patras, Greece) and Prof. Alexandre Campeau-Lecours (Laval University, Canada) without additional funding. The experiments were conducted in the labs in Greece and Canada.

6 Size-Weight Illusion in Human-Robot Collaboration

Schmidtler, J. & Bengler, K. (2016). Size-Weight Illusion in Human-Robot Collaboration. In *Proceedings of the 25th IEEE International Symposium on Robot and Human Interactive Communication*, 874-879, DOI: 10.1109/ROMAN.2016.7745222.

"Reality is merely an illusion, albeit a very persistent one."
~Albert Einstein

Summary [xiv]

For the first time this chapter investigates size-weight-illusion (SWI, see also 1.3) in large-scale full body planar manipulations with large objects and high inertia. In the process of manipulating an object, the mismatch between existing knowledge (top-down process), evoked by visual perception of the object's size (first bottom-up process), and somatosensory information of the object's inertial mass (second bottom-up process), can cause heaviness illusions. In turn, this fact can lead to usability and acceptance issues of novel hHRC due to unintended robotic behavior. The empirical study presented in this section serves as a replication study of classical SWI studies, with movement types, inertia, and object sizes not tested up to this date though.

A sample of 30 participants took part in this experiment. A non-powered omnidirectional four-wheeled trolley, alternately carrying two different sized objects (small and large) and two hidden different weight conditions (40 and 70 kg), was used. Height adjustable handles provided adjustability to different anthropometrics and measured forces applied by the participants (KISTLER hand force measuring handles, 50 Hz, six dimensions). The task consisted of pushing the initially static trolley from a defined starting point over a three-meter straight path, decelerate and pull the trolley back to where the trial started. Before each trial the participants had to assess their expected strain and after each trial over their experienced stress on a 5-point rating scale. The object size and weight combinations were randomized as well as the interaction types hands on payload and hands on handles, vision, and no vision.

Results show significant influence of object size on expected strain but no conclusive outcomes for the rated experienced strain (applying a 5-point rating scale) were present in the data set. It is noticeable that haptic object size information (hands on payload condition) evoked high SWI effects, which confirms the results found in the literature. Sensorimotor prediction, analyzed via the initial maximum force ($F_{max\_1stpeak}$) and force rate ($FR_{max\_1stpeak}$) did clearly reveal high influences of object size cues. Larger objects are significantly manipulated with higher initial force and force rate.

In conclusion, humans are prone to the SWI in the considered new manipulation types. Especially, if haptic information about object size is present (hands-on payload mode). A possible Bayesian approach to incorporate the initially introduced PRAS framework (1.3) is introduced and future work to analyze the influence of size cues on usability is proposed.

[xiv] The experiments in this article were conducted together with Sarah Guggenmos and Florian Auracher at the Chair of Ergonomics.

7 Influence of Size-Weight Illusion on Usability in Haptic Human-Robot Collaboration

Schmidtler, J. & Bengler, K. (2017). Influence of Size-Weight Illusion on Usability in Haptic Human-Robot Collaboration. *IEEE Transaction on Hapti*cs, 2017, 11(1), 85-96.
DOI: 10.1109/TOH.2017.2757925.

"The pessimist complains about the wind; the optimist expects it to change; the realist adjusts the sails."
~William Arthur Ward

Summary [xv]

This article investigates, whether haptic illusions and especially size cues should be considered for the design of physically assisting devices in terms of optimizing simultaneously their usability and stability. Based on the initially introduced PRAS framework (see 1.3), the underlying cognitive processes, usability, and potential enhancement of information was investigated.

A within-subjects design was applied with the three factors *size* (small, large), *weight* (0, 50, and 100 kg additional mass), and *movement type* (fast-imprecise, slow-precise). The sample consisted of 40 participants and was controlled in terms of age, gender, and anthropometric properties. Three different hHRC strategies were implemented. In the *compensatory* mode (chance), the admittance parameters (2) were expected to be higher for larger and lower for smaller objects to compensate higher forces and accelerations due to object size and hence increase stability of the system. The *static* mode (nuisance) represented the contrasting design decision, where no adaption and a priori fixed admittance parameters should increase learnability of the assistance. A control group was implemented applying a third mode called *mismatch* (challenge), where faulty admittance parameters display small objects heavier than larger ones. Based on these modes different temporal representations of inertial mass and object size were presented to address three main questions:

Does SWI occur in fast-imprecise and slow-precise manipulation? Sensorimotor prediction (load force analysis) caused significant higher forces for larger objects in fast-imprecise and for smaller objects in slow-precise manipulations. The subjective 100-point scale revealed a clear SWI in fast-imprecise movements and diminishing illusory effects in the slow-precise positioning.

Do visual object size cues influence task performance? Although size cues induced larger initial forces, no significant effects on task performance in the fast-imprecise movement were present in the data set. Object size cues showed significant effects on effectiveness and efficiency in the slow-precise manipulation though.

Does the assistance strategy (compensatory, static, or mismatch) influence the usability of the system? The three different control strategies did not show significant effects on task performance. Qualitative findings highlight a symmetrical 50/50 distribution between preference of an object size related assistance strategy and a static assistance strategy.

[xv] The students Michael Mühlbauer, Sebastian Harslem, and Moritz von Freymann were involved in conducting the studies in this article.

8 Complementary Studies

"Stay hungry, stay foolish."
~Steve Jobs

This chapter summarizes additional studies conducted within the scope of this dissertation. A short summary of the studies is given:

Schmidtler, J., Harbauer, C., & Bengler, K. (2014). Investigation of Human Behaviour in Pushing and Pulling Tasks for Direct Manipulation of a Collaborative Robot. In *Proceedings of the Human Factors and Ergonomics Society Europe Chapter*, 2014. DOI: 10.13140/RG.2.1.4230.1601

Summary: For the first time, this study addresses the potential disturbing effects of differing visual object size cues and inertia in large-scale whole-body pushing and pulling movements. Twenty-two participants manipulated a four-wheeled trolley equipped with force-measuring handles and laden with three different weights and three different object sizes. Results have shown a strong effect of object size cues on expected strain and manipulation behavior.

Schmidtler, J., Petersen, L., & Bengler, K. (2016). Human Perception of Velocity and Lateral Deviation in Haptic Human-Robot Collaboration. In *2. Transdisziplinäre Konferenz "Technische Unterstützungssysteme, die die Menschen wirklich wollen"*, SmartASSIST 2016, Hamburg.

Summary: This work is a psychophysical study that was conducted to obtain information about human perception of velocity and lateral deviation in haptic Human-Robot Collaboration. Passively perceived velocity and lateral deviations were presented throughout a 1.5 m long path using a Reis Robotics RV20-16. A simple-staircase method was applied to obtain results from 21 participants for differential thresholds for velocity (reference stimulus at 500 mm/s; JND = 11.6 %) and an absolute threshold for lateral deviation (M = 41.33 mm, SD = 18.50 mm). A linear regression was applied to model acceptance (Acc) as a function of velocity v: Acc(v) = 0.747 + 0.004 · v + ε; R^2 = .678, $F(1,229)$ = 482.69, $p < .001$.

9 Discussion

"There is no real ending. It's just the place where you stop the story."
~Frank Herbert

This chapter provides the general discussion of the results, conclusions, limitations of the experiments performed, and recommendations for implementation as well as potential future research. The aim of this thesis was to optimize haptic Human-Robot Collaboration (hHRC) in terms of usability and acceptance, by applying the proposed perception-related assistance strategy framework (PRAS, Fig. 8).

9.1 Results and Conclusions

Facing current and future social and industrial challenges, hHRC and especially IADs provide promising approaches. Offering physical and cognitive support they are supposed to extend human capabilities, such as force, reach, and perception. In order to live up to their high expectations they will have to incorporate human- and system-centered design perspectives (Hoc, 2013; Kidd, 1992; Lotter et al., 2016). Based on the Man-Machine System by Rühmann and Bubb (1981) and the concept of haptic Human-Robot Collaboration (Section 1.1), a human-HCAA-interaction[xvi] model was introduced, describing an interdisciplinary approach to generate *knowledge* about acceptance and well-being; it provides recommendations for the *design* and *evaluation* of the human-machine interface to positively *influence* overall performance of the system (Section 2). The given research focus from a human factors point of view, in increasing task performance and safety, while reducing stress for the human was itemized and extended by the optimization criteria given in Section 1.4. Objective and subjective tools in form of metrics (Section 4) and an appropriate questionnaire (QUEAD, Section 5) are validated and provide the basis for future hHRC assessment. The PRAS framework, a novel control approach incorporating object size and inertia, is proposed and a region of potential design latitude for LoHS is defined. This bandwidth is defined by minimum human force input $F_H = 0$ and a gender, age, and posture related OL (Section 1.3).

9.1.1 Human perception of inertial mass

In order to inform the PRAS framework (Fig. 8) about the required resolution of different LoHS in the continuum between OL and $F_H = 0$ two distinctive models to describe human perception of inertial mass have been introduced.

Since many studies modelling psychophysical data violate the assumption of independence of errors (see review within article of Section 2), linear mixed effects models (LME)[xvii] have been applied to incorporate individual differences and sequential effects. Not least because of the longitudinal character of psychophysical threshold determination, it is desirable to know if individual differences affect haptic perception in a meaningful way. By applying LMEs it is possible to account for learning effects and fatigue unfolding during the experiment through trial repetition,

[xvi] HCAA–Human Centered Assistance Applications (article of Section 2)
[xvii] The *lme4* package (Bates, Mächler, Bolker, & Walker, 2015) within the R-studio environment (R Develpoment Core Team, 2008) was used to fit the LME function.

individual subject-specific variability (Moscatelli, Mezzetti, & Lacquaniti, 2012), and other potentially relevant covariates (Baayen, Davidson, & Bates, 2008).

A linear model to describe inertial mass perception (according to Weber's law[xviii]), considering random influences by the subjects (slope and intercept) and a fixed task-dependent effect (*movement type*) has been established. Transforming the outcome variable JND [kg m/s^2] with a common logarithm (log10) provided homoscedastic residuals and normal distributed results. A fixed effect with two ordinal levels (1 = imprecise, 2 = precise) has been added to account for systematic effects of *movement type* (fast-imprecise, slow-precise) present in the data set. Inferential statistics as well as information criteria AIC and BIC confirmed its informative character. Additional effects have been tested, such as *direction*, *gender*, *number of iterations*, and *subject* influences that did not show systematic effects and therefore were considered to be probabilistic and random. Therefore, correlated random intercepts and slopes for these effects were modeled and tested according to model prediction, significance, and information criteria (AIC, BIC). The random effect ($mass_{ref}$|*subject*)[xix] significantly contributed to the model. It describes random intercepts and slopes according to individual perceptibility of reference stimuli $mass_{ref}$ of the involved subjects. Via the mentioned model comparisons, the following linear equation evolved:

$$JND_{log10} = 0.016 + 0.009 \cdot mass_{ref} - 0.220 \cdot movement.type + \varepsilon. \tag{5}$$

Retransforming (5) to the initial range of numbers leads to an intercept and thus approximated absolute threshold of 1.038 kg m/s^2. This value is considerably higher compared to relevant findings of Vicentini et al. (2010) and Feyzabadi et al. (2013), which is very likely due to the type of interaction (bimanual, whole-body, and large-scale manipulation) and signal noise near the perceptual boundary in the experiments of this thesis.

In order to generate a more general description of human inertial mass perception two exponential models describing non-linear behavior near the perceptual boundary have been introduced[xx] (Debats, Kingma, Beek, & Smeets, 2012; Vicentini et al., 2010). The first one, solely based on the experimental results of the study (Section 2) resulted in the following approximation (Weber fraction k = JND%/100; $I_{RS} = mass_{ref} \cdot 1s^2/kg\ m$):

$$k_{specific} = 0.069 + 0.744 \cdot e^{-0.444 \cdot I_{RS}}. \tag{6}$$

The second one additionally included the values of the literature review (Section 2) and therefore provides a model on a more general basis without constraints of involved limbs, movement types, and applications as well as more detailed information for low inertia:

$$k_{general} = 0.057 + 0.203 \cdot e^{-0.102 \cdot I_{RS}}. \tag{7}$$

[xviii] In the first ever published psychophysical work "*Elemente der Psychophysik*" [elements of psychophysics], Gustav Theodor Fechner introduced Weber's law and Fechner's law. They constitute the beginning of interdisciplinary studies of human magnitude perception, which are relevant until today.

[xix] Notation format of the statistics software R.

[xx] The *nls* package (Baty et al., 2015) within the R-studio environment (R Develpoment Core Team, 2008) was used to estimate the parameters of a transformed linear function, power function, and exponential function.

The results of (6) and (7) are in line with latest findings in the literature, depicting an exponential increase of the Weber fraction near the perceptual boundary (Debats et al., 2012; Höver, Luca, & Harders, 2010; Khabbaz et al., 2016; Newberry, Griffin, & Dowson, 2007; Vicentini et al., 2010).

Despite the long-held assumption of a linear relationship of reference stimulus and corresponding perception, this thesis could prove that a decrease in the magnitude of the reference stimulus (explorative force) is accompanied by an increase in perceptual noise for bimanual manipulations.

According to the results of the presented study this statement is true until inertia smaller than 10 kg m/s^2 and for combined findings with values from the literature until smaller than 30 kg m/s^2 (consider Fig. 4 and 5 of the publication of Section 3, Appendix B). At these values, the established exponential models show asymptotic behavior following an approximately constant threshold and, therefore, determine the limit of validity of Weber's law. Both introduced models show comparable intercepts of around 26 % differential threshold at the perceptual boundary. This translates in the finding that if a hHRC application is designed with the goal of displaying minimal resistive forces, differences within a quarter of the actual force are not perceivable. This will allow future engineers a certain margin in the selection of appropriate sensors and actuators (Section 9.3 provides further information). In comparison with the descriptive results of the partial studies an average JND% of M = 8.4 % (SD = 4.2 %) was measured, which lies very much above the modeled asymptotic values of 6.9 % for higher inertia (> 10 kg m/s^2), the 5.1 % of the transformed linear function (5), and the more general model results of 5.7 % (> 30 kg m/s^2). This fact demonstrates that these single values, as they are often used blindly by practitioners, are only informative for high inertia. Especially for low inertia (< 10 kg m/s^2 for bimanual, < 30 kg m/s^2 in general) and differing movement types it is highly recommended to apply the elaborated equations (5–7).

Following the psychophysical accepted values reported by Snook and Ciriello (1991) see TABLE 3, a relative difference between initial and sustained force for pushing (female: 41 %, male: 40 %) and pulling (female: 41 %, male: 30 %) has informative character and therefore can be applied as initial gender-related RL in the PRAS framework.

To conclude, the present study has demonstrated that especially for small inertia, a high variability and exponential relationship of the Weber fraction is present, confirming findings in the current literature. Boundaries for a “true” constant behavior as proposed by Weber’s law are introduced. Based on the initial assumption to utilize the haptic channel between human and robot, with simultaneously high informative communication, the presented results support the idea to design control strategies that operate in the constant perceivable area. This area clearly is not located near the human perception boundary, but rather over at least 10–30 kg m/s^2.

Hence, this thesis disagrees with conservative perspectives of minimizing human force inputs regardless of human inertia perception and possible communication losses.

The results of the presented study provide information for a larger range and higher inertia with different movement types. As a consequence, the behavior of the exponential function, as proposed by the abovementioned authors, was confirmed and additionally extended for the first time.

9.1.2 Perception and behavior substantially depend on movement type

There is a considerably high influence of movement type on perception, apparent in the lower JND values in slow-precise than fast-imprecise movements (descriptive and inferential statistics are provided in the article of Section 2). This translates in the fact that LoHS-changes have to be much stronger in fast-imprecise movements than in slow-precise movements to be perceptible. This result is not trivial since many studies in the consulted literature on hHRC do not incorporate different control strategies or feedback for different movement types. Often, they only address one movement type or even mix the mentioned ones in the evaluation. For instance, current exoskeleton concepts, no matter if passive or active, only display one and the same control strategy for picking up, fast moving, and accurately placing the object at a designated space. If, for example, several objects on a pallet have to be arranged, which can be a combination of imprecise and precise tasks, especially if they are stacked up high and have to have certain orientations on the pallet. The human is able to adapt his/her manipulation characteristics (e.g., different arm damping and stiffness; M. M. Rahman et al., 1999) to different task types and requirements with the help of our internal motor control apparatus (1.2.1). In this way, we are able to learn new or unknown characteristics and get the chance to optimize our operations via training and pre-planning (Burdet et al., 2013).

Leaving the robotics domain for a moment and looking at one of the most common human haptic interactions with a machine leaves us at power assisted steering in the automotive area. The first ever power steering system in an automobile was already installed in 1876 (Schultz, 1985). It took almost a century when the first speed sensitive steering (high assistance at low speed, light assistance at high speed) was implemented in the Citroën SM in 1970 (Shoar, 2014). Ever since, these systems have increasingly gained in popularity and acceptance, but one may ask why it took so long to introduce an adaptive system after the initial idea of power assistance. These considerations have continued to this day and are attracting increasing attention, especially in the field of shared control systems that demonstrate significant safety and performance benefits (Abbink et al., 2012; Petermeijer, Abbink, & de Winter, 2015).

Toyota's Skill-Assist already considered different admittance behavior for different movement types (viscous for precise, inertial for fast; Bicchi et al., 2008; Yamada et al., 1999), but they were static and a priori fixed, as well as tested single-handed and unidirectional. The first study, which we found that explicitly addresses the speed-accuracy trade-off[xxi] in hHRC was conducted by Marayong and Okamura (2004). They developed an algorithm to select an appropriate admittance ratio based on the nature of the task (path following, off-path targeting, and obstacle avoidance) and found a linear relationship between admittance ratio (ranging from complete guidance to no guidance) and performance. Since they applied virtual walls and were interested in guidance only, they did not evaluate LoHS on a general basis. Fixed strength of guidance force turns out to be insufficient for complex tasks, such as assembly (contrary to driving a car), and adaptable control strategies based on operator inputs (e.g., operator grip force) allow higher usability and reduce operator effort (Smisek, Mugge, Smeets, van Paassen, & Schiele, 2017). Outside proactive guidance, Lecours et al. (2012) implemented variable admittance strategies, in passive robot control (see 1.2.2), based on the inference of human intentions using desired velocity and acceleration. Based on the idea to eliminate trade-offs inherent in static admittance control (mutual interference of stability and usability; see 1.4). They found beneficial effects on usability but remain owing sufficient evidence via a user study.

In addition to reaching and cyclic movements (Burdet, 1965; Fitts, 1954; Gentry, Feron, & Murray-Smith, 2005; Reed, Peshkin, Colgate, & Patton, 2004), we replicated the speed-accuracy trade-off in large-scale whole-body movements using different instructions, validating *TTC* and *SDLP* as potential usability measures (Section 4) and different movement types according to an automotive assembly scenario (fast-imprecise bringing and slow-precise positioning, Section 7). The main conclusion is that for scenarios dominated by efficiency (e.g., transition movements without confined spaces), the human operator should be supported by the robot with low damping for fast movements and adapted inertia to ensure stability, which will result in measurable and significant improvements in *TTC*. In scenarios with focus on high accuracy (e.g., precise assembly), inertia may not play the lead role, since participants (study of Section 7) replied that the three different inertia conditions did not result in perceptible different difficulty levels. According to the applied *100-point scale* (subjective strain) they significantly felt the inertia-differences, which did not lead to statistical influences on task performance (*DF* and *PPL*). This result fits to the abovementioned conclusion that humans perceive very small inertia differences in slow-precise movements and adds the information that inertia can be adapted in accuracy tasks (e.g., to ensure stability, if the human stiffens or in contact with the stiff environment) without decreasing task

[xxi] High speed of user actions is incompatible with precise motor control and vice versa (Burdet, 1965; DIN EN ISO 9241-920, 2015; Fitts, 1954).

performance. These findings are in line with Dimeas and Aspragathos (2015), who also found great influence of displacement on task performance (effort and *TTC*). They added that the participants were able to subjectively perceive different control strategies "clearer" with more displacement. Therefore, we conclude that short and precise movements are easier to handle from a control perspective, whilst large-scale movements will need special attention, nonetheless because they have so far been greatly neglected in the literature.

In order to address the mentioned control challenges many articles report on the implementation of human physiological and human motor function data to inform robotic control strategies. For instance, Grafakos et al. (2016) adjusted virtual damping, besides force inputs, via EMG (operator muscle activation) in two simulated movements (high accuracy and fast transition movements) applying one-handed control of a 7-DOF LWR KUKA. They found a significant reduction of operator effort and movement accuracy, but applied a contra-intuitive approach, in which higher muscle co-activation increased damping. At first (for a roboticist) this is intuitive and beneficial, since it increases stability when the human arm stiffens, but high muscle co-activation will also take place in fast transition and the increased damping simultaneously will hinder fast movement (Peternel et al., 2017). This could be one reason why they struggled to find *TTC* improvements. We agree to their first assertion that humans tend to increase muscle activation when they attempt to stabilize dynamic environments, but we have to disagree with the latter one that humans apply high muscle activation for tasks with accuracy. Our results, especially the findings of Section 4 and 7, show that humans behave in the very opposite to this statement. While maneuvering the object to its final position, participants frequently used only their fingertips without a full-grasp of the handles which is a prominent indicator for low muscle contraction. Force and acceleration values verify this assertion. In the preparations for Section 7's experiments, we found that especially in the slow-precise positioning EMG signals were not sufficient to accurately infer human intention[xxii]. According to our experience, the current successes applying human physiology and human motor function information in robotic control strategies reported in several articles, have to be taken with a grain of salt.

9.1.3 Perception-related assistance strategies are not mandatory, but favorable

> "When executing movements humans make both random and systematic errors"
>
> (Mugge et al., 2016, p. 1).

As stated in Section 1.2.2 many studies are addressing human signals (e.g., force, kinematics, EMG) and involve contextual and task specific factors in human behavior models. In order to enable the

[xxii] These results can be found in the Master Thesis of Sebastian Harslem, "*Evaluation of a Shared Control Approach in Human-Robot Collaboration*", conducted at the Chair of Ergonomics, at the Technical University of Munich in 2016.

robotic control strategy to incorporate enhanced information about the task, we looked closer at object characteristics that decisively influence human manipulation behavior.

Systematic errors can arise from human idiosyncrasies such as the fact that we invest higher forces on larger than on smaller objects, which can lead to illusory effects if two different sized objects are displayed with the same admittance (SWI). A considerable amount of literature exists about the influence of visually and/or haptically perceived object size cues on interaction force (see articles of Section 6 and 7) and their interdependence with subjective impression. According to DIN EN ISO 9241-920 (2015, p. 3), "maintaining coherence between modalities" is a general design goal for haptic devices. The standard follows that incoherence, based on the influence of visual perception on haptic perception, can lead to confusion and instability in the control of multimodal systems.

The frequently studied Size-Weight Illusion and its smaller in impact, but not negligible neighbor, the Material-Weight Illusion, are robust and strong examples for incoherent modalities (Lederman & Jones, 2011). Sequentially manipulating two objects of equal mass – displayed by an IAD – can result in illusory and thus usability and acceptance lowering effects. These illusions are caused by mismatches between the expected dynamics of the manipulation, which are efferent signals stemming from the CNS (Fig. 5) in a top down process (feed-forward, Fig. 4) and the somatosensory consequences of the manipulation itself, which are afferent signals informing the

Thus, the system should maintain coherence between haptic and other modalities (e.g., vision) in order to reach optimized hHRC.

CNS in a bottom-up process (feed-back, Fig.4, measured by GTOs and MSs; Ellis and Lederman, 1998; Nicolas et al., 2012). Literature proposed that in these cases the CNS expects certain dynamics and as a consequence pre-programs initial interaction forces that can lead to illusions at the human side (Buckingham & MacDonald, 2016; Flanagan & Beltzner, 2000) and instabilities at the robot's side (DIN EN ISO 9241-920, 2015). The trade-off between stability and usability represents one of the main challenges in hHRC (Buerger & Hogan, 2007; Hirche, 2014) and many approaches devote themselves seeking to estimate the varying endpoint stiffness of the human (Dimeas & Aspragathos, 2016). Again, there are articles working on this topic applying online human signals such as EMG (Gallagher, Gao, & Ueda, 2014) and human grasp force (Podobnik & Munih, 2007), with the earlier mentioned drawbacks of movement types, delays, and human diversity. In order to provide information about the haptic interaction, prior and within the initial onset of a manipulation, this thesis ties on the trade-off by investigating the influence of size cues and timely inform potential anticipating control strategies (Section 1.3 and 7).

A significant body of work deals with SWI, but all of them have in common that they had been conducted in vigorously controlled lab settings, with only very short lifting movements[xxiii], with one hand (most of the time only index finger and thumb), and very small masses involved. Since these manipulation types, inertia in the low gram region, and small hand-sized objects do not represent the motivation given at the beginning of this thesis[xxiv], literature lacks of certain *ecological validity* (representative design; Brunswik, 1956) for future real-life industrial or domestic applications[xxv]. Thus, we decided to investigate size cues and SWI in large-scale whole-body manipulation of larger and heavier objects. We successfully replicated the SWI for inertial influence in the studies of Section 6 and 7 and confirmed that inertial (here: pushing and pulling), instead of additional gravitational cues (lifting), reveal analogous results (Amazeen & Turvey, 1996; Plaisier & Smeets, 2012; Platkiewicz & Hayward, 2014). As a consequence, this thesis should write about Size-Mass Illusion (SMI), but in terms of traceability of our results and since the conclusions are the same, we consistently used the more popular term SWI, as literature proposes it (Plaisier & Smeets, 2012).

Consistently in our studies, participants expected larger objects to be heavier than smaller ones prior to the manipulation (Schmidtler & Bengler, 2016, 2017; Schmidtler et al., 2014). Thus, the large influence of object size cues on subjective expectation is trivial (Buckingham, 2014; Buckingham & MacDonald, 2016; Nicolas et al., 2012). This prior knowledge can, for instance, be based on **motor learning** (see 1.2.1), **expert knowledge** (Ellis & Lederman, 1998), or even **social cues** and **stereotypes**[xxvi] (Dijker, 2008). This prior knowledge affects our initial interaction force. These indices for sensorimotor prediction are measured and inferred via the initial force and force rate peak at the onset of a movement ($F_{1stpeak}$ and $FR_{1stpeak}$; Flanagan and Beltzner, 2000; Plaisier and Smeets, 2012). There is an ongoing discussion about the application of the peak values (Buckingham, Michelakakis, et al., 2016) as opposed to the first peak (Flanagan et al., 2008) within the onset of a manipulation as indices of sensorimotor prediction (Buckingham, Reid, & Potter, 2017). In order to avoid the pitfall of subjectively choosing a first peak within a set of sequential peaks and the simpler operationalization, we followed the approach of Buckingham et al. (2017) and used the peak value in the initial acceleration (in our case within the first 1000 ms and $v_{start} > 0.01$ m/s).

Whereas our first study on SWI (Section 6) gave the impression that the illusion disappears with increasing mass, the follow-up study (Section 7) clearly disproved this statement and consistently showed significant and robust results for SWI and sensorimotor prediction. Possible reasons for this discrepancy are the relative difference of object sizes used, their position on the trolley, and the applied subjective scale to assess heaviness. The first study used a common four-wheeled trolley placing the two different sized objects on top of it. The larger object occupied the whole provided space, whilst the smaller object was shifted to the front to fit the trolley's front edge. Thus, the outer lines of the whole object-trolley structure with the small object were very much the same as with the large object. According to Plaisier and Smeets (2016) the determining factor for object

[xxiii] Only one exception was found. The authors used a suspended pendulum and participants had to push small lightweight objects (250 g) over a distance of 50 cm (Plaisier & Smeets, 2012).

[xxiv] Medical areas such as rehabilitation and prosthetics in hHRC will very likely be interested in these regions.

[xxv] Further information about this topic can be found in the Limitations Section 9.2.

[xxvi] "Why Barbie feels heavier than Ken", equally weighing dolls, differing in sex, age, and physical strength cues, induced SWI. Stereotypically lighter dolls, induced by social cues, have been perceived to be heavier.

size perception is not volume (contrary to previous opinions) but the limiting contour of the whole structure that is moved. Therefore, size perception is not veridical but rather depends on contour closure and therefore is greatly influenced by object boundaries (Makovski, 2017)[xxvii]. This fact was considered in the follow-up study in the way that the objects differed in height that automatically increased the contour closure of the whole IAD-object structure. This is permitted, since this would also be the case in real scenarios using IADs for different sized objects. The other limitation of the first study that probably led to inconclusive SWI results, is the low resolution of the five-point Likert-scale that was used. The follow-up study addressed this flaw by applying a *100-point scale* as proposed by Buckingham and MacDonald (2016), to precisely resolve different perception and provide better discriminability, which is an expected quality of psychophysical studies (Shen & Parsons, 1997).

With this knowledge, it was possible to replicate the SWI in large-scale whole-body planar movements for fast-imprecise movements. Due to the characteristic of this special movement type, incorporating high acceleration and force gradients, it will be particularly susceptible to unstable robotic behavior. Again, the high influence of visual object size cues in form of higher initial force peaks ($F_{1stpeak\_fast}$) as indices for sensorimotor prediction have been present in the data and resulted in an average initial force increase of M = 7.9 % (SD = 2.7 %) for the larger object. SWI diminished in slow-precise movements and the sensorimotor predictor ($F_{1stpeak\_precise}$) was inverted. This translates in the finding that smaller objects were initially manipulated with higher forces than larger ones (M = 17.3 %, SD = 4.1 %), which has not been reported in the literature before. Since we counterbalanced the movement types, this result may very likely be true for automotive assembly tasks in general. Very slow manipulation (with low force and acceleration changes) does not evoke the size-cue-related sensorimotor prediction, at least not in a way that it will matter for real-world hHRC applications. We see a very strong connection to findings discussed in Section 9.1.2 on different movement types and according perception and behavior. The participants seemed to be more confident in manipulating smaller objects precisely and therefore applied higher initial forces. The subjective *100-point scale* revealed the SWI in fast-imprecise but not in slow-precise movements. Whereas participants reported that they did not perceive differences during the slow-precise positioning, larger objects significantly were rated lighter in fast-imprecise manipulation. This fact fits to the statement that participants replied they were concentrating on the correct execution of the positioning task. In doing so, it felt obviously easier with the smaller object and therefore, in our opinion, they were more confident. This could also explain the higher interaction forces for smaller objects in slow-precise positioning, which is contrary to sensorimotor prediction as stated above. Especially this fact points out the tremendous influence of task and context. To this date, no source has been found that focusses on especially these influences on stability considerations. Especially fast-paced environments, such as automotive assembly lines, will amplify these challenges. Personal communication with assembly line workers (at three different German automobile manufacturers) revealed the presence of time pressure in their working environments.

[xxvii] Implies that if it is possible to grab different sized objects in a way that their contour closure fits the same space, the illusion would very likely diminish.

There is no time and no motivation for adaption to a machine, from both a personal and industrial point of view, which meets the HCAA design considerations.

Similar to the results of Dimeas and Aspragathos (2016), we found no influence of mass on manipulation performance in slow-precise tasks and significant influence for larger displacements and fast-imprecise movements. Visual size cues influenced task performance in slow-precise positioning (longer manipulation *PPL* and less precision *DF*). Mass had no statistical influence on precisely positioning the objects, which is backed by comments of the participants. It's very likely that the low accelerations of the inertial mass did not result in greatly different situations. Qualitatively, 75 % of the sample did correctly perceive three different mass conditions. Combined with the human mass perception model (Section 3 and 9.1.1), the range of mass differences from 13 % to 54 %, had been strong enough to evoke perceptible different LoHS conditions.

We found no statistical influence of visual object size cues on task efficiency in fast-imprecise manipulation, which confirms in similar ways the work of Luebbers, Buckingham, and Butler (2017) and Rahman and Ikeura (2012b). The chance to perform the given tasks faster was given. However, the results imply that the assumed time reduction, caused by different initial forces, is compensated by the longer task execution. A remarkable variation in *TTC* was present for larger objects, especially large-light objects induced significantly shorter manipulation times than large-heavy objects. At first glance, this is caused by the high influence of mass on manipulation efficiency, but two additional results are contrary to this assumption. First, there is no such variation present for the small object condition. With a mean difference of 0.1 s, it is trivial to confirm equivalence[xxviii] of the three mass conditions. Second, the complementary results in Schmidtler et al. (2014) indicate higher median velocity and acceleration of the heavy-small compared to the light-large condition. Hence, the *TTC* results are not completely conclusive and could potentially change with growing experience. The articles of Section 4 and 7 found significant influence of mass on *TTC* in fast-imprecise movements. Additionally, mass did not reveal significant influence on *SDLP* in fast-imprecise (Section 4) and *DF* and *PPL* in slow-precise movements (Section 7). We assume that especially the magnitude of mass in fast-imprecise movements has to be designed accordingly in admittance control (2). Section 4 applied a well-trained second person (human dyad) as force and guidance support. It has been found that a moderate increase in mass can be beneficial to increase stability in precise motions without major concessions to task performance and effort (Dimeas & Aspragathos, 2016; Schmidtler & Bengler, 2017).

Similar results have been found for visual object size cues. There are no significant effects of control strategy (chance, challenge, or nuisance) on task performance present in the data set of Section 7. Which is indeed a promising result, since it grants the possibility to deploy variable admittance controls incorporating object size in order to parameterize target mass m_t and damping c_t (2). This approach can be favorable to tackle the initially mentioned trade-off between stability and usability. Firstly, PRAS provides the potential for intuitive and as a consequence more usable systems that will eventually lead to higher acceptability. Secondly, via the PRAS larger objects would inherently be displayed with higher admittance than a previous smaller object, which in turn

[xxviii] Practical no difference between two mean values. The equivalence region has to be defined by means of engineering or psychological information. More detailed information on equivalence testing can be found in Lakens (2017).

guarantees higher stability in the case of higher interaction force gradient. Mugge et al. (2016) found out that intuitive haptic guidance leads to improved motor performance, while non-intuitively presented haptic information leads to ignoring. This conclusion fits quite nicely to qualitative answers of our sample (Section 7), who did not strictly prefer one control strategy over the other (50 % static, 50 % compensatory mode), but clearly rejected the control condition (0 % mismatch mode). Hence, an intuitive way of adapting LoHS according to object size is in principle possible. If it is not implemented, people most likely will just not be aware of the fact that it would actually be possible.

The more detailed concept of *ecological validity* (in perception), describes the *informativeness of a sensory cue* (Brunswik, 1956; Hammond, 1998). It can be explained with the following two examples:

A) An object that looks heavy is heavy. This example represents high sensory cue informativeness because an object's real mass highly correlates to its appearance. This assertion is based on our previous experiences and stored in our long-term memory in form of prior conceptual knowledge (Gregory, 1997; see also Fig. 7).

B) An object, in a group of different colored objects, is blue and it is heavy. The color cue in this example has low sensory cue informativeness, since in most cases the sheer information of the color of an object does not correlate to its mass. Thus, this thesis follows with the conclusion that PRAS does not elicit task performance in our data set, but it provides high sensory cue informativeness and as a consequence enables the operator and the robot control to facilitate a priori information about the actual and anticipated status of operation.

9.1.4 Objective and subjective evaluation of hHRC

The article of Section 2 describes three promising methods to objectively evaluate hHRC, namely motion tracking, force measuring, and respiratory analysis. The first two are applied in this thesis to analyze human manipulation behavior and task performance for the purpose of human intention modelling. The articles of Section 4, 5, 6, and 7 as well as complementary studies by the author (Section 8) found *TTC*, *SDLP*, *DF*, *PPL*, *COL*, $F_{1stpeak}$, and $FR_{1stpeak}$ to be reliable and valid measures.

Recorded and processed motion tracking data was used to obtain the dependent measures *TTC* (efficiency, Section 4,5, and 7) and *SDLP* (accuracy, Section 4) for imprecise movements and *PPL* (efficiency, Section 7) and *DF* (effectiveness, Section 7) for precise movements. The respective equations for post-processing of the position data can be found in the stated articles. Additionally, it was applied to infer velocity and acceleration from position over time. Incidentally, it is very important to point out that the derivation beyond acceleration is not recommended in any case[xxix] (e.g., to analyze minimum jerk trajectories). With each derivation, the signal becomes increasingly noisy. Derivation of the signal was done applying a five-point stencil in one dimension (Buckingham, Michelakakis, et al., 2016; Schmidtler & Bengler, 2017; Schmidtler et al., 2014; Schmidtler, Körber, & Bengler, 2016). To be able to precisely determine peak values we applied dual pass fourth-order Butterworth filter to smooth the velocity and acceleration signal, as

[xxix] Ten VICON motion tracking cameras were used, recording at 100–120 Hz. Large-scale movements, including periods of short walking, entail large tracking areas (~4 × 4 m). To keep marker detection at a high level, resolution of the cameras has to be sufficient, which implies a ceiling effect for maximum frame rate. VICON Nexus was used for pre-processing and MATLAB for post-processing.

recommended by Buckingham et al. (2009, 2016, 2017). Additionally, we recommend to keep the frame rate of the motion tracking system, no matter if optical, inertial, or absolute, as high as possible. Considering reliable marker detection, the signal then should be sufficient for post-processing. As a side note, we also tried to use acceleration sensors of common smartphones (e.g., Section 6) but they did not prove themselves as very reliable, due to sensor noise and drift.

Groten (2011) points out that *behavioral measures* have so far only rarely been studied in the field of hHRC. She provided an extensive overview of efficiency, effort, and dominance measures that should be considered in the design and evaluation of future hHRC. Additionally, she suggests the use of *physiological measures*, such as EMG or cardiopulmonary signals[xxx], and *subjective measures*, obtained from questionnaires. The quote by Nielsen (1997, p. 110),

> “
> many aspects of usability
> can best be studied by simply asking the users
> ”

still retains its importance today and especially in the field of hHRC. Serious applications of subjective measures in hHRC are rare but were found in the articles of Mörtl et al. (2012) and Medina et al. (2015). The former used a combination of specifically designed questions for haptic shared (virtual) environments (Basdogan, Ho, Srinivasan, & Slater, 2000; Kucukyilmaz, Sezgin, & Basdogan, 2011) and more general standardized questionnaires from other domains such as the NASA TLX (Hart & Staveland, 1988). The range of variables can be positively highlighted – performance, emotional reaction, collaboration, interaction, comfort and pleasure, workload, trust, and role assignment. Whilst some of the applied questions are already evaluated due to reliability and validity their combination and transferability to hHRC is not ensured. Especially in HCI and the transportation sector there are many existing questionnaires to assess *usability* (Brooke, 1996; Figl, 2009; Gediga, Hamborg, & Düntsch, 1999), *acceptance* (Van Der Laan, Heino, & De Waard, 1997), *attitude* (Hassenzahl, Burmester, & Koller, 2003; Minge & Riedel, 2013), *emotion* (Russell, Weiss, & Mendelsohn, 1989; Thompson, 2007), *perceived exertion* (Borg, 1990), *satisfaction* (Demers, Weiss-lambrou, & Ska, 2002), and *trust* (Charalambous, Fletcher, & Webb, 2016), just to mention some of them. They all have in common that they do not address the scope and different requirements of haptic interaction with physical augmenting devices. According to the optimization goals of hHRC (given in Section 1.4), two distinctive subjective measures have been introduced by this thesis. In order to assess subjective physical strain, the interval-scaled single-item *100-point scale* (see Section 7 and 9.1.3) was introduced. We assume that the construct physical strain in hHRC is easy to understand and recall for participants. Since the question is directly related to the previous manipulation trial the single-item scale can be accepted as reasonable (Diamantopoulos, Sarstedt, Fuchs, Wilczynski, & Kaiser, 2012). The single-item approach had been chosen to not distract from the essentials. In this way the benefits of single-item scales listed by Fuchs and Diamantopoulos

[xxx] As said before, these are not addressed in this thesis. To get more information about the application of respiratory analysis to evaluate power augmenting devices please consider the dissertation by Knott (2017).

(2009), such as less monotony and time-consumption, should enable us to momentary assessments (e.g., immediately before and after a manipulation took place). We did not see a chance to accurately assess the participants' physical strain right at the onset of a manipulation. Thus, in order to not disturb the task, we had to wait until the manipulation was over to ask for the participants' subjective impression. This confinement pointed to the trade-off of a more or less overall estimation of the whole last manipulation task, which supports our decision of using a single-item scale at this point (Fuchs & Diamantopoulos, 2009). Still the mentioned drawbacks of single-item scales regarding longitudinal studies and their influence on possible subjective changes due to learning and fatigue (see Section 3 and 9.1.1 on mixed-effects models) have to be considered. We are aware of the fact that single-item scales are more vulnerable to random errors that cannot be redeemed by additional items as they are available in multi-item scales (Emons, Sijtsma, & Meijer, 2007). Multi-item scales are less susceptible to misunderstandings and unknown biases (Hoeppner, Kelly, Urbanoski, & Slaymaker, 2011) and enable the measurement of complex behavioral concepts. Besides psychophysical evaluation and modeling of human behavior it was our goal to assess the complex construct of usability and acceptance of hHRC.

Based on the technology acceptance model TAM (Davis, Bagozzi, & Warshaw, 1989), its extension the unified theory of acceptance and use of technology UTAUT (Venkatesh & Davis, 2000), the technology acceptance model for Human-Robot Cooperation in production systems (Bröhl et al., 2017, 2016), the usability construct in haptic systems (DIN EN ISO 9241-11, 2016; DIN EN ISO 9241-920, 2015), and expert knowledge from Lecours-Campeau, Dimeas, and Surdilovic (personal communications, 2014-2017). The TAM provided the relevant factors perceived usefulness (PU) and perceived ease of use (PEU) and their influence on attitude towards using (A) of novel technology and the UTAUT added expectancies about performance and effort. However, because of their close relation to HCI, both models did not incorporate physical discomfort (C) and emotions (E) while using new systems. The scales have been added and combined with the model of Bröhl et al. (2017, 2016). They applied the TAM and developed a technology acceptance model for Human-Robot Cooperation in production systems, based on earlier concepts and an online survey. After applying the QUEAD in an experiment, Canada (Section 5), the questionnaire was shortened from 26 to 16 items, without sacrificing reliability. The second study (Section 5) revealed again high reliability and acceptable validity of the QUEAD to evaluate novel hHRC applications. Since then, the QUEAD was applied in several studies and demonstrated its usefulness and validity[xxxi]. The correct and intended use of the QUEAD will be

This fact encouraged us
to design and evaluate a multi-item scale called
QUEAD – *questionnaire for the evaluation of physical assistive devices.*

[xxxi] Virtual Reality Simulator for Human-Robot Interaction (interdisciplinary project by Merkourios Simos, TU Munich), Design of an Augmented Reality Interaction Concept for Intuitive Robot Programming (master thesis by

crucial to obtain reliable and valid results. Since psychological properties are changing over time, especially in longitudinal within-subject designed experiments, learning, adapting, and fatiguing effects have to be considered. Thus, we highly recommend to diligently randomize the QUEAD's items, set defined anchors at the start of the experiment, and make sure each participant understands the questions asked. Within the experiments, we found very high effects of point of time and bias of the participants. This means, asking the participants after each trial proved to produce much more reliable results than asking after longer periods of time. Secondly, we also found strongly left-skewed distributions in the participants' answers, since people are often overestimating their performance. Therefore, we recommend to leave the intentionally reversed items that are in certain scales (PEU, E, and C), in their original format. The mentioned crucial speed-accuracy trade-off (see 9.1.2) has been taken into account. The questions have to be evaluated accordingly. Consequently, the QUEAD can be used for fast-imprecise and slow-precise manipulations. Until there are no benchmark applications, the questionnaire is intended to compare between at least two control strategies or two devices. A preliminary manual how to use the QUEAD is provided online[xxxii].

9.2 Limitations

The main limitations that potentially impact the operationalization of the research questions and hypotheses as well as the quality of our findings, can be categorized in **psychophysical methods**, **experimental conditions**, **validity**, and **application of the results**.

Reflecting on the applied staircase method (Section 3), an adaptive **psychophysical procedure** first introduced by Dixon and Mood (1948) that searches for thresholds via increasing and decreasing stimulus steps, limitations have to be mentioned. Staircase methods form the basis for most psychometric testing today (Kingdom & Prins, 2010; Leek, 2001) but are nowadays accompanied by many new computationally intensive procedures. The Parameter Estimation by Sequential Testing (PEST) method, introduced by Taylor and Creelman (1967), for instance, applies changing step sizes and provides fast and systematic convergence on a threshold. Maximum-likelihood procedures, such as the QUEST (Watson, 1983), a Bayesian adaptive psychometric method, are able to rapidly converge and at that utilize the full data collected in a trial. PEST as well as maximum-likelihood procedures bring along very complex stimulus adjustment rules, the need for online threshold estimates, and the QUEST additionally requires assumptions of the particular form of the underlying psychometric function (Leek, 2001). In contrast, staircase methods do not depend on assumptions, involve only manageable algorithms for stimuli placement and slope estimation. Thus, they are simpler and more flexible which led to their rapid adoption as the procedure of choice in many laboratories (Leek, 2001). Their drawback is longer and greater number of trials for threshold estimations. This effect mainly originates in the fact that the threshold estimate is more accurate and reliable with higher number of reversals at the expanse of experimental time (Bernstein & Gravel, 1990). Recommendations for the necessary number of reversal points vary and range in most cases from four to eight or in exceptional cases

Annika Wohlschläger, TU Munich), and Effects of Time Delay, Packet Loss, and Quality of Force Feedback on Human Operating Performance in Teleoperation (master thesis by Gideon Kloss, TU Munich).

[xxxii] Available to download at DOI: 10.13140/RG.2.2.31113.44649.

even up to forty (Kühner, Bubb, Bengler, & Wild, 2012; Sincock, 2008). Thus, we chose the adaptive staircase method with six reversal points to be able to acquire data from a large sample (165 participants, Section 3) and simultaneously used mixed models instead of simple regression models to incorporate human variability and longitudinal effects (e.g., learning, fatigue) in psychophysical experiments (B. Winter & Wieling, 2016).

Consequently,
we see a high likelihood that the replicated effects, results,
and their conclusions are valid for hHRC in general.

The **experimental conditions** applied entail limitations that have to be considered. All manipulations, except for the QUEAD's validation studies (Section 5), were bimanual, involving large-scale whole-body movements. No lifting or combined ballistic movements have been addressed by this thesis. As stated at several points, many studies already dealt with SWI in lifting movements and there is a tremendous amount of literature on pointing and reaching movements, investigating Fitts' law for different scenarios and applications. It is needless to say that movement optimization especially in the context of hHRC and systems such as exoskeletons and robotic prosthetics is one major field of Human Factors and Ergonomics. Nevertheless, this thesis mainly focused on human idiosyncrasies, the influence of object size cues, human mass perception, a possible perception-related assistance strategy, and the evaluation of hHRC. Elaborating on these research ideas, it was our interest to define manageable movements and feasible experiments, which are representative for current production schemes such as automotive assembly lines. If a semi-automated robotic companion picks-up a part, to reduce non-value-adding activities (Michalos, Makris, Papakostas, Mourtzis, & Chryssolouris, 2010), the main manipulation types a human workers will perform are pushing and pulling movements (Argubi-Wollesen, Wollesen, Leitner, & Mattes, 2017). However, not only automotive assembly lines employ planar manipulation and provide possible fields of application. Supported and augmented transport and positioning of objects in unstructured heterogeneous environments in areas such as hospitals and medical care (Wiggermann, 2017), commissioning and logistics (Glitsch et al., 2007; Jung, Haight, & Freivalds, 2005), garbage collection (Backhaus, Post, Jubt, Ellegast, & Felten, 2013), and construction and built environment (Balaguer & Abderrahim, 2008; Bock et al., 2012), will be of major interest. Beyond that, it has to be mentioned that the findings of this thesis are very likely transferable to other movements as named before. Many conclusions found in the literature, e.g., object size cues influence sensorimotor prediction and following subjective impression in lifting manipulations, have been confirmed and transferred to planar manipulation by this thesis.

These statements lead us to reflect on **validity** and **application** of our results and conclusions. *Internal validity* is defined as "the degree to which a study or experiment is free from flaws in its internal structure and its results can therefore be taken to represent the true nature of the phenomenon [soundness of results]" (VandenBos, 2015, p. 553). Since we diligently designed and conducted our experiments and all results in this thesis have been subject to peer-review, we assume that internal validity of our conclusions is broadly given. Transferability of the results beyond the sample and the conditions that have generated them defines *external validity* (VandenBos, 2015). In this case one clear limitation to mention is the mean age of the chosen sample (< 30 years) which excludes elderly participants. Buckingham et al. (2017) examined how visual size cues influence sensorimotor prediction (fingertip forces) and perception of heaviness in a group of older participants. They found that robust SWI was present in this group and a similar degree of weight difference was experienced by both, the older and younger group. But they also found that the older group showed no evidence that size cues influenced the way they initially gripped and lifted objects, which is an indicator for age-related perceptual decline. This result somehow reduces the generalizability of our results, but on the other hand gave us the opportunity to test a more homogenous group, since there is no societal group more heterogeneous than elderly (Adamo et al., 2007; Rinkenauer, 2008). Hence, we tested healthy participants living in their prime, without noticeable cognitive, perceptual, or motoric decline (Salthouse, 2009), which is favorable for perception experiments (e.g., threshold detection and SWI). The second main limitation in terms of external validity, are the implemented conditions. As stated in Section 1.2.2 we simulated a hHRC by adapting inertial mass, which corresponds to the target mass m_t in the admittance equations (1) and (2). Since we used passive non-actuated systems, we did not have to deal with instabilities in a way today's robot controls have to. Thus, we could implement any given inertia condition, as long as it was within the stated OL of the PRAS (Section 1.3). It might be the case that actual hHRC systems will have to deal with more restrictive selection of mass m_t and damping c_t. For instance, most previous approaches used damping to stabilize hHRC systems, because of its effectiveness, accepting decreasing transparency and task-performance (Campeau-Lecours et al., 2016; Dimeas & Aspragathos, 2016). Additionally, we assume that inertial mass in object manipulation can be perceived more intuitively than damping and consequently should be the main parameter to investigate in hHRC.

This thought leads us to *ecological validity* or representative design[xxxiii] (Brewer & Crano, 2000; Brunswik, 1956), which is defined as "the degree to which results obtained from research or experimentation are representative of conditions in the wider world" (VandenBos, 2015, p. 349). Considering the results of the SWI studies in this thesis, one has to question if these effects are oversimplified and only occur in lab settings, or if they have true influence on real-world scenarios. It was our goal to be as comparable as possible to actual applications, in this thesis automotive

One and the same assistance device will have to be applied to manipulate, transport, and change different sized and weighted objects.

[xxxiii] Brunswik's initial definition of ecological validity as *informativeness of a cue* (in perception) is used under Section 9.1.3. At this point, his inheritance of ecological validity (in psychology) as *representative design* of an experiment is used.

assembly, to show the ecological validity of SWI and size-related interaction forces. Accordingly, we designed the experiments with larger objects, higher inertia, and appropriate movement types in contrast to existing SWI and threshold detection studies, to ensure the representation as good as possible. Flanagan and Beltzner (2000) found that sensorimotor prediction diminishes with trial repetition due to motor learning (Burdet et al., 2013). This might lead to the remark that the studies of this thesis deployed only few trial repetitions, which indicates flawed ecological validity. Following the popular perspective of smart factories (Bauernhansl et al., 2014), hybrid assembly consisting of human and robot teams will have to overcome pressing challenges of flexible and interchangeable production of customized products (Fogliatto et al., 2012; Lotter et al., 2016).

Therefore, it will not be possible to solely rely on the flexibility and adaptability of humans in hHRC, but the robotic companion has to be adaptive and aware of various situations as well. Stepping outside of fairly structured environments such as production into heterogeneous areas such as construction (Bock et al., 2012) or domestic areas, this effect will even amplify the stated considerations on perception-related control strategies.

9.3 Recommendations

In conclusion, this thesis provides a perception-related assistance framework (PRAS, Fig. 8), which bridges the gap between the classical technical robotic-centered view on hHRC and a psychological user-centered perspective and provides applicable recommendations.

Our main recommendation is to sequentially adapt LoHS by application of perception-related variable admittance control incorporating the proposed human mass perception model.

Following the PRAS framework (section 1.3), human well-being and acceptance of the specific hHRC application will be ensured via intuitive, transparent, and usable control strategies. Hence, we propose to apply the PRAS approach to avoid unintentional disturbances of perception by means of informative sensory cues and, as a consequence, ensure optimized interaction (section 1.4). The framework should be used to combine stability considerations, using virtual mass to virtual damping ratios, over the sole use of only damping (Campeau-Lecours et al., 2016; Ikeura, Monden, & Inooka, 1994; Linde, Lammertse, Frederiksen, & Ruiter, 2002). By application of perception-related control, increased stability can be ensured, using higher masses for larger objects, which induce higher interaction forces, without deficiencies in usability (section 7). If the operator chooses the system to rather convey static and a priori fixed feedback, independently from object characteristics, the robot control still can apply the presented human mass perception model (section 3) and change the LoHS within the margin of equal perception (given a certain RL).

At this point, one could ask, why we still bother the human operator with physical stress and present haptic information at all? Vision on its own cannot adequately compensate for the absence of haptic feedback (Robles-de-la-torre, 2006). Every technical and biological information processing system only can build a robust percept with the information from multiple senses (Helbig & Ernst, 2008). Hence, we recommend to provide the human operator with sufficient and diligently designed haptic feedback. We advise developers against blindly maximizing the LoHS in every situation or striving towards minimum human input. Application of the human mass perception model to actively communicate intentions, choose appropriate sensors and actuators, and in this way, provide a human centered application can facilitate the design, adoption, and usage of hHRC systems. Additionally, we suggested designing the robotic support in a homogenous and as a consequence manageable human perception area. According to the results of the human perception model of section 3, inertia m_t values above 10 kg m/s^2 for bimanual and 30 kg m/s^2 in general, provide steady and consistent perception for a great part of the population. Additionally, the high influence on perception and behavior of different movement types (e.g., fast-imprecise and slow-precise) have to be incorporated in prospective applications. We also suggest using the QUEAD (Section 5) to design and evaluate hHRC systems in combination with objective results to obtain a holistic basis of decision making. The articles of section 6 and 7 additionally provide the concept to apply a Bayesian framework to incorporate the sequential effects of different sized objects and update the robot's internal prior knowledge about the expected human behavior.

This thesis follows the opinion of Alami et al. (2006, p. 5) who quotes the American National Standards Institute committee on the published draft safety standard for IADs (Robotic-Industries-Association, 2002):

> "IADs should have few modes,
> well understood by the operator,
> well communicated to the operator and
> well commanded by the operator to the IAD."

A completely unidirectional adaption where the robot is adapting to the human or the human is adapting to the robot will not be successful. This fact is apparent since there are still no or only few commercially applied IADs (see section 1.1.3). There are technical (mainly stability of the control system) and usability boundaries that are limiting fully human-centered or robot-centered design philosophies. Following the human-machine-system centered perspective of Hoc (2013) that are in line with the "ten challenges for making automation a team player" (Klein et al., 2004) and the human centered assistance applications (HCAA) design and evaluation philosophy of this thesis (see section 2), a main collaboration paradigm has to be ensured. Maximize positive interference with the human operator, where the machine should have an explicit model of its human partner and the human operator should have a minimal model of the machine in mind. The partners have to be able to "adequately model the other participants' intentions and actions vis-à-vis the joint activity's state and evolution" (Klein et al., 2004, p. 92). Therefore, mutual goals, shared knowledge, and understood intentions form the basis of successful collaboration.

> “Only with a proper design for […] cooperative human-machine systems, these advances will make our lives easier, safer and enjoyable rather than harder and miserable”
>
> (Flemisch et al., 2012, p. 3).

9.4 Future Directions

Future work needs to transfer these findings to novel variable admittance concepts and to refine future hHRC concepts. From our experience, it appears that robotic systems are often developed before or separated from analyzing and evaluating intended purposes and human interaction. Inference drawn from this perspective often does not reflect what humans in interaction with robots really need to fulfill the mentioned well-being and acceptance criteria. Our perspective on future directions structures in **intent estimation and assistance customization**, **assessment**, and **application**.

Estimation of human intent and customized assistance:
Effective robot controls will need to incorporate various factors additionally to force inputs, object size, and human perception models. Geometric and physical properties such as material and shape will be helpful, but especially task and environment related aspects, such as scenario (e.g., hectic or tranquil, wide or narrow spaces), prior knowledge and experience (e.g., professional or laypeople), human prerequisites (e.g., disabilities or age), and online interaction modalities (e.g., human fatigue, attention, changing goals) will very likely seal the deal. Novel robots will have to be able to sense or at least be informed about object characteristics and contextual circumstances. Vision is a promising possible information channel here. Vision is currently used to avoid dangerous collisions via human motion tracking and interpretation applying probabilistic algorithms (De Santis, Lippiello, Siciliano, & Villani, 2007; Pereira & Althoff, 2017). In hHRC applications are already able to balance a ball on a human-robot jointly carried table via incorporating vision and haptic information (Agravante et al., 2014). Similar applications adapt to individual users, tasks, and environments applying machine learning (Argall, 2015; Beckerle et al., 2017). For instance in relation to human fatigue, EMG (Grafakos et al., 2016; Peternel et al., 2017; Peternel, Tsagarakis, Caldwell, & Ajoudani, 2016) or a respiratory index (Knott, 2017), provide further information. Haptic interaction patterns (Madan et al., 2015), human-like behavior (Maurice, Huber, Hogan, & Sternad, 2018; Rozo, Calinon, Caldwell, Jimenez, & Torras, 2016) incorporating haptic dominance (Groten, 2011), different interaction roles (Jarrasse et al., 2013; Mörtl et al., 2012), or providing the user with the possibility to change systems states as they please (Gopinathan, Otting, & Steil, 2017), additionally will be interesting fields of research in hHRC.

One-size-fits-all solutions will not be successful or even impossible to implement (Garcia & Berkeley, 2010). There is only rarely a best solution for human-centered design. Most of the time the question to whom, to which percentile, range, or average should be centered, diversifies the possibility of appropriate solutions. A striking example for when these measures do not apply can be found for instance in the late 1940s where the US Air force tried to solve a problem with too many (noncombat) crashing fighter planes (Carlson, 2017; Rose, 2016). Their main hypothesis was that the average American fighter pilot simply had outgrown the cockpit, designed in World War I, after of course ruling out pilot and machine error. New measures of 4,063 young pilots have been taken to create the new average pilot. After calculating the average of ten physical dimensions of the gathered data, not one pilot out of the sample fitted all of these ten new averages. This anecdote emphasizes that if power assistance is tailored to a however derived average of a sample, will very likely fit no one. We found out that humans are very heterogeneous when it comes to haptic perception and interaction. Incorporating diversification characteristics (e.g., age, gender, or physical capabilities) and longitudinal effects while using physical assistive devices (Knott, 2017; Meyer et al., 2014) will supplement available information about the individual collaborating person (see reference level in the PRAS framework, section 1.3). Besides deriving these estimates, an adjustment within limits by the user (see adaptability in the PRAS framework, section 1.3), will provide the chance of creating a form of self-efficacy in terms of assistance and in this way, very likely, will be able to compensate for idiosyncrasies of the individual human operator.

Future approaches have to answer if inherent passive systems or proactive systems adding sensors and autonomous control paradigms, are more suitable to solve the trade-off between stability and usability. “Achieving a balance in control sharing that is both effective at accomplishing tasks and accepted by the human user is crucial for autonomous assistive robots–particularly those that provide physical assistance to the user” (Argall, 2015, p. 1). This claim contains a long-known and frequently addressed question of human factors researchers. Making machines more adaptive and as a consequence possibly solve many problems, reasoning from inflexibility or design decisions, is in contrast to legible and predictable behavior of more static and rigid concepts. Mörtl et al. (2012) found better task performance applying dynamic role assignment policies in contrast to constant ones, but the participants subjectively preferred the latter because of its higher predictability and therefore subjectively easier operation. “Ironically, by making agents more adaptive [adaptable], we might also make them less predictable” (Klein et al., 2004, p. 92). One also has to consider that attitude, intention, and actual behavior are not in a deterministic but a probabilistic relationship (Ajzen & Fishbein, 1980). Hence, human idiosyncrasies should be incorporated in novel control strategies to constantly update the robot’s and with adequate feedback the human’s prior knowledge before and during an actual interaction.

Assessment of Human-Robot Collaboration:

Classical ergonomic tools such as checklist-based evaluation of workstations (e.g., EAWS, LMM, OWAS, NIOSH) are commonly used but they do not apply for hHRC and physical assistance devices. There is a tremendous need for evaluation, design, and application guidelines. The German accident insurance (Deutsche Gesetzliche Unfallversicherung, DGUV) is currently pooling resources and information on exoskeletons in production environments. They are addressing pressing questions such as, which tasks or work can be effectively supported by hHRC, what are the requirements that hHRC effectively are able to support, what are possible hazards in using hHRC, and what are the according safety guidelines? Answering these questions is closely related to develop appropriate evaluation methods and guidelines. Besides the reported methods on usability (section 4 and 7), biomechanical (Argubi-Wollesen et al., 2017), respiratory (Knott, 2017), or subjective analysis (section 5), neuroergonomics can provide a promising approach. It is focusing on the knowledge of human brain activities in the relation to the control and design of physical tasks (Karwowski, Siemionow, & Gielo-Perczak, 2003). To understand brain structures, mechanisms, and functions during work, neuroimaging techniques are applied to assess performance at work and other everyday settings (Mehta & Parasuraman, 2013; Parasuraman, 2011). These, similar to neuroscience approaches, can help to dig deeper into human behavior and intention modelling for future hHRC applications. Besides classical HRI evaluation it is not always important to be fastest from point A to point B or to reduce human inputs to a minimum. Social interactions and understanding HRI on a holistic level, overcoming classical usability evaluation, will become increasingly important (Yanco et al., 2004). Especially user experience (UX) is progressively recognized also in HRI but is also often taken for granted. UX in HRI, as for any other human-machine system, has to be systematically designed and evaluated (Lindblom & Andreasson, 2016).

Transferring the results to other hHRC domains and applications:
Other hHRC domains such as exoskeletons, robotic prosthetics, powered wheelchairs, and rehabilitation devices will need suitable feedback design for the human operator as well as for the robot control. Jarrasse et al. (2013) introduced education schemes, where the human can teach the robot such as learning by demonstration (Argall, Chernova, Veloso, & Browning, 2009; Billard, Calinon, Dillmann, & Schaal, 2008; Schaal, 1997), the robot teaches the human companion in rehabilitation and training, or just supports to move more precisely, more efficiently, with less effort, and in a health-preserving way (Boy, Burdet, Teo, & Colgate, 2003, 2007). Robots can relax assistance by simultaneously satisfying performance goals and gradually minimizing involvement in the task completion to encourage the human and accelerate motor skill training (Lum, Burgar, Shor, Majmundar, & Van der Loos, 2002; Reinkensmeyer & Patton, 2009). Following this rehabilitation approach and transferring it to the production and domestic environment yields the previously introduced topic about self-efficacy. Thinking of a robot that helps a person to evolve from the need for support to at least the perception that a certain task was done mainly by oneself can be very beneficial. Future HRI research should especially address this fact, not least because factor analyses have shown high effects on acceptance (Bröhl et al., 2017, 2016), which is a prerequisite for adoption and continuous use.

Sedentary lifestyles and less physical activity are risk factors for cardio metabolic morbidity and all-cause mortality (Baddeley, Sornalingam, & Cooper, 2016; Gerstacker, 2014). It is crucial to understand that we cannot "erase the lifetime spent sitting at the desk [or in a car] with a few weekly trips to the gym" (Baddeley et al., 2016, p. 258). This inconvenient truth can be tackled by skillfully applying novel working concepts based on hHRC. If it gets reality that many of today's physical work will be replaced by automation, new concepts for human physical activity, including fitness, training, and sport have to be developed.

Robots are increasingly merging from factories to human environments (De Santis et al., 2008) and "[…] will play an important role in providing physical assistance and even companionship for the elderly […], will probably help people with disabilities, and extend […] strength and endurance" (Gates, 2008, p. 65). The next big step will be robots outside of production environments and in every home – personal robots "we probably will not even call them robots" (Gates, 2008, p. 65).

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Appendix

A| Human Centered Assistance Applications for the Working Environment of the Future

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C| A Trouble Shared is a Trouble Halved – Usability Measures for Human-Robot Collaboration

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D | A Questionnaire for the Evaluation of Physical Assistive Devices (QUEAD) – Testing Usability and Acceptance in physical Human-Robot Interaction

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E| Size-Weight Illusion in Human-Robot Collaboration

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"Hasta la vista, baby."

~The Terminator

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