Driver Body-Height Prediction for an Ergonomically Optimized Ingress Using a Single Omnidirectional Camera

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***Abstract*—Maximizing passengers comfort is an important research topic in the domain of automotive systems engineering. In particular, an automatic adjustment of seat position according to driver height significantly increases the level of comfort during ingress. In this paper, we present a new method to estimate the height of approaching car drivers based on a single omnidirectional camera integrated with the side-view mirror of a car. Towards this, we propose mathematical descriptions of standard parking scenarios, allowing for an accurate height estimation. First, approaching drivers are extracted from image frames captured by the camera. Second, the parking scenario and height are initially estimated based on gathered samples of angles to head and foot-points of an approaching driver. An iterative optimization process removes outliers and refines the initially estimated scenario and height. Finally, we present a number of experimental results based on image sequences captured from real-life ingress scenarios.**

I. Introduction

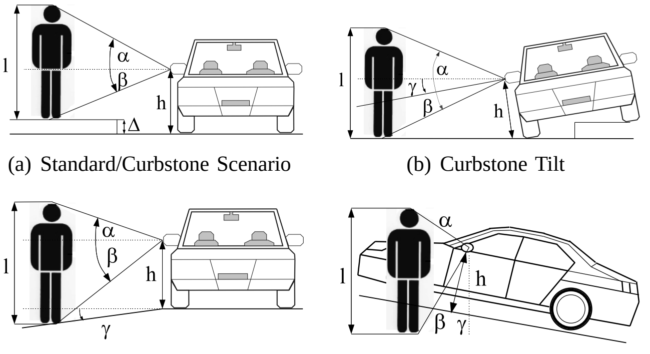
Passenger comfort related issues are now active research topics in the area of automotive ergonomics, in particular for ingress/egress to/from a car. An ergonomic adjustment of the seat position according to driver height significantly increases the level of comfort. For this purpose, automatic passenger seat adjustment has recently attracted a lot of attention [1]. However, one drawback of known solutions lie in storing individual driver height in the car system or in a personal key. This results in a number of problems. Storing the driver's height is not suitable for rental cars. Further, accidents may happen if a tall person mistakenly uses the key of a shorter one and the system adjusts the seat according to the height of the shorter person. To overcome these limitations, we propose a new method to estimate the absolute height of approaching car drivers using an omnidirectional camera integrated with the side-view mirror of the car. The estimated height is used for pre-adjusting the seat for better ingress.

II. Related Work and Our Contribution

Tracking of people and height estimation using vision sensors is an important requirement for a growing variety of applications such as activity recognition [2], pedestrian detection in the vehicle surroundings [3], [4], gait analysis [5] and estimation of anthropometric data like height and size of athletes or passengers [6], [7], [8]. Bovyrin et al. [9] presents a robust method for 3D-road map detection and human height estimation using a single perspective camera. The method proposed in [9] requires a top-down view of a distant scene, which is hard to realize in automotive systems. Furthermore, the road map as well as the human height can only be estimated up to a scale factor, whereas the absolute height of the driver is necessary for optimized seat pre-adjustments. In our setup – due to space and cost constraints – we use a *single* omnidirectional camera attached to the side-view mirror of the car. The height of the camera from the ground surface is assumed to be known. The absolute height of approaching drivers can be determined if information on camera orientation relative to the road surface is available. But unfortunately, this orientation information is only partially available due to missing position sensors and due to unknown parking situations. In this paper, we propose a method for driver height estimation by grouping the most standard parking situations into five precisely defined scenarios. This seems to be a loss of generalization, but studies illustrate a distinct dominance of one of the five scenarios in all variants of general parking situations. For these scenarios, we introduce specific mathematical descriptions allowing for an absolute height estimation as well as an estimation of the driver's distance to the car during approaching. Firstly, our algorithm extracts approaching drivers using Kalman-based estimation techniques and generates a set of head and foot *angles* (α_i, β_i) $\forall i \in 0, \ldots, n$. Here, α represents the angle of the highest and β the angle of the lowest point of a driver as seen by the camera (see Fig. 1). Due to an approximately fixed driver height (the height varies when walking), the foot angles (β_i) are related to the head angles (α_i) so that α can be expressed as a function $\alpha = f(\beta)$. In other words, when the driver moves straight towards the car, the foot angles (β_i) specify all head angles (α_i) depending only on the driver height and the parking situation. This property may be used to initially deduce the scenario from the characteristics of function $\alpha = f(\beta)$ which is generated from the input data (α_i, β_i). Using this, an initial estimation of the driver's height can be obtained. This is followed by an optimization process to removes outliers, to refine the scenario and to improve height estimation.

III. Height Estimation

A major challenge towards obtaining a general solution for height estimation using a single camera lies in determining the scale factor for absolute height estimation. To overcome



(a) Standard/Curbstone Scenario (b) Curbstone Tilt (c) Slope (d) Parked on Slope

Fig. 1. This illustrates the most typical parking situations. The known distance h and the input angles α, β are used for estimating the height l.

this difficulty, we defined mathematical models for the most standard parking situations (see Fig. 1) that allow an exact estimation of the driver height l. The height l can be estimated using a function g that depends on the input angles α, β (i.e., $l = g(\alpha, \beta)$).

A. Scenarios

The *Standard* and *Curbstone* scenarios represent situations where one walks straight ahead on the road ($\Delta = 0$, Scenario 0) or on an elevated footpath ($\Delta \neq 0$, Scenario 1) towards a horizontally parked vehicle (see Fig. 1(a)). Eq. 1 expresses this relation where h represents the distance from the camera to the road surface:

$$l = (h - \Delta) \cdot \left(1 - \frac{\tan\alpha}{\tan\beta}\right) \tag{1}$$

The distance between driver and car can be computed following Eq. 2

$$d = (h - \Delta) \cdot (\tan\beta)^{-1} \tag{2}$$

The *Curbstone Tilt Scenario* describes tilt situations, where one walks straight ahead towards a tilted vehicle (Scenario 2, see Fig. 1(b)). The height can be estimated taking into account the forward tilt γ of the camera, as shown by Eq. 3:

$$l = h \cdot \cos\gamma \cdot \left(1 - \frac{\tan(\alpha + \gamma_{rel})}{\tan(\beta + \gamma_{rel})}\right), \gamma_{rel} = \sin(\theta) \cdot \gamma \tag{3}$$

and the distance between driver and car following Eq. 4

$$d = h \cdot \cos\gamma \cdot (\tan\beta + \gamma_{rel})^{-1} \tag{4}$$

In the *Slope Scenario*, one walks upwards or downwards towards a horizontally parked vehicle (Scenario 3, see Fig. 1(c)). The relative motion between the driver and the camera is parallel (see Eq. 5) in contrast to Scenario 2.

$$l = h \cdot \frac{(\tan\beta - \tan\alpha)}{(\tan\beta - \tan\gamma_{rel})} \text{ with } \gamma_{rel} = \sin\theta \cdot \gamma \tag{5}$$

Knowing the scenario and the driver height, the distance d can be computed following Eq. 6:

$$d = h \cdot (\tan\beta - \tan\gamma_{rel})^{-1} \tag{6}$$

Scenario 4, the *Parked on Slope Scenario* describes situations where one walks towards a vehicle parked in an inclined position (see Fig. 1(d)).

$$l = h \cdot \cos\gamma \cdot \left(1 - \frac{\tan(\alpha + \gamma_{rel}) - \tan\gamma_{rel}}{\tan(\beta + \gamma_{rel}) - \tan\gamma_{rel}}\right) \text{ with } \gamma_{rel} = -\cos\theta \cdot \gamma \tag{7}$$

Following Eq. 8, the distance d can be determined depending on angle β and the camera tilt γ.

$$d = h \cdot \cos\gamma \cdot (\tan(\beta + \gamma_{rel}) - \tan\gamma_{rel})^{-1} \tag{8}$$

B. Driver and Head/Foot Point Extraction

First, all people in the neighborhood of the car door are tracked using Kalman-based foreground extraction techniques [10]. In [11], Kalman-filtering is used to model the dynamic of the background and to extract foreground pixels. This approach was extended in [10] to adapt illumination changes and to better suppress shadow pixels in gray-scaled images. Shadow pixels classified as valid foreground lead robust height estimation to fail since foot points of approaching drivers can be located at wrong image positions. Doing so, the car driver and its silhouette can precisely be determined. A car driver is the subject whose trajectory is approximately a straight line towards the car door. Samples of head and foot angles $(\alpha_i, \beta_i)\ \forall i \in 0, \ldots, n$ of the driver for a fixed direction θ (see Fig. 2) are determined using a Kalman-based gait model. Here, α represents the angle of the highest and β the angle of the lowest point of the driver captured by the camera. A gait model initially removes outliers using median filtering and takes into account the variation of the extracted angles during walking. This is necessary as we cannot expect that the height of walking pedestrians measured from the ground as seen by the camera remains constant as assumed in [9]. The physical height of pedestrians is constant,

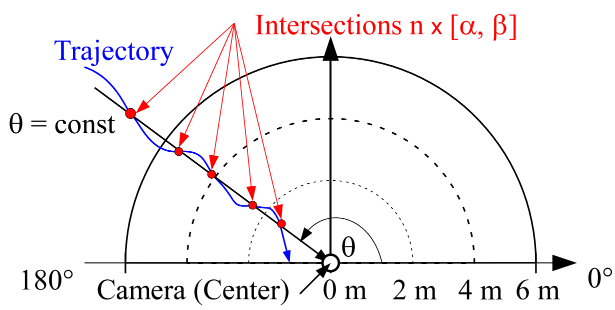


Fig. 2. Maximum detection range and data generation (head and foot angles, $n \times [\alpha, \beta]$, fixed direction θ) for height estimation.

C. Initial Scenario Estimation

Each scenario requires a particular mathematical solution to precisely determine the absolute driver height. Hence, the scenario in question needs to be identified from the input data ($n \times [\alpha, \beta]$). As α can be expressed as a function of β, a quadric function $\alpha_i = f(\beta_i) = a\beta_i^2 + b\beta_i + c$ is generated and interpolated from the input samples (α_i, β_i) (see Fig. 3). As the characteristics of $f(\beta)$ vary with each scenario, the scenarios can initially be identified using the coefficient c:

- If $c \approx 0$, the target scenario might be 0,1 or 4.
- If $c < 0$, the appropriate scenario might be 2 $(\gamma > 0)$ or 3 $(\gamma < 0)$.
- If $c > 0$, the target scenario might be 3 $(\gamma > 0)$ or 2 $(\gamma < 0)$.

Using the above, it is not possible to distinguish between Scenarios 0, 1 and 4, or Scenario 2 and 3. This can be solved by scenario refinement and optimization of height estimation.

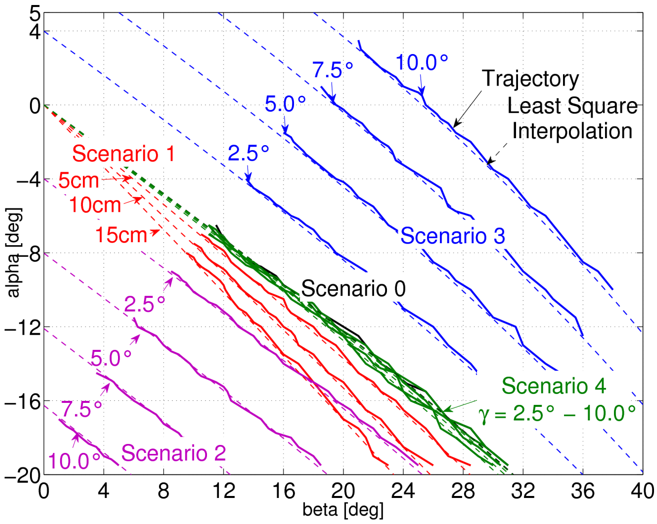


Fig. 3. This figure illustrates the characteristics of function $\alpha = f(\beta)$ based on the set of input angles $n \times [\alpha, \beta]$ for different scenarios. The y-axis intersection point $c = f(0)$ is used for scenario classification.

D. Height Estimation and Refinement

Eqs. (1-7) describe the approaching driver's height in the five different scenarios. Since the driver's height l in Eqs. (1-7) is a constant (which we wish to determine) and does not change within one scenario, we can obtain (Eq. 9) (see below).

$$l = g_0(\alpha_0, \beta_0) = g_1(\alpha_1, \beta_1) = \cdots = g_n(\alpha_n, \beta_n) \qquad (9)$$

A specific mathematical characteristic of Scenarios 0 and 1 is their approximately constant ratio $r_i = \frac{\tan \alpha_i}{\tan \beta_i} \approx const$. This can be used to distinguish Scenario 4 from Scenarios 0 and 1 ($r_i \neq const$). For each of the Scenarios 2 and 3, we compute an array of height estimations, which are solutions to the equations $g_i = g_j \; \forall i, j \in 0, \ldots, n$. In other words, each array location contains different values of the estimated height. For such a given array A, let $x = \max_n A[n]$, $y = \min_n A[n]$ and $d = x - y$. From the two arrays corresponding to the scenarios 2 and 3, the one with the smaller d represents the correct scenario. To approximately determine the height of the curbstone Δ, additional information like the lowest and the highest border of the curbstone is necessary and is extracted from the image frames captured by the camera. Calculating the average of all height values for an identified scenario using least mean square (LMS) is not the most adequate solution due to the large influence of outliers. To possibly refine the scenario, we developed a method that relies on generating additional synthetic angles α over those captured by the camera as follows. For each of the possible scenarios, our algorithm computes an array of angles $\alpha_i = g_i^{-1}(\beta_i, l_i)$ using the extracted input values β_i and the computed heights l_i. Next, a comparison matrix based on synthetic and measured α values is built. Based on this matrix, an algorithm chooses the α values — and therefore the heights — that represent the least possible divergence. The most adequate height values and scenario are the ones that result in a better similarity between the synthetic and the original data. This data is then used as input for further iterations. The process stops if there are no significant changes compared to previous iteration steps, and the final height and scenario is determined using LMS. The iteration also stops if there is a wrongly classified initial scenario and therefore the height estimations within the arrays vary too much. In such a case, a default value is provided allowing for an acceptable seat position both for short and tall drivers. Fig. 4 illustrates the proposed algorithm in a block diagram format.

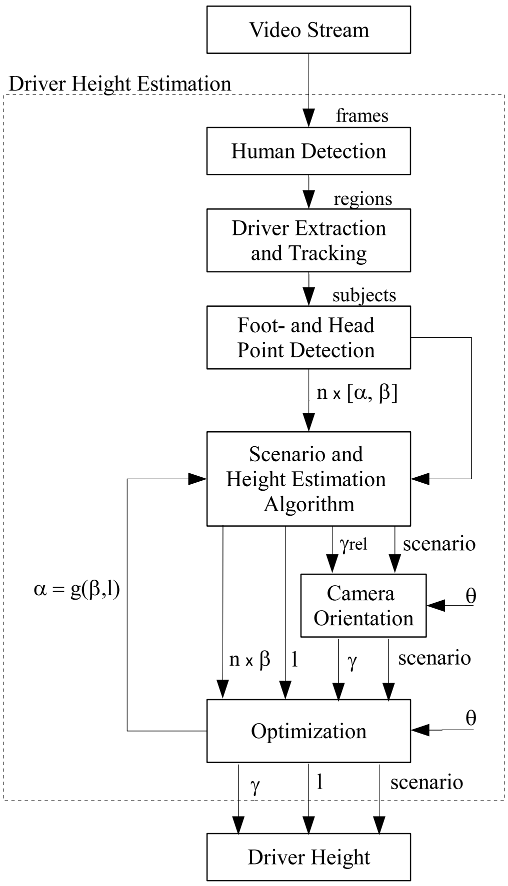


Fig. 4. Block diagram of the proposed height prediction algorithm.

IV. Experimental Results

The proposed method was implemented in a car prototype for individual height-based seat pre-adjustments. This implementation was tested and validated with both simulations and real-life experiments. We set up experiments for scenario classification using various camera and road orientations. The detection rate for scenario classification is presented in Table I. We also conducted experiments with previously measured subjects under various scenarios $(0-4)$. Driver heights could be

Scen.	Rate	Misclassfied Scenario			
0/1	92%	0/1: -	2: 2%	3: 2%	4: 4%
2	93%	0/1: 1%	2: -	3: 4%	4: 2%
3	91%	0/1: 2%	2: 5%	3: -	4: 2%
4	89%	0/1: 8%	2: 3%	3: 0%	4: -

TABLE I
ACCURACY RATE OF SCENARIO CLASSIFICATION.

estimated with an accuracy of upto $2-3cm$ (see Fig. 5) within three iteration steps. Within the domain of ergonomics, an accuracy up to $7cm$ for individual seat pre-adjustments is considered to be sufficient. However, high-heel shoes or hairstyle influences height measurements significantly. Unfortunately, these cannot be compensated for as only the highest and the lowest points of the walking subjects were extracted. Figure 6

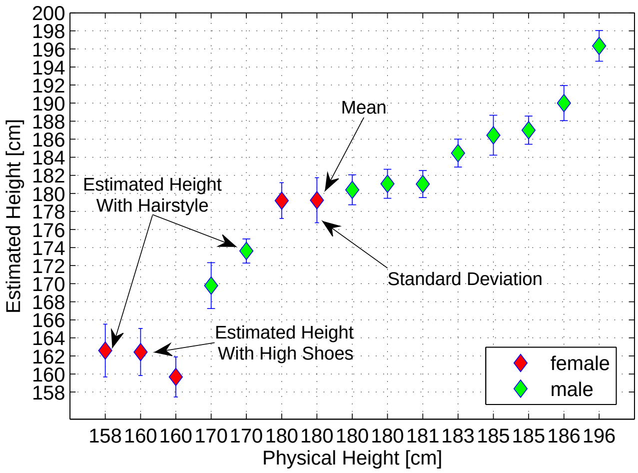


Fig. 5. Selection of estimated body heights and their standard deviations for various, previously measured subjects (males and females).

demonstrates the application of our algorithm integrated in a car prototype. The driver is recognized and his/her height estimated whereas other humans in surroundings of the car are ignored. The execution time of this algorithm required $\approx 65ms$ on an AMD Phenom 9650 processor @ 2.54 GHz, for height estimation using 40 input data sets. It may be noted that three input data sets would theoretically be sufficient. Using at least 15 samples was found to be sufficient to overcome the effects of noise.

V. CONCLUDING REMARKS

We proposed an image-based algorithm for absolute height estimation of approaching drivers, for height-based seat pre-adjustment in cars. Our algorithm relies on using a single omnidirectional camera because of cost and space constraints. A set of head and foot points were extracted for scenario and height estimation, and the results were refined using an iterative optimization process. Experiments with real-life subjects showed the robustness of our approach. This technique could also be used in conjunction with personal keys for accident prevention. As a part of future work, we plan to develop a more general model to capture combinations of scenarios

Fig. 6. Examples of height estimation for (a) a short lady, and (b) a tall man, using our car-prototype.

and also to account for the influences of shoe heights and hairstyles. Thereby, the main challenge is in finding a general mathematical description for absolute height estimation.

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