Motion Prediction Influence on the Pedestrian Intention Estimation Near a Zebra Crossing

Júlia Škovierová, Antonín Vobecký, Miroslav Uller, Radoslav Škoviera and Václav Hlaváč
Czech Technical University in Prague, Czech Institute on Informatics, Robotics and Cybernetics, 166 36 Praha 6, Dejvice, Jugoslavskych partyzanu 1580/3, Czech Republic

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Abstract: The reported work contributes to the self-driving car efforts, more specifically to scenario understanding from the *ego-car* point of view. We focus on estimating the intentions of pedestrians near a zebra crossing. First, we predict the future motion of detected pedestrians in a three seconds time horizon. Second, we estimate the intention of each pedestrian to cross the street using a Bayesian network. Results indicate, that the dependence between the error rate of motion prediction and the intention estimation is sub-linear. Thus, despite the lower performance of motion prediction for the time scope larger than one second, the intention estimation remains relatively stable.

1 INTRODUCTION, CONCEPTS

Despite the progress in autonomous cars, many unsolved problems have remained, including driving in highly populated areas. UP-DRIVE project, in which we participate, addresses these issues. In this paper, we consider traffic situations from the autonomous vehicle point of view; We name it the *ego-car*.

UP-DRIVE consortium has been developing a demonstration platform consisting of an automated car, a sensor-rich electric car, VW e-Golf, and a cloud environment to demonstrate automated transportation in urban environments. UP-DRIVE explores as background knowledge the know-how and the technology of the V-CHARGE project (project-V-Charge, 2015). The overall UP-DRIVE scientific and technological scope has been framed by the automated parking and driving in urban environments with speeds up to 30 km/h.

The reasoning part of UP-DRIVE deals with the unavoidable K. Gödel's logical incompleteness and the grounding problem (Harnad, 1990). We approach both these problems rather pragmatically as most other approaches do. The *objects*, i.e. entities of interest, distinguish important information from the unimportant *background* for a particular task and a needed *resolution* of detail. We take into account *detectable objects* only. The object detector is set/learned statistically for a particular detected entity, e.g. a car or a lamppost. The relation between the syntax (observation) and its semantics (a particular type of objects from the considered logical model) is innate to objects in our construction. For our specific traffic scenarios, we divide objects into two classes, (a) *static objects*; (b) *dynamic objects*, e.g. a walking pedestrian, a riding cyclist. If a dynamic object does not move for a short time it is still considered a dynamic object.

In the self-driving domain, one of the most challenging tasks is the detection of dangerous situations and finding appropriate mitigation procedure for each of them. The *ego-car* has to perceive and understand what is happening in its surrounding. Static objects, dynamic objects, *traffic participants* (objects relevant to a particular situation) have to be detected, represented in such a way that the relations among them can be expressed, usually in a form of a graph. Having past data and stored experience of this application domain, enables the *ego-car* to predict intentions, heading, and position of other traffic participants. The context related to the particular situation enhances the *ego-car* competence and success in the superordinate decision making process.

There is a need to establish a hierarchy, still from the *ego-car* point of view. A more general concept is the (traffic) *scenario*, e.g. approaching the zebra crossing or avoiding a car, which stopped ahead of the *ego-car*. A particular (traffic) scenario consists

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of several (traffic) *situations*. As the example, consider a traffic *scenario* when the *ego-car* approaches a zebra crossing. The related traffic situations might be: checking if there is a car in front of *ego-car* giving the way on the crossing already, checking if there are no pedestrians on the crossing, checking if there are pedestrians on both sides of the road and predicting the probability they will intend to cross the road at the considered crossing. The given example was a simplistic one because the scenario consisted of a linearly ordered chain of situations. Actually, situations may be organized in a more complicated way. We order the possible approaches from the simplest to the most difficult one: (a) a nondeterministic finite automaton; (b) a Markov field or (c) a predicate calculus-based logic dealing with uncertainty (Russell, 2015).

The contextual information and information about the intentions of other participants is necessary to cope with rather different traffic situations. For example, the car ahead of the *ego-car* may stop because of another car or it intends initiating a parking maneuver or a pedestrian plans to cross the street. Each of these situation is different; also due to the relevant contextual information.

2 TASK FORMULATION

The intention estimation of other traffic participants is crucial for correct scene understanding for autonomous driving. We deal with the intention prediction task for dynamic objects, i.e. the pedestrians.

In this paper, we deal specifically with the traffic scenario where the *ego-car* approaches a zebra pedestrian crossing. Even more specifically, we studied and proposed the *method estimating the pedestrian's intention and predicting the pedestrian's motion in a one, two, and three seconds time horizon*. We also investigated the impact of motion prediction algorithm on the result of intention estimation.

However, the suggested approach is rather general. It can be applied to other (traffic) scenarios and situations as well.

3 RELATED WORK

Understanding the current traffic situation is a crucial intermediate step on the way towards a self-driving car. The *dynamic objects* motion prediction based solely on physical laws (inertia) does not suffice. The intentions of other dynamic objects, traffic participants, has to be estimated and taken into account in the reasoning module. Let us divide the state-of-the-art analysis relevant to our task formulated above into three parts.

3.1 Motion Prediction

Authors of the survey (Lefèvre et al., 2014) focused on the motion prediction and the risk assessment in traffic situations. They claim that there are three main groups of motion prediction and intention estimation models:

- *Physics-based* models (e.g. (Ammoun and Nashashibi, 2009), (Brännström et al., 2010)). Such motion models are the simplest ones, which consider that the motion of vehicles depends on the laws of physics only. They can reliably predict the motion of other traffic participants for up to 1 second into the future. Physics-based models have been used most widely.
- *Maneuver-based* motion models (e.g. (Kumar et al., 2013), (Morris et al., 2011), or (Tamke et al., 2011)) are more complex than physics-based models because intentions of other traffic participants are taken into account. A trajectory prediction with maneuver-based motion models relies on the early recognition of the maneuvers that a driver intends to perform. The approach is based either on prototype trajectories or on maneuver intention estimation. The disadvantage is that interactions between traffic participants are not considered.
- *Interaction-aware* motion models are most complex and consider the inter-dependencies between maneuvers of multiple traffic participants. They take into account interactions between different traffic participants, which contributes to a better understanding of the situation. However, the complexity of these models is very high. These models are based either on prototype trajectories (e.g. (Kfer et al., 2010)) or on Dynamic Bayesian Networks (DBN) (e.g. (Tay, 2009), (M. Liebner and Stiller, 2012), (Gindele et al., 2010), (Lefvre et al., 2012), (Lefèvre et al., 2013)).

  The *interaction-aware* motion models allow longer-term predictions compared to *physics-based* motion models. They are also more reliable than *maneuver-based* motion models because they take into account dependencies among dynamic traffic scenario participants. It is very difficult to use *interaction-aware* models in real-time risk assessment, because the computation of the potential trajectories of the vehicles is computationally very expensive. For this reason, some risk assessment techniques have been proposed recently, which do not rely on trajectory prediction.

3.2 Intention Estimation

Estimating the intentions of other traffic participants (pedestrians, cyclists, and vehicles) is not easy. There are several approaches to motion planning, intention estimation, and motion prediction. The latter two approaches are interrelated. The estimation of the particular traffic participant's behavior is usually based on observations of the surrounding context and previous motion patterns of other involved traffic participants.

In (Armand et al., 2014), the authors proposed ontology-based context awareness for driving assistance systems. They used the contextual information for the prediction of other traffic participants behavior. They formulated the ontology representing the vehicle, perceived entities, and context. The proposed ontology allows for a coherent understanding of the interactions between perceived entities and contextual data. However, the approach considers only a one-dimensional driving space. Therefore, more research in this area is needed.

A framework for estimating a driver's decisions near intersections was presented in (Gadepally et al., 2014). The authors suggested an architecture describing the coupling between the vehicle and the driver through Hybrid-State-Systems (HSSs). In order to estimate the state of a vehicle, the authors used a framework, which consists of HSSs and Hidden Markov Models (HMMs). This framework provides more accurate results than the human observer.

Another approach for learning continuous, non-linear, and context-dependent behavior models of other traffic participants was presented in (Gindele et al., 2015). The authors proposed a Bayesian model for the estimation and prediction of traffic situations, where the context-dependent policy model is used to predict the behavior of other traffic participants based on contextual information. Expectation Maximization (EM) approach for learning the model from unlabeled observations was used. This model can cope better with noisy sensors and uphold a valid estimation even if the traffic participants are occluded for longer periods of time. The approach allows more precise long-term (up to 6 seconds) predictions without neglecting the uncertainty.

3.3 Pedestrians Safety

The safety of the traffic participants and especially pedestrians in the complicated traffic situations is crucial. Based on the (WHO, 2013), 1.2 million people in the world die in traffic accidents each year. In the study (Hamdane et al., 2015), the authors analyze real crashes involving pedestrians in order to evaluate the potential effectiveness of Autonomous Emergency Breaking system (AEB) in pedestrian protection. The achieved results of this study can be also used in other areas such autonomous driving. It has been found, that until 1.5 second, the position of the pedestrians relative to the vehicle are still scattered and will largely not invoke any response from AEB system. Therefore the prediction of the motion and intention of pedestrians can be very helpful in an successful effort to avoid accidents.

4 DATA USED IN EXPERIMENTS

The data used in this paper come from a real traffic captured by UP-DRIVE experimental car. Current experiments use range data taken by several Velodyne VLP-16 Puck LiDARs, which are placed on the roof of the UP-DRIVE experimental car.

Using the data received from the LiDARs and the GPS position of the *ego-car*, information about other traffic participants is calculated. The data contain position, speed and orientation information about all traffic participants. For traffic participants other than the *ego-car*, classification is also available (e.g. car, pedestrian,...).

In other related papers, more information is usually used (e.g. pose of pedestrians). However, in our project, we are focusing on developing a prediction algorithm with as little information as possible, due to the lower computation demands.

5 SIMPLE MOTION PREDICTION

Correct short-term prediction of pedestrian motion is an important issue when dealing with pedestrian safety in traffic situations. We used a simple physics-based prediction (Sec. 3.1), which explores the previous position of the pedestrians. The presented motion prediction consists of two steps:

1. filtration of the input data;
2. linear regression of the motion.

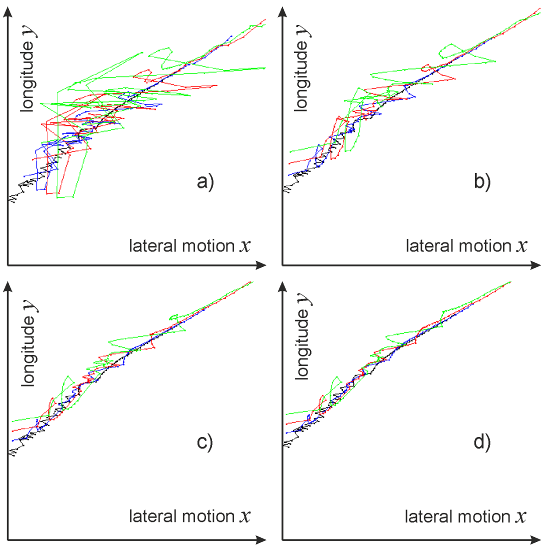

Figure 1: Motion of a pedestrian: a) Without filtering; Cubic filtering with previous positions gathered from: b) 1 second window; c) 2 seconds window, d) 3 seconds window into the past.

The filtering step was used for smoothing out a noisy input data. Several different filtering methods were applied: average, linear, exponential, quadratic, and cubic. The input data from several previous measured steps were filtered and subsequently the linear regression was used for estimating the future position of the pedestrian. The filtering was performed with different time window size (one, two and three seconds from the past) on previous measured data. The visualization of the results of cubic filtering and predictions for different window sizes is shown in Fig. 1, where the y-axis represents the longitudinal and x-axis represent the lateral position of the pedestrian. The curve itself is parametrized by time. The whole curve corresponds to about 8 seconds duration. The sampling is every 0.1 seconds. The black curve represents the actual motion of the pedestrian, the blue curve represents the motion prediction in time $t+1$ second, the red curve represents the prediction in time $t+2$ seconds, and the green curve represents the prediction in time $t+3$ seconds.

The quality of the predicted pedestrian's position was determined based on the difference between the predicted position and the real measured position in time t_i given in meters. Two requirements on the quality of the prediction that were used in this application are:

1. If the difference of the predicted pedestrian's position and the real measured position in time t_i is lower than one meter, this prediction is considered as successful.
2. The distance between one and three meters is decreasing exponentially and slowly. The three-meter break point is based on the width of the road line.

Table 1: The success rate of the motion prediction for various data filtering methods.

Method	Time prediction 1s	2s	3s
	Quality [%]		
Average	62.9	53.0	42.8
Linear	80.1	70.1	61.1
Exponential	83.5	73.5	64.6
Without smoothing	91.6	80.5	68.8
Quadratic	88.5	79.1	70.0
Cubic	**91.8**	**83.6**	**74.3**

The prediction of the motion was set for three different time intervals from the current time t, i.e.: $t+1$, $t+2$ and $t+3$ seconds. The obtained results are presented in Table 1, which shows individual filtering methods and the corresponding prediction results of the future position. The results are listed from the lowest achieved score for time $t+3s$. The absolute prediction deviations of used filtering methods in considered time intervals are shown in Fig 2.

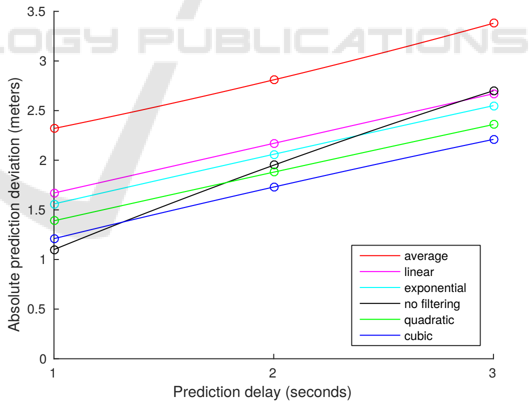

Figure 2: Absolute motion prediction deviation.

As it can be seen,the smallest deviation for the one second prediction is for prediction without filtering. However, the prediction worsens in the next two time instances drastically. The cubic filtering has only slightly worse prediction error in the first second, but it showed the best absolute prediction for the remaining time instances as well as the best overall prediction quality. Based on these results, we have decided to use the cubic filtering.

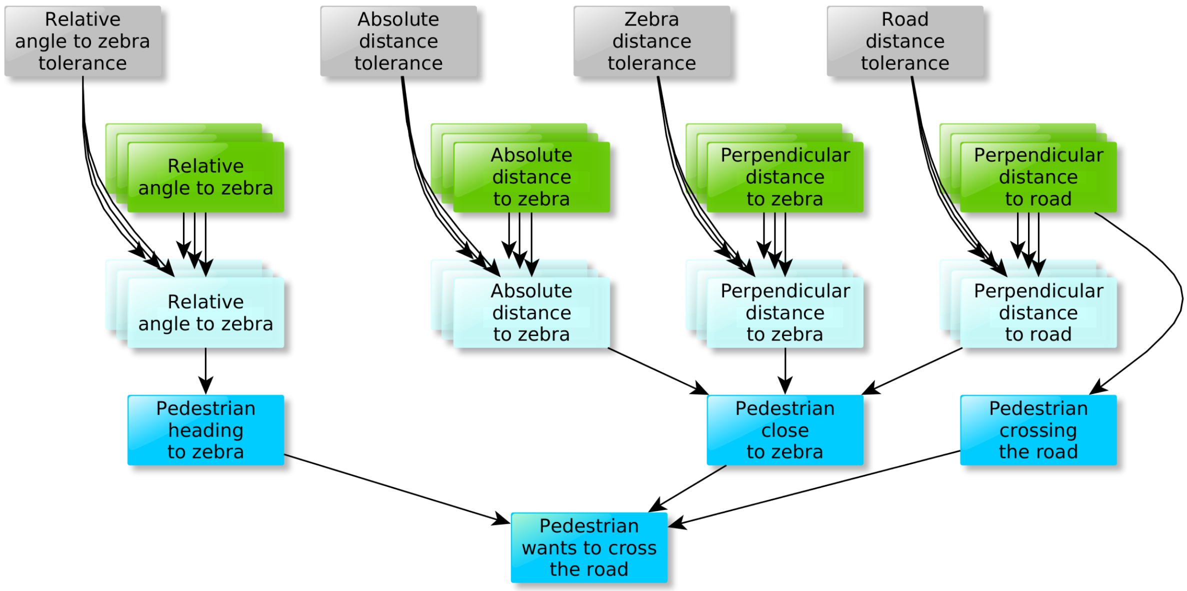

Figure 3: Proposed Bayesian network for the pedestrian intention estimation.

6 INTENTION ESTIMATION OF PEDESTRIANS

For the situations near zebra crossing, it is important to predict the future intentions of pedestrians, especially the intention to cross a street. Several different approaches can be used for estimating the pedestrian's intention. The most often used methods use graphical models such as Bayesian networks (e.g. (Gindele et al., 2015), (Kooij et al., 2014)) or Hidden Markov Models (e.g. (Song et al., 2016),(Gadepally et al., 2014)). Another approach in modeling the behavior of the agents are Finite-State Machines (FSM). Based on our findings, we decided to use Bayesian networks as well.

The proposed Bayesian network was designed for the intention estimation of pedestrians near a zebra crossing. This network works with measured input data, which are captured by sensors used in UP-DRIVE project car. Input information such as map (e.g., the location of the zebra crossings, traffic light, road crossings), the *ego-car* position, speed, acceleration, etc., and other traffic participants were considered. The proposed Bayesian network is shown in Fig. 3. Besides the current measured state, it also takes into account several previous states. The nodes in the presented Bayesian network (Fig. 3) can be divided as follows: **Tolerance node** (gray), **Measured data node** (green), **Likelihood node** (light blue) and **Conditional probability tables node** (dark blue).

Tolerance Node

The tolerance node provides a control parameter for a likelihood function. It represents a threshold, under which the likelihood remains equal to 1. For example, if the distance of a pedestrian to a zebra crossing is lower than the tolerance, the likelihood of the pedestrian present on the zebra crossing is 1.

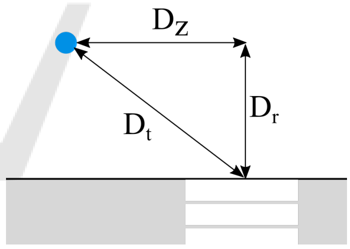

Figure 4: Demonstration of the distance computation.

Measured Data

The measured data nodes provide second control parameters for the likelihood functions. Based on the measured data, we are computing several quantities:

- *Pedestrian distance to the zebra* (D_z) in the direction parallel to the road (Fig. 4).
- *Pedestrian distance to the road* (D_r), which can have both positive and negative values. Negative values mean that the pedestrian is walking on the road meaning he/she is most likely already crossing the road.

- *Total distance* (D_t) to the zebra crossing. This distance is measured as a direct (absolute) distance between the pedestrian and the zebra crossing.
- *Angle between the pedestrian's heading and the direction towards the zebra crossing*. The value of this angle is the difference between the current direction (vector) of pedestrian's walking heading and a vector parallel with the zebra crossing, illustrated in Fig. 5. If we would measure the difference of these directions just clockwise or counterclockwise, it would be possible to measure even greater differences (in $\langle 0, 2\pi)$). Therefore we choose the smaller value of difference in clockwise or counterclockwise and take its absolute value.

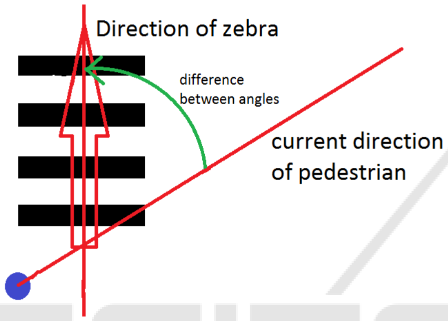

Figure 5: Angle of the pedestrian towards the zebra crossing.

Likelihood Node

In the likelihood nodes, the measured data, along with the tolerances, are used as control parameters for a likelihood function. This way, the measurements are converted into likelihoods that can be further used to calculate the desired probabilities. There were two requirements on the likelihood function used in this application.

1. The likelihood must remain 1 until the quantity reaches some threshold, e.g. the width of the road when considering the likelihood of a pedestrian being on the road.
2. Beyond the threshold, the likelihood must decay quickly at first and decay to zero slowly afterwards until the measured quantity reaches some maximal value.

The function that satisfies these requirements can be constructed by combining a constant function with an exponential function, which is the approach chosen for this paper (see eq. 1).

$$\mathcal{L}(x|t) = \begin{cases} 1 & x < t \\ \lambda \exp(-\lambda x) & x \geqq t \end{cases} \qquad (1)$$

Conditional Probability Table (CPT)

The conditional probability distribution is the probability of the assignment to a variable, given known assignments for another variable(s). $\mathcal{P}(X|Y)$ is the probability of every possible assignment to X, for every possible assignment to Y, for discrete variables.

The example of such conditional probability used in this contribution is presented in Table 2. The table shows the CPT for the conditional probability $\mathcal{P}(X|Y,Z,W)$, where Y,Z,W is the evidence (Y = *pedestrian is crossing the street*, Z = *pedestrian is close to zebra*, W = *pedestrian is heading towards zebra*), and X is the requested result describing the probability that the pedestrian intends to cross the street. Currently, a simplistic approach sets each measured value to true or false by thresholding each calculated likelihood values. Based on these thresholded values, we can determine overall probability of the considered phenomenon, e.g. probability of the pedestrian's intention to cross the street.

Table 2: Conditional probability table for the output node of the proposed BN.

Pedestrian crossing the road	Pedestrian close to zebra	Pedestrian heading towards zebra	Pedestrian will cross the street	
			true	*false*
true	*any*	*any*	1.0	0.0
false	*true*	*true*	0.9	0.1
false	*true*	*false*	0.7	0.3
false	*false*	*true*	0.5	0.5
false	*false*	*false*	0.0	1.0

The individual probabilities of pedestrian's intention to cross the street were computed for each motion prediction estimated 1, 2, and 3 seconds into the future. Consequently, the overall probability of pedestrian wanting to cross the street was computed as a weighted sum of the probabilities for each time instance.

The visualization of the processed data is presented in Fig. 6. The pedestrians are represented by simple rectangles, where the movement direction for each pedestrian is displayed. The color of each pedestrian is changing in dependence of the probability that the pedestrian crosses the street. The blue color represents the zero probability (e.g. a pedestrian is walking away from the road) and is changing through purple to red, where the probability is highest (e.g. pedestrian is on the road). For each pedestrian, the probability of crossing the street is displayed, where the first number represents the probability, where the future position is considered, and the second number represents the probability of a pedestrian crossing the street in the current time.

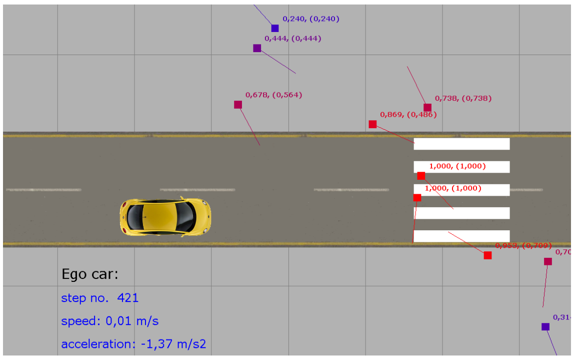

Figure 6: Visualization of pedestrian intention estimation.

7 EVALUATION OF RESULTS

We implemented the reported method in Java. We used the add-on, the probabilistic programming language Figaro, which constitutes a Turing-complete system. Figaro is a functional language. Bayesian network for pedestrian intention estimation was implemented in Figaro.

We evaluated the motion prediction capabilities of methods described in this contribution. The motion predictions were computed for three instants ahead of the current time: one, two and three seconds. The results for the average success rate of the predictions are presented in Table 1. It can be seen that the one second ahead prediction using the cubic filtering achieved 91.8% success rate. The success rate for two and three seconds predictions decreased. This is an expected result because of physics-based motion estimation properties.The median deviation of predicted position and measured prediction for the cubic filtering case was 1.21 meter. This was the best value obtained when compared to the other tested filtering methods. This simple prediction can be improved by using more complex systems such as maneuver-based or interaction-aware motion models. However, these models are more time consuming, which is their disadvantage in comparison to physics-based models.

Table 3: Consistency of predictions.

Time scope (seconds)	**Motion prediction error (%)**	**Intention prediction error (%)**
$t+1$	8.2	15.4
$t+2$	16.5	17.4
$t+3$	25.7	17.7

The correct intention estimation of other traffic participants is closely related to their motion prediction. Thus, the other phenomenon, which we focused on, was the influence of decreasing success of motion prediction on the pedestrian intention estimation. The average error rates for motion prediction and intention estimation for different time intervals are shown in Table 3. The relationship between motion prediction and intention estimation error rate is displayed in Fig. 7. The dotted line represents a trend line that should be followed by linearly dependent phenomena.

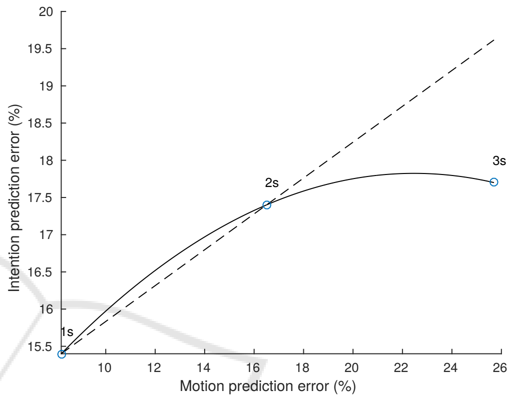

Figure 7: The relationship between motion prediction error and the intention estimation error.

As it can be seen, the relationship between motion prediction and intention estimation error is not linear. It is in fact sub-linear, i.e. a lower accuracy of motion prediction does not affect the accuracy of intention estimation to a large extent. Since the relationship between motion prediction and intention estimation is not linear, we can focus largely on improvements in intention estimation independently of the motion prediction.

8 CONCLUSION AND FUTURE WORK

The traffic scenario and situation understanding of the environment surrounding the *ego-car* is an important step towards a self-driving car. This task includes motion prediction and intention estimation of other traffic participants. For the motion prediction, we used simple physics-based prediction, which achieved satisfying results for the prediction up to the three second look ahead time interval. If we used the same prediction method for longer time intervals, the precision dropped sharply.

The pedestrian intention estimation near zebra crossing was calculated by the proposed Bayesian network. In this contribution, we focused on the relationship between the motion prediction and the intention estimation. We observed that these two phenomena are dependent, however, the dependence is only sub-linear. Despite the decreasing success of motion prediction beyond 1st second, the intention estimation was stable up to three seconds.

Our future work will aim at improvements in the intention estimation independently on motion prediction. We will test the success of the estimation. We will also implement more sophisticated and computationally intensive motion predictors for comparison.

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