Recognition and Prediction of Situations in Urban Traffic Scenarios

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Abstract

The recognition and prediction of intersection situations and an accompanying threat assessment are an indispensable skill of future driver assistance systems. This study focuses on the recognition of situations involving two vehicles at intersections. For each vehicle, a set of possible future motion trajectories is estimated and rated based on a motion database for a time interval of 2–4 *s ahead. Possible situations involving two vehicles are generated by a pairwise combination of these individual motion trajectories. An interaction model based on the mutual visibility of the vehicles and the assumption that a driver will attempt to avoid a collision is used to rate possible situations. The correspondingly favoured situations are classified with a probabilistic framework. The proposed method is evaluated on a real-world differential GPS data set acquired during a test drive of* ~ 10 *km, including three road intersections. Our method is typically able to recognise the situation correctly about* 1.5–3 *s before the distance of the vehicles to the intersection centre becomes minimal.*

1. Introduction

The recognition of the situation into which a vehicle is currently involved is an important information for an advanced driver assistance system (ADAS). The goal of such systems is to increase passenger comfort and safety by supporting the driver with environmental information such as the current and expected future behaviour of traffic participants and obstacles (cf. e.g. [4, 5]). Of particular interest are cooperative situations, where an ADAS estimates and predicts the motion states of the traffic participants, performs a threat assessment [2], and considers the possible interaction behaviour [1].

In this study, we regard the interaction between pairs of vehicles in order to recognise the current situation and provide a prediction for the next few seconds. We furthermore introduce a threat assessment approach based on an interaction model motivated by the idea of a rating of each predicted situation according to the mutual visibility of the vehicles.

2. Motion Representation and Motion Database

In our system we utilise the long-term motion prediction framework presented in [3, 6]. The motion patterns of vehicles are represented by trajectories, which are defined as ordered tuples combining states (position, yaw angle, velocity, yaw rate) with a time stamp. Our basic approach in this study is to learn motion patterns by building a motion database consisting of observed trajectories. As a measure for the similarity between trajectories we use the quaternion-based rotationally invariant longest common subsequence (QRLCS) metric. A particle filter framework simultaneously tracks a large number of motion hypotheses and assigns a likelihood value to them. Knowledge about the lane geometry extracted from a map is used for penalising unlikely predictions such as those crossing the edge of the road.

3. Situation Classification

A situation depends on the temporal behaviour of two or more traffic participants acting dependent on each other. For simplification, it is assumed here that two vehicles A and B approach an intersection from different directions at the same moment in time. The intersection is taken to consist of two perpendicular roads. At this point, the predicted motion of each vehicle does not yet depend on the motion of the other vehicles. In the context of the particle filter, at every time step the

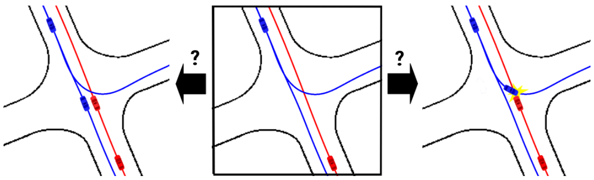


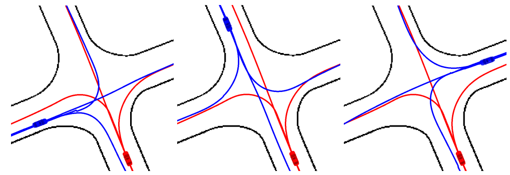
Figure 1. Two different situations (left and right) resulting from different individual motion predictions (centre).

motion prediction yields for both vehicles a set of future trajectories $X_A^{(1)}, ..., X_A^{(N)}$ and $X_B^{(1)}, ..., X_B^{(M)}$ with associated likelihoods $P_A^{(1)}, ..., P_A^{(N)}$ and $P_B^{(1)}, ..., P_B^{(M)}$. Each trajectory is the concatenation of a "history part" and a "prediction part". Both parts have the same temporal length of 2.5 s, where the history part is identical for all predicted trajectories of the same vehicle. A trajectory pair $(X_A^{(n)}, X_B^{(m)})$ represents one possible situation with the occurrence probability $P^{(nm)} = P_A^{(n)}\, P_B^{(m)}$ as long as the vehicle movements are regarded as mutually independent. We assume that the vehicles are able to turn right (R), turn left (L), or drive straight on (G), which results in the set Ω of possible situation classes with $\Omega = \{LL, LG, LR, RL, RG, RR, GL, GG, GR\}$.

An example of two predicted situations is depicted in Fig. 1 using real trajectory data. Each pair of motion trajectories $(X_A^{(n)}, X_B^{(m)})$ yields a so-called multiple participant trajectory (MPT) $T^{(nm)}$ which consists of difference components of the yaw angles and velocities of two vehicles. A Chebyshev decomposition [7] is applied to each of these feature trajectories, resulting in a merged coefficient vector $\mathbf{T}_c^{(nm)}$. In order to infer the current situation class, we use a hierarchical classifier structure. The approaching directions of the vehicles are determined based on their yaw angles. For each of the three cases shown in Fig. 2, a polynomial classifier is trained based on a labelled set of MPTs. Confidence mapping [8] is applied to transform classifier outputs into probabilities $Q_k(\mathbf{T}_c^{(nm)})$ with $k = 1, \ldots, 9$ for each situation class k. The overall probability $W(k)$ for situation class k is given by

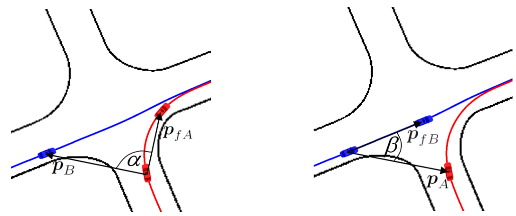
$$W(k) = \eta_w \sum_{n=1}^{N} \sum_{m=1}^{M} \rho^{(nm)}\, P^{(nm)}\, Q_k(\mathbf{T}_c^{(nm)}) \quad (1)$$

with η_w as a normalisation constant. To take into account the interaction between the traffic participants, the occurrence probability $P^{(nm)}$ is extended by an interaction weight $\rho^{(nm)}$ in Eq. (1) which is described in the following section.



(a) Case 1 (b) Case 2 (c) Case 3

Figure 2. Cases of initial orientation.



(a) (b)

Figure 3. Definition of the visibility angles α and β.

4. Interaction Model, Threat Assessment

We propose an interaction model based on the assumptions that (i) all drivers have the intention to avoid a collision and (ii) that the threat increases when the position of one vehicle is outside the main viewing direction of the driver of the other vehicle. The aim of the interaction model is to decrease the weight of trajectory pairs which lead to a collision as long as the mutual visibility is high and the time to collision $t_c^{(nm)}$ is significantly longer than a suitably chosen interaction time scale $t_r^{(nm)}$. Thus, we introduce for $\rho^{(nm)}$ the relation

$$\rho^{(nm)} = (1 - \rho_{\min})\, e^{-\frac{1}{2}\left(\frac{t_c^{(nm)}}{t_r^{(nm)}}\right)^2} + \rho_{\min} \quad (2)$$

with $\rho_{\min}$ as the minimum possible weight value. The time to collision $t_c^{(nm)}$ is determined based on the trajectory pair (nm). If no collision occurs we have $\rho^{(nm)} = 1$.

The visibility constraint is proposed in [2] as a criterion for threat assessment. In our model, the viewing direction of each driver is approximated by the "focus vector" $\mathbf{p}_f$ from the current position of the corresponding vehicle to its predicted position in 2 s, i.e. we assume that the view of the driver is focused on the direction into which the corresponding vehicle is moving. We use the angles $\alpha^{(nm)}$ and $\beta^{(nm)}$ according to Fig. 3 between the focus vectors $\mathbf{p}_{fA}$ and $\mathbf{p}_{fB}$ and the vectors $\mathbf{p}_B$ and $\mathbf{p}_A$ pointing to the other vehicle, respectively, as measures for the mutual visibilities, where the interaction time scale is assumed to be proportional to the mean value of the individual visibilities according to

$$t_r^{(nm)} = \frac{1}{2\,b}\left(\alpha^{(nm)} + \beta^{(nm)}\right) \quad (3)$$

with $b = 0.6$ as an empirically chosen constant. The interaction time scale and the probability of a collision trajectory pair (nm) to occur increases with decreasing visibility $\rho^{(nm)}$ due to increasing angles $\alpha^{(nm)}$ and $\beta^{(nm)}$.

The overall collision probability W_{coll} is given by

$$W_{\text{coll}} = \sum_{n=1}^{N}\sum_{m=1}^{M} \rho^{(nm)}\,P^{(nm)}\,P(C|T^{(nm)}) \quad (4)$$

with $P(C|T^{(nm)}) \in \{1, 0\}$, where 1 denotes the occurrence of a collision for trajectory pair (nm) and 0 the absence of a collision.

5. Evaluation

The data set used in the evaluation consists of real-world differential GPS positions acquired during a test drive of about 10 km. It includes three intersections with vehicles approaching from all possible directions, respectively. The test vehicle with the differential GPS sensor had no further sensors for environment perception. In order to construct a situation at an intersection, we therefore synchronised two separately recorded manoeuvres. Since the individual motion trajectories were acquired in real traffic, we expect the correspondingly constructed situations to be fairly realistic.

Time $t = 0$ is defined as the moment in time when both vehicles have passed their minimum distance to the centre of the intersection. For each test situation, we determine the earliest moment in time at which the situation class according to Eq. (1) is recognised correctly. The number of particles in the particle filter has been set to 50, all other parameters of the motion prediction framework described in Section 2 are identical to those in [6]. Specifically, the influence of the interaction model on the threat assessement is examined based on two situations in which one of the vehicles ignores the right of way of the other vehicle.

5.1. Prediction of Situation Classes

For each situation class k the probability $W(k)$ is estimated by the polynomial classifier according to Eq. (1). We define the certainty γ_{k_r} of a situation class $k_r = \text{argmax}_{k\in\Omega} W(k)$ by its difference to the situation class with the second-largest probability $k_{r2} = \text{argmax}_{k\in\Omega\setminus\{k_r\}} W(k)$ as $\gamma_{k_r} = W(k_r) - W(k_{r2})$. If γ_{k_r} exceeds the empirically chosen threshold of 0.2, the recognised situation class is accepted. At each test intersection I_n for each initial orientation case (cf. Fig. 2) and each situation class a representative scenario was generated based on the individual trajectories. Table 1 displays the values of t_{rec} indicating the moment in time from which on the situation is classified correctly according to the γ_{k_r} criterion until the end of the situation at $t = 0$. The values of t_{rec} for a certain intersection I_n were obtained using the trajectories of the other two intersections $I_{m\neq n}$ as training data in a leave-one-out manner. The values in Table 1 were inferred from single runs of the particle filter. We found that the standard deviation of t_{rec} is typically of the order 0.3 s. The fact that all obtained t_{rec} values are negative indicates

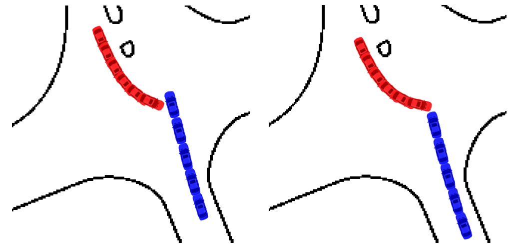
Table 1. Results of situation prediction for two vehicles. The class indices denote the initial orientation case according to Fig. 2.

Class	I_1 [s]	I_2 [s]	I_3 [s]	median [s]
GG_1	-2.54	-3.26	-2.66	-2.66
GG_2	-2.62	-2.20	-2.82	-2.62
GG_3	-1.90	-2.00	-2.12	-2.00
GL_1	-3.18	-1.80	-3.30	-3.18
GL_2	-2.76	-2.22	-2.80	-2.76
GL_3	-2.48	-2.40	-3.08	-2.48
GR_1	-3.20	-1.08	-3.64	-3.20
GR_2	-2.24	-2.06	-1.50	-2.06
GR_3	-1.56	-2.08	-1.68	-1.68
LG_1	-2.90	-1.46	-3.86	-2.90
LG_2	-2.50	-1.10	-2.66	-2.50
LG_3	-2.58	-1.20	-0.96	-1.20
LL_1	-1.02	-1.52	-4.49	-1.52
LL_2	-1.68	-1.38	-3.56	-1.68
LL_3	-1.48	-0.50	-1.12	-1.12
LR_1	-1.64	-1.54	-2.96	-1.64
LR_2	-1.68	-1.54	-3.24	-1.68
LR_3	-0.38	-1.28	-1.90	-1.28
RG_1	-0.62	-2.68	-3.68	-2.68
RG_2	-1.24	-3.40	-4.14	-3.40
RG_3	-1.32	-1.28	-2.34	-1.32
RL_1	-1.52	-1.10	-2.36	-1.52
RL_2	-1.86	-1.88	-1.62	-1.86
RL_3	-0.28	-1.36	-1.72	-1.36
RR_1	-1.82	-2.32	-2.12	-2.12
RR_2	-1.70	-1.56	-3.78	-1.70
RR_3	-1.88	-2.44	-0.64	-1.88

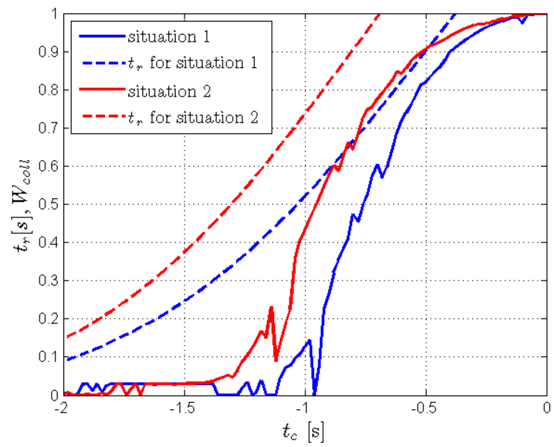
that all examined 81 situations have been successfully recognised at the end. Some situation predictions are rather late, especially for intersection I_1. This observation can be explained by the fact that the lanes of intersection I_1 are wider than those of the other intersections and turning manoeuvres are thus initiated later. The median values of t_{rec} are between -1.1 s and -3.4 s, indicating a reasonably early correct prediction.

5.2. Influence of the Visibility Constraint

A typical hazardous situation occurs when one vehicle ignores the right of way of the other vehicle. Two typical scenarios of such collision situations are shown in Fig. 4. If we consider the collision detection for both situations according to Eq. (4), the threat given by W_{coll} begins to increase towards its final value of 1 by about 0.2 s earlier for situation 2. This behaviour is due to the fact that situation 2 is characterised by a lower mutual visibility since early in the course of the situation, the focus vector of the red vehicle is directed towards the intersecting road rather than towards the blue vehicle. In situation 1, the focus vector of the red vehicle is always directed towards the blue vehicle and vice versa until the mutual distance has become very low. The correct situation class is recognised for these two situations at $t_{\mathrm{rec}} = -1.30$ s and $t_{\mathrm{rec}} = -1.84$ s, respectively.



(a) Situation 1 (b) Situation 2



(c) Interaction time scale t_r and collision probability W_{coll}

Figure 4. Two different collision situations with threat assessment results.

6. Summary and Conclusion

In this study we have regarded the recognition and predictions of situations involving two vehicles at intersections. For each vehicle, a set of possible future motion trajectories is estimated and rated based on a motion database for a time interval of 2–4 s ahead. Possible situations involving two vehicles have been generated by a pairwise combination of individual motion trajectories. An interaction model based on mutual visibility and the assumption that a driver will attempt to avoid a collision have been used to rate the possible situations. The correspondingly favoured situations have been classified with a probabilistic framework. The proposed method has been evaluated on a real-world differential GPS data set acquired during a test drive of ~ 10 km, including three different road intersections. Our method is typically able to recognise the situations correctly about 1.5–3 s before the distance of the vehicles to the intersection centre becomes minimal.

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