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INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET EN AUTOMATIQUE

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N° 7604

April 2011

Robotics

Rapport de recherche

ISSN 0249-6399 ISRN INRIA/RR--7604--FR+ENG

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centre de recherche GRENOBLE - RHÔNE-ALPES

Modelling Dynamic Scenes at Unsignalised Road Intersections

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Theme : Robotics
Perception, Cognition, Interaction
Équipe-Projet e-Motion

Rapport de recherche n° 7604 — April 2011 — 17 pages

Abstract: Understanding dynamic scenes at road intersections is both crucial and challenging for intelligent vehicles. In order to detect potentially dangerous situations, algorithms are needed that can interpret the behaviour of the actors in the scene and predict its likely evolution. The difficulty of this task arises from the large number of possible scenarios. The conventional answer to this issue is to discard vehicle interactions in the manoeuvre prediction process, i.e. to infer the manoeuvre performed by each vehicle from its past and current behaviour, independently from the other vehicles in the scene. In this report we show how this affects collision risk estimation in very common scenarios, making it unusable in practice for Advanced Driver Assistance Systems (ADAS) applications. As an alternative we propose a probabilistic model for vehicles traversing unsignalised intersections that accounts for the mutual influence between vehicle manoeuvres. The focus is on the utilisation of contextual information (i.e. layout of the intersection, presence of other vehicles and traffic rules) to interpret a vehicle's behaviour. We show how the model can be used for accurate situation and risk assessment.

Key-words: Intelligent Transportation Systems (ITS), Advanced Driver Assistance System (ADAS), situation assessment, manoeuvre estimation, collision risk estimation

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Modélisation de scènes dynamiques aux intersections non signalisées

Résumé : La compréhension de scènes dynamiques aux intersections est une tâche à la fois cruciale et difficile pour les véhicules intelligents. Afin de détecter les situations potentiellement dangereuses, il faut des algorithmes capables d'interpréter le comportement des acteurs de la scène, et de prédire l'évolution de celle-ci. La difficulté de cette tâche vient du grand nombre de scénarios possibles. La solution classique à ce problème est de laisser de côté les interactions entre véhicules lors de l'estimation de manœuvre, c'est-à-dire d'estimer la manœuvre exécutée par un véhicule uniquement à partir de son comportement passé et présent, indépendamment des autres véhicules. Dans ce rapport, nous montrons que cette simplification affecte l'estimation du risque de collision dans des situations très courantes, la rendant ainsi inutilisable en pratique pour les systèmes d'aide à la conduite (ADAS). Comme alternative nous proposons un modèle probabiliste pour des véhicules négociant une intersection non signalisée qui prend en compte l'influence mutuelle des manœuvres exécutées par les véhicules. On s'intéresse en particulier à l'utilisation d'information contextuelle (agencement de l'intersection, présence d'autres véhicules, règles de circulation) pour interpréter le comportement d'un véhicule. Nous montrons comment le modèle peut être utilisé pour l'estimation de situation et de risque.

Mots-clés : Systèmes de transport intelligents (ITS), aide à la conduite (ADAS), comprehension de situation, estimation de manœuvre, estimation du risque de collision

1 Introduction

The recent achievements by the Intelligent Transportation Systems (ITS) community are very promising regarding the ability for intelligent vehicles to assist human drivers and to navigate autonomously in real traffic. Current research on future Advanced Driver Assistance Systems (ADAS) include active safety applications that avoid or mitigate accidents by warning the driver of upcoming dangers or by taking control of the vehicle when an accident is imminent [1]. The success of the DARPA Urban Challenge [2] in 2008 and the recent autonomous driving demonstration by Google [3] show that intelligent vehicles can handle complex navigation tasks autonomously in urban environments. However, a number of challenges remain. The authors of [4] investigated the causes of collisions between robots during the DARPA Urban Challenge and concluded that currently the main challenges for intelligent vehicles are: (1) Perception of the environment, (2) Situation assessment (in particular driver intention estimation) and (3) Smart obstacle avoidance. This report addresses the second problem and focuses on unsignalised road intersections (i.e. all types of intersections except the ones ruled by traffic lights).

Situation assessment can be defined as “the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” [5]. It is a crucial task for intelligent vehicles because the appropriateness of the decisions made by the system directly depends on the system’s ability to assess the situation correctly. In the case of road intersections the difficulty lies in the high number of possible scenarios (many possible intersection layouts and interactions between the vehicles in the scene). In the literature the conventional way to handle this issue is to assume independence between the manoeuvres performed by the different vehicles in the scene [6, 7, 8]. We show in Section 2 that there are significant negative consequences for collision risk estimation.

In this report we propose a model for vehicles traversing unsignalised road intersections that accounts for the mutual influence between vehicle manoeuvres. Knowledge about the intersection layout, the presence of other vehicles and the traffic rules is combined in a probabilistic manner to interpret the behaviour of each vehicle in the scene. We claim that this allows for a better interpretation of the scene and a more reliable assessment of the situation and collision risk.

The remainder of this report is organised as follows. Section 2 defines the problem of situation assessment at unsignalised intersections and shows the importance of taking into account vehicle interactions when predicting the manoeuvre performed by a vehicle. In Section 3 a review of existing work on situation assessment at road intersections is presented. The proposed model is specified in Section 4, and its use for manoeuvre prediction and risk assessment is described in Section 5. Finally Section 6 reports our conclusions about the proposed approach, as well as our intentions regarding its implementation and testing in the near future.

2 Problem statement

2.1 Situation assessment at unsignalised intersections

The problem addressed in this report is situation assessment at unsignalised intersections. It requires interpreting the behaviour of all the vehicles in the scene, i.e. to infer high-level features like driver manoeuvre intention and driver yielding intention from observations on a vehicles' behaviour.

At unsignalised intersections, the way a driver executes a manoeuvre is highly dependent on the presence of other vehicles and on traffic rules. For example a vehicle might have to slow down or stop before entering the intersection in order to yield to a vehicle which has priority or because of the presence of a stop sign. Our representation of the influences on a vehicle's behaviour at an unsignalised intersection is illustrated in Figure 1. The graph conveys our claim that a *Vehicle's behaviour* (i.e. successive poses, speeds and accelerations) is influenced by both the *Driver's intention* (i.e. manoeuvre intention, yielding intention) and the *Context* (i.e. intersection layout, presence of other vehicles and traffic rules). A manoeuvre corresponds to a pair "lane used by the driver to enter the intersection" - "lane used by the driver to exit the intersection". An intention to yield translates as the driver making sure that his speed is compatible with stopping at the intersection (whether the reason is the need to yield to vehicles with right-of-way or the reason is the presence of a stop sign).

In this report situation assessment is defined as the problem of estimating - for all the relevant vehicles in the scene - the *Driver's intention* from observations on the *Vehicle's behaviour* and knowledge about the *Context*. The terms "estimate the driver's manoeuvre intention", "predict the manoeuvre" and "recognise the performed manoeuvre" are used interchangeably, since they convey equivalent information about the situation (e.g. estimating the driver's intention or recognising the manoeuvre that is being currently performed allows to predict the future of a manoeuvre).

2.2 On the importance of Context for situation assessment and risk assessment

As was mentioned in the introduction, it is current practice to predict a vehicle's manoeuvre at an intersection independently of the other vehicles. Using the formalism defined in Section 2.1, this corresponds to estimating a driver's intended manoeuvre using only observations on the vehicle's behaviour and knowledge on the intersection layout. The yielding intention, the presence of other vehicles and the traffic rules are not considered. In this report we claim that it is necessary to take into account vehicle interactions to be able to reliably interpret the behaviour of a vehicle negotiating an unsignalised intersection.

2.2.1 Taking into account vehicle interactions for manoeuvre prediction reduces false alarms

Figure 2 illustrates this statement. In this scenario, a vehicle is accelerating from a stop at the entrance of an intersection ruled by a stop sign. Another vehicle is approaching the intersection at high speed from the right, without decelerating. A human observing the scene would conclude that the red vehicle

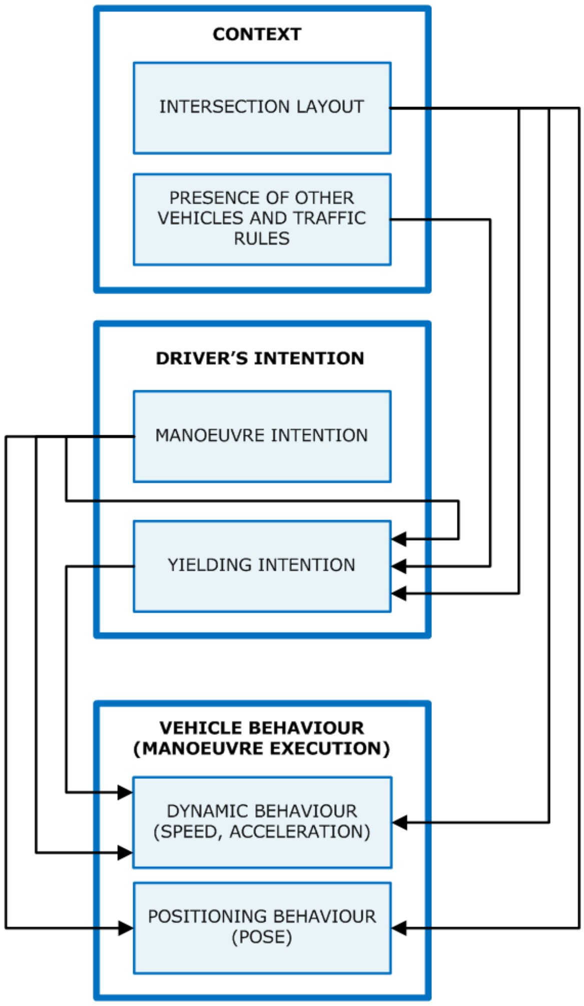

Figure 1: Block diagram of the influences on a vehicle's behaviour at unsignalised intersections

is starting to execute a right turn after stopping at the intersection, and that the green vehicle is driving at high speed because it has priority and intends to go straight at the intersection. This is actually a very common scenario and no driver would expect or want to receive an ADAS warning; in this case a warning would be considered to be a false alarm.

The conventional approach (top row) predicts the manoeuvres of each vehicle independently, based only on each vehicle's behaviour and using knowledge about the layout of the intersection. Manoeuvres 1 and 2 are therefore equally probable for the red vehicle, and manoeuvre 4 is much more probable than manoeuvre 3 for the green vehicle. This approach finds that the pairs (1,3) and (1,4) - which are the pairs that lead to a collision - are quite probable. The resulting estimated collision risk is high and the ADAS will warn the drivers.

The approach proposed in this report (bottom row) uses additional contextual information during the manoeuvre prediction process (presence of other vehicles, traffic rules). The additional information does not change the interpretation of the green vehicle's behaviour but allows to identify that the red vehicle is probably performing manoeuvre 2. This leads to a better assessment of the risk: the probability of the pairs (1,3) and (1,4) is low, therefore the collision risk is low and the ADAS will not send a warning to the drivers.

2.2.2 Drivers tend to respect traffic rules

This can seem like a strong assumption, but it is one that humans make while driving in order to not overestimate the collision risk. In the previous paragraph we showed that making this assumption for manoeuvre prediction leads to less false alarms by the ADAS. In this paragraph we show that a system that makes this assumption is still able to detect dangerous situations where a driver does not comply with the traffic rules.

Figure 3 illustrates this statement. The difference with the scenario in Figure 2 is that this time the traffic rules do not provide an indication on the manoeuvre performed by the red vehicle, since neither executing manoeuvre 1 nor executing manoeuvre 2 is in accordance with the traffic rules. A human would conclude that manoeuvres 1 and 2 are equally probable, and so do both approaches (conventional approach and proposed approach). Therefore the collision risk is found to be high and the drivers receive a warning. Assuming that drivers tend to respect traffic rules does not prevent the approach from detecting that the situation is dangerous.

One can also wonder what would happen in the scenario of Figure 2 if the red vehicle happened to turn left in the end. In this case, shortly after the red vehicle enters the intersection its behaviour (in particular its position and orientation) will leave no doubt on the driver's manoeuvre intention. At this point a right turn is made impossible by the physics of the vehicle. Therefore the outcome will be the same as in Figure 3: the ADAS will send a warning to the drivers.

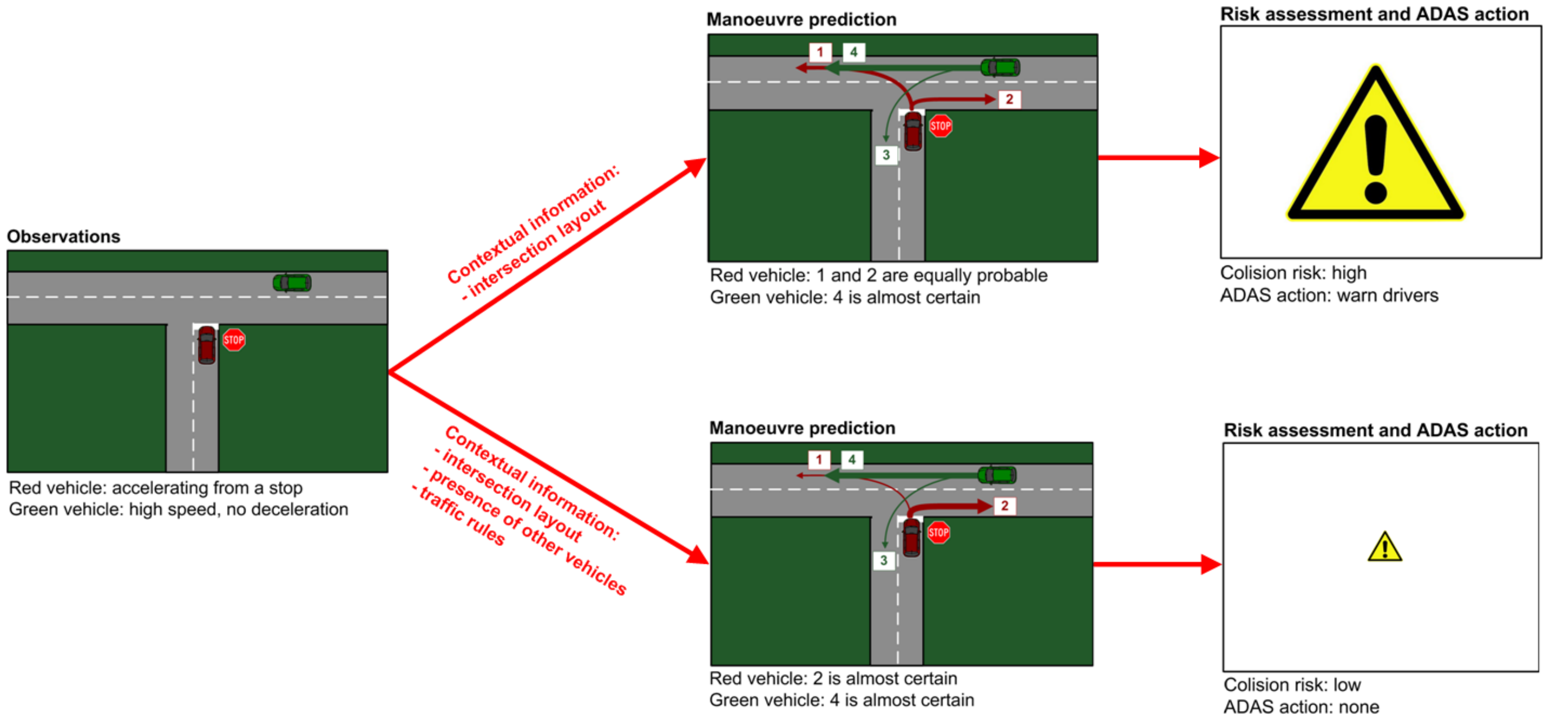

Figure 2: Illustration of a scenario where the advantage of taking into account the interactions between vehicles for manoeuvre prediction is obvious for ADAS applications. The behaviour of the red vehicle is interpreted differently depending on whether or not the interactions with the green vehicle are considered. When they are not (conventional approach, top row), the manoeuvre of the red vehicle is predicted less accurately; as a result the collision risk is overestimated and the ADAS will warn the drivers of an upcoming collision. This is a false alarm, since a human confronted with this (very common) scenario would conclude that the red vehicle is turning right and that therefore the collision risk is low. An approach that takes into account the interactions between the vehicles during the manoeuvre prediction process (proposed approach, bottom row) reaches the conclusion that the risk is not high enough that the drivers should be warned.

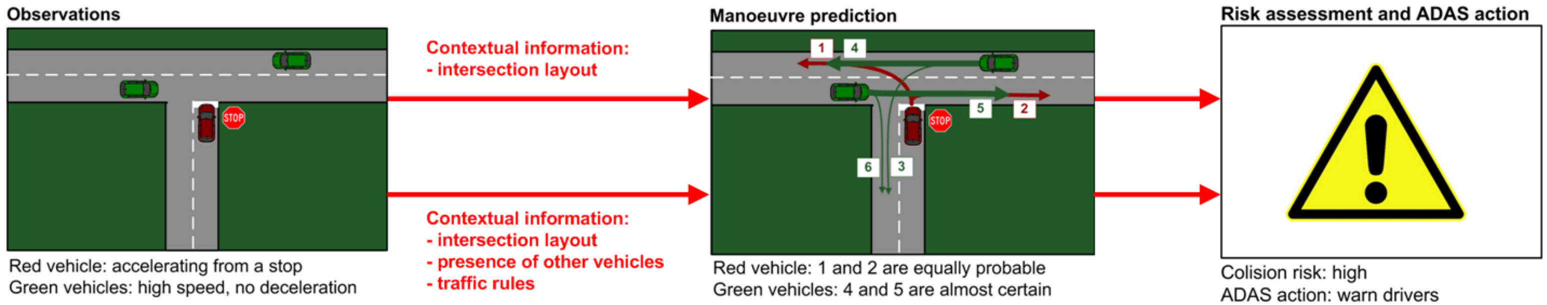

Figure 3: Illustration of a scenario where there is no safe explanation for the red vehicle's behaviour. The conventional approach (top row) does not take into account vehicle interactions for manoeuvre prediction and therefore concludes that manoeuvres 1 and 2 are equally likely and that the collision risk is high. Our approach (bottom row) uses clues from the traffic rules and the presence of other vehicles to predict the red vehicle's manoeuvre. Since neither executing manoeuvre 1 nor executing manoeuvre 2 is in accordance with the traffic rules, both manoeuvres are found to be equally probable. Therefore the collision risk is high and the ADAS warns the drivers.

2.2.3 Conclusion on the importance of Context

The examples given in the last two paragraphs illustrate why taking into account the presence of other vehicles and the traffic rules for manoeuvre intention estimation is important. The use of *Context* information allows to determine whether or not the behaviour of a vehicle can be explained by a manoeuvre which respects the traffic rules. The improvement over approaches that do not consider *Context* information is that the risk will not be overestimated in scenarios like Figure 2, and the system can be all the more trusted when it detects a high collision risk (like in Figure 3). This is of great importance for ADAS applications, since a system that overestimates risk and therefore triggers false alarms frequently is not acceptable for the end-users.

3 Related works

The interest for situation assessment at intersections has been rising lately, as perception capabilities of intelligent vehicles have improved and have made high level interpretation of scenes feasible. In particular, a lot of attention has been given to the general problem of manoeuvre recognition in traffic scenarios.

A popular approach is to decompose manoeuvres into sequences of events that are easier to recognise, and to learn the probabilities of transitions between the events during a manoeuvre. Hidden Markov Models (HMMs) are particularly well suited for this task. They have been used by [9] for recognising passing, aborted passing, and following manoeuvres. Coupled HMMs have been introduced by the authors of [10] as a solution to model interactions between vehicles over time during the execution of a manoeuvre. In [8] Hierarchical HMMs are used to estimate manoeuvre intention. The possible evolution of the vehicle motion for a given manoeuvre is represented in a probabilistic manner by Gaussian Processes. This representation makes it possible to integrate information about the road geometry as well as uncertainties on the realisation of a manoeuvre. The solution proposed by [7] is to characterise simple events using Fuzzy Logic and to apply Bayesian filtering for manoeuvre prediction. The transition probabilities between events are set by Probabilistic Finite-State Machines. A Dynamic Bayesian Network that combines vehicle tracking and generic behaviour recognition is presented in [11]. The approach uses factored states to allow for the representation of interactions between vehicles while limiting the computational complexity of the inference process.

An alternative to the generic probabilistic manoeuvre models described above is to cluster a set of recorded trajectories in order to retrieve typical motion patterns for a specific intersection [6]. In [12], the trajectory of a vehicle is compared with reference trajectories from a motion database. The manoeuvre recognition is then refined using an "interaction variable" that penalises manoeuvres that lead to a collision with another vehicle. The assumption is that drivers tend to avoid collisions with other vehicles when possible.

None of the approaches mentioned above propose a solution to the problem stated in Section 2.1. When addressing the problem of situation assessment at intersections, it is current practice to assume independence between vehicles executing manoeuvres, and this solution was adopted by [6, 7, 8]. In Section 2.2 we showed the limitations of making such an assumption. Interactions between vehicles are taken account in [9, 10], but not within the framework of intersections. If they were to be applied to the problem of manoeuvre prediction at unsignalised intersection the computational complexity would increase exponentially with the number of vehicles in the scene and quickly become intractable, because these methods consider pairwise interactions. In order to avoid this problem, the authors of [11] use factored states to analyse the scene globally instead of the interactions between each pair of vehicles. The framework is generic and could in theory be applied to the problem of manoeuvre recognition at intersections, although it would require some adaptation (such as the introduction of traffic rules and yielding intention). The authors of [12] accounted for the interactions between vehicles for manoeuvre recognition at intersections. Their results support our claim in Section 2 that the information on the presence of other vehicles in the scene is useful for making a better interpretation of a vehicle's behaviour. However they do not consider the clues provided by traffic rules to interpret a scene.

In the next section we describe a probabilistic model for vehicles traversing unsignalised intersections that incorporates contextual information about the layout of the intersection, the presence of other vehicles and the traffic rules.

4 Model description

4.1 Representation of a road intersection

From a digital map we automatically extract a set of attributes that characterise an intersection: courses, yield points and traffic rules (stop, give way). A course is a typical path that can be followed by a vehicle while approaching and traversing the intersection, i.e. one course corresponds to one possible manoeuvre in the intersection. Each course is assigned a unique yield point, which can be located at the entrance of the intersection (on a stop or give way line) or inside the intersection (for left turn across oncoming traffic manoeuvres). Courses are defined even for forbidden manoeuvres, such as going straight from a "left turn only" lane. Courses comprising two possible yield points (e.g. left turn across oncoming traffic courses) are split into two courses with one yield point each. This representation is illustrated by Figure 4.

4.2 Relevant variables

We define variables relevant to the problem defined in Section 2.1. When taking into account the interactions between vehicles in a model, one issue is the computational complexity. For methods that consider pairwise interactions between vehicles, the number of possible interactions grows exponentially with the number of interacting objects and the problem becomes quickly intractable. For this reason, instead of modelling the yielding intention between each pair of vehicles we choose to use factored states and to have only one "intention to yield" variable per vehicle. It corresponds to an intention to stop at the intersection as a consequence of the context (presence of other vehicles and traffic rules), not to an intention to yield to a specific vehicle.

For each vehicle $n \in [1, N]$ in the scene,

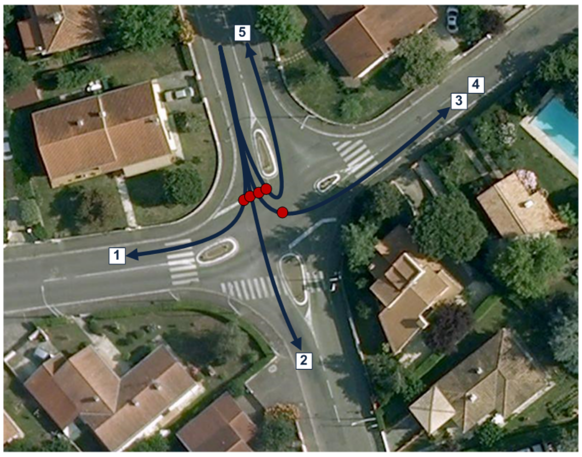

Figure 4: Representation of a road intersection: as an example, the courses (blue arrows) and associated yield points (red points) originating from one road are displayed. Courses 3 and 4 correspond to the same manoeuvre with a different yield point.

4.2.1 The state of the vehicle is characterised by:

- $P_n = (x, y, \theta) \in \mathbb{R}^3$: the pose (x position, y position, orientation).
- $S_n \in \mathbb{R}$: the speed.
- $A_n \in \mathbb{R}$: the acceleration.
- $T_n \in \{left, right, none\}$: the turn signal.

4.2.2 The positioning of the vehicle w.r.t. the layout of the intersection is characterised by:

- $C_n \in \{c_i\}_1^{N_C}$: the course that the vehicle is on (see definition in Section 4.1).
- $D_n \in \mathbb{R}$: the distance to the yield point of the course the vehicle is on. D_n will be positive when the vehicle has not yet reached the yield point, and negative after the vehicle passed the yield point.

4.2.3 The yielding behaviour of the vehicle is characterised by:

- $Y_n \in \{yield, noyield\}$: the driver's intention to yield (see definition in Section 2.1).
- $Y'_n \in \{yield, noyield\}$: the necessity for the driver to yield. It is derived from the context of the scene, i.e. the presence of other vehicles and the traffic rules.
- $\lambda_n \in \{true, false\}$: a "consistency" variable that represents the consistency between Y_n and Y'_n. The concept of consistency variables was introduced in [13] as a Bayesian method to fuse different sources of knowledge

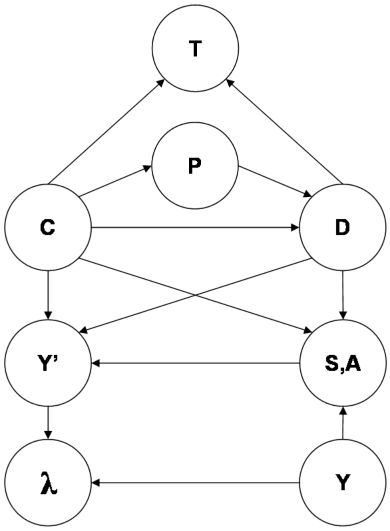

Figure 5: Graphical representation (Bayesian Network) of the decomposition proposed in Section 4.3.

about a variable without having to define the conditional probabilities between them. In our case the insertion of a consistency variable allows to fuse the knowledge about the necessity for the driver to yield with the apparent intention of the driver. λ_n is the key variable to model the mutual influence between the manoeuvres performed by the vehicles in the scene.

The corresponding factored states are denoted $P, S, A, T, C, D, Y, Y', \lambda$ where $P = (P_1, ..., P_N)$ (and similarly for all the other variables).

4.3 Joint distribution

We propose the following decomposition to model vehicles negotiating an unsignalised intersection:

$$\begin{aligned} &P(P \wedge S \wedge A \wedge T \wedge C \wedge D \wedge Y \wedge \lambda) \\ &= P(C) \times P(P|C) \times P(D|P \wedge C) \times P(T|C \wedge D) \times P(Y) \\ &\quad \times P(S \wedge A|Y \wedge C \wedge D) \times P(Y'|C \wedge D \wedge S \wedge A) \times P(\lambda|Y \wedge Y') \end{aligned} \tag{1}$$

The corresponding graphical representation is shown in Figure 5, and the parametric forms of the different distributions are described in the next paragraph.

4.4 Parametric forms

In what follows, the parametric forms of the distributions in Equation 1 are specified.

4.4.1 $P(C) = \prod_{n=0}^{N} P(C_n)$

Prior on the course. Independence between the vehicles is assumed. For each vehicle, the road through which it reached the intersection is known and therefore we set $P([C_n = c_i]) = 0$ for all the courses c_i which do not originate from that road. The probability of courses that correspond to forbidden manoeuvres is set to a low value. All other manoeuvres are assumed to be equally probable.

4.4.2 $P(P|C) = \prod_{n=0}^{N} P(P_n|C_n)$

Probability of a pose, knowing the course. Independence between the vehicles is assumed. The likelihood of a pose while on the course c_i is defined as a bivariate normal distribution with no correlation between the position (x, y) and the orientation θ:

$$P(P_n|[C_n = c_i]) = \frac{1}{2\pi\sigma_\delta\sigma_\theta} \times e^{-\frac{1}{2}(\frac{\delta_i^2}{\sigma_\delta^2} + \frac{\theta_i^2}{\sigma_\theta^2})}$$

where δ_i is the distance between the vehicle's position (x, y) and its orthogonal projection (x', y') on course c_i, θ_i is the angle between the vehicle's orientation θ and the orientation of course c_i at point (x', y'). σ_δ (resp. σ_θ) is the standard deviation set for the distance (resp. the angle).

4.4.3 $P(D|P \wedge C) = \prod_{n=0}^{N} P(D_n|P_n \wedge C_n)$

Probability of a distance covered on a course (with the yield point of the course as a reference), knowing the course and the pose. Independence between the vehicles is assumed. This is a Dirac, since D can be calculated without uncertainty from the orthogonal projection of the pose P on the course C.

4.4.4 $P(T|C \wedge D) = \prod_{n=0}^{N} P(T_n|C_n \wedge D_n)$

Probability of a turn signal knowing the course and the distance covered on this course. Independence between the vehicles is assumed. This conditional probability is set by a rule-based algorithm that takes into account the geometrical and topological characteristics of the intersection. Details on this algorithm can be found in [14].

4.4.5 $P(Y) = \prod_{n=0}^{N} P(Y_n)$

Prior on the intention to yield. Independence between the vehicles is assumed. Since without any context we have no prior knowledge on a driver's yielding intention, it is set to uniform.

4.4.6 $P(Y'|C \wedge D \wedge S \wedge A) = \prod_{n=0}^{N} P({Y'}_n|C \wedge D \wedge S \wedge A)$

Probability that it is necessary for the driver to yield. The vehicles are not assumed to be independent. The necessity to yield is derived from the context of the situation: the traffic rules, the position on the road network of all the vehicles as well as their speed and acceleration. More specifically, $P([{Y'}_n = \mathit{yield}]|C \wedge D \wedge S \wedge A)$ is defined using information available in the literature about the typical behaviours of vehicles at intersections. In [15, 16, 17, 18], statistical analysis and probabilistic models are provided for gap acceptance, stopping behaviour, etc. From these, it is possible to derive an indication of the necessity for a vehicle to yield. For example if a vehicle v_n is heading towards a give way intersection the calculation could be:

(1) Calculate the expected time t_n for v_n to reach the yield point of the course it is on : $t_n = f(C_n, D_n, S_n, A_n)$

(2) For all vehicle v_m on a priority road,

- calculate the expected time t_m for v_m to reach the point where C_n and C_m intersect: $t_m = f(C_n, C_m, D_m, S_m, A_m)$

- derive the available gap t_n^m for v_n to execute its manoeuvre before v_m reaches the intersection: $t_n^m = f(t_n, t_m)$

- calculate the probability p_n^m that the gap is sufficient using a gap acceptance model (e.g. [16])

(3) Derive the necessity for v_n to yield:

$$P([Y'_n = yield]|C \wedge D \wedge S \wedge A) = 1 - min_m(p_n^m)$$

4.4.7 $P(S \wedge A|Y \wedge C \wedge D) = \prod_{n=0}^{N} P(S_n \wedge A_n|Y_n \wedge C_n \wedge D_n)$

Probability of a joint speed and acceleration knowing the course, the distance covered on this course and the yielding intention. Independence between the vehicles is assumed. The distribution is generated using typical speeds and accelerations and take into account the shape of the course (e.g. speeds are typically lower for turn manoeuvres because the course is curvy), the distance covered on the course (e.g. for a vehicle that will yield, its typical speed will become lower as it gets closer to the yield point), and the limitations on vehicle dynamics (acceleration, braking capability).

Available additional information such as the characteristics of the intersection (e.g. visibility) and of the driver (e.g. age, gender, affective state) can be used to further improve the model.

4.4.8 $P(\lambda|Y \wedge Y') = \prod_{n=0}^{N} P(\lambda_n|Y_n \wedge Y'_n)$

Probability that the yielding intention is consistent with the necessity to yield. Since Y_n and Y'_n are consistent only when they are equal, the following parametric form is used:

$$P([\lambda_n = 1]|Y_n \wedge Y'_n) = \begin{cases} 1 & if\ Y_n = Y'_n \\ 0 & if\ Y_n \neq Y'_n \end{cases}$$

5 Questions

Among all the possible questions that can be asked to the model described in Section 4, two are particularly relevant for the problems of situation assessment and risk assessment at intersections.

5.1 Manoeuvre prediction

Our first proposition is to use the model to jointly infer the manoeuvre performed by all the vehicles in the scene, using observations on the vehicles' behaviour and our knowledge that drivers tend to respect traffic rules. The question to be asked in this case is:

$$\begin{aligned}
&P(C|p \wedge s \wedge a \wedge t \wedge [\lambda = 1]) \\
&\propto \textstyle\sum_D \sum_Y \sum_{Y'} P(C) \times P(p|C) \times P(D|p \wedge C) \\
&\quad \times P(t|C \wedge D) \times P(Y) \times P(s \wedge a|Y \wedge C \wedge D) \\
&\quad \times P(Y'|C \wedge D \wedge s \wedge a) \times P([\lambda = 1]|Y \wedge Y') \\
&\propto \textstyle\sum_{Y=Y'} P(C) \times P(p|C) \\
&\quad \times P(t|C \wedge [D = f(p, C)]) \\
&\quad \times P(s \wedge a|Y \wedge C \wedge [D = f(p, C)]) \\
&\quad \times P(Y'|C \wedge [D = f(p, C)] \wedge s \wedge a)
\end{aligned} \tag{2}$$

The advantage of this approach over conventional approaches for manoeuvre prediction is that it takes into account the fact that the context (layout of the intersection, presence of other vehicles, traffic rules) puts constraints on the execution of a manoeuvre by a driver. As was shown in Section 2.2, this plays a important role for accurate manoeuvre prediction.

5.2 Risk assessment

As a solution to the problem of risk assessment at intersections, we propose to use the model to jointly estimate the manoeuvre intention and yielding intention of the drivers, using observations on the vehicles' state and our knowledge that drivers tend to respect traffic rules:

$$\begin{aligned}
&P(C \wedge Y|p \wedge s \wedge a \wedge t \wedge [\lambda = 1]) \\
&\propto \textstyle\sum_D \sum_{Y'} P(C) \times P(p|C) \times P(D|p \wedge C) \\
&\quad \times P(t|C \wedge D) \times P(Y) \times P(s \wedge a|Y \wedge C \wedge D) \\
&\quad \times P(Y'|C \wedge D \wedge s \wedge a) \times P([\lambda = 1]|Y \wedge Y') \\
&\propto P(C) \times P(p|C) \\
&\quad \times P(t|C \wedge [D = f(p, C)]) \\
&\quad \times P(s \wedge a|Y \wedge C \wedge [D = f(p, C)]) \\
&\quad \times P([Y' = Y]|C \wedge [D = f(p, C)] \wedge s \wedge a)
\end{aligned} \tag{3}$$

It is then possible to identify potential conflicts using the position, intended manoeuvre and intention to yield of all the vehicles. When compared with conventional methods, this approach has the advantage of a reduced number of false alarms while still being able to detect dangerous situations (as was shown in Section 2.2).

6 Conclusions and future works

Situation assessment is crucial for intelligent vehicles, since a good understanding of the scene is necessary for the system to make relevant decisions (such as emergency braking or driver warning). The task is particularly challenging at road intersections because of the large number of possible scenarios. It is current practice to simplify the manoeuvre prediction problem by assuming independence between the vehicles in the scene. In this report we show that this leads to overestimating the risk in very common scenarios, making this approach unusable in practice for ADAS applications. As an alternative we propose a probabilistic model for vehicles traversing an unsignalised intersection that accounts for the mutual influences between the vehicles in the scene. The approach incorporates knowledge about the traffic rules and the layout of the intersection. It can be used for manoeuvre recognition or risk assessment and does not suffer from the shortcomings mentioned above.

The system is in the process of being implemented with a framework similar to the one used in our previous work [19, 14]. The approach will be evaluated by measuring how early it is able to make a correct prediction of the manoeuvre performed by a driver (evaluation similar to [12] and [19]). Comparing the model with a simpler version of the model (without Y, Y' and λ) will allow to evaluate the impact of taking into account vehicle interactions.

Acknowledgement

The authors would like to thank Dr. J. Diard for useful discussions about the model.

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Éditeur
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ISSN 0249-6399