Action Recognition And Prediction For Driver Assistance Systems Using Dynamic Belief Networks

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Abstract: The design of advanced driver assistance systems always aims at enabling the driver to master today's traffic in a more safe and comfortable way. In order to judge the risks in a situation and initiate precautionary actions, future systems have to possess the capability to predict the behavior of surrounding traffic participants. This paper outlines an approach to predictive situation analysis for driver assistance systems and discusses one key issue in more detail - namely the predictive action recognition. In this context, a situation representation formalism will be introduced that exploits time as a compact physical measure. Furthermore, it will be shown how probabilistic networks can be used for reasoning about driver (action) intentions and how such networks can help to cope with uncertainty resulting from inaccuracy in models and sensor data. First results are shown in simulation for highway overtake scenarios. In the situations presented the prediction for an upcoming lane change can be made by the assessment of the time gaps to the nearest neighbors of that specific vehicle.

Key words: prediction, situation model, situation analysis, traffic actions, dynamic belief networks.

1. Introduction

The challenging vision of research in the field of driver assistance is to develop a scene understanding methodology for advanced assistance systems that can cope with complex traffic scenarios. The aim is that the next generation of driver assistance systems is able to optimize their information, warning and control strategy by considering driver preferences, driver intentions and the overall traffic situation. As an example, early recognition of an intervening vehicle would help to adapt the control strategy of an ACC (Adaptive Cruise Control) system early enough to avoid that the safety distance is violated by a lane changing vehicle. Obviously, a strict control strategy that only considers the distance to the front vehicle is not capable to handle such a situation appropriately. Therefore, it becomes important that assistant systems are provided with concepts and techniques that enable prediction of future situations.

This article presents a general scheme for reasoning about driver motivations, goals, plans and actions that facilitates prediction at the planning and action level. According to this scheme, one aspect - the action (and action intention) at action level - is discussed in more detail. The approach taken at this level is to take typical driver behavior from driver models and field experiments and model this knowledge within

a probabilistic network, that can deal with uncertainty resulting from inaccuracy in models and sensor information.

1.1. Context

In a complex traffic situation with many vehicles, taking all possible actions into account would lead to combinatory explosion and is intractable. Therefore, prediction must be concentrated on relevant and probable driving behavior. Plan recognition is a reasonable concept to define plausible behavior that can help to focus the prediction of future situations. Looking at the variety of actions that a vehicle can perform in a dynamically evolving traffic situation, it is very difficult to predefine sequences or patterns of actions which match the behavior of drivers. Therefore, a plan recognition approach with pre-defined behavior patterns is less effective for driver assistance systems. Instead of modeling fixed plans for plan recognition, it proves better to predefine abstract motivations and to deduce goals and plans dynamically for all relevant vehicles in the scene.

Therefore, the general scheme introduced in the following suggests that plan recognition is based on dynamic, search-based planning, requiring only a set of abstract motivations which are defined beforehand by the designer.

Motivation-based behavior recognition and prediction, as in [Dagli et al. 02], is based on the idea that driving behavior is strongly affected by the motivations of the driver and that these motivations can be - at least for highway traffic - formulated with a few sentences. Therefore, the concept assumes that the drivers of all surrounding vehicles have a set of motivations. Furthermore, it assumes that the driver has situation dependent goals according to the given motivations. After setting the goals, the driver develops plans to achieve those goals and chooses the one with the highest probability of success, the highest convenience, or the minimum risk. The driver executes the plan, monitors the progress of the situation continuously and re-plans if the outcome becomes less attractive than in the initial situation.

The concept introduced here assumes a predefined set of possible and relevant motivations (relevant for the assistance system) for each driver in every situation. The system assigns possible goals to each of the vehicles in the scene and creates possible plans according to the goals and motivations. The plan recognition module takes these plans and assigns probability hypotheses according to the current observations. The early discovery of conflicts in plans of two or more vehicles require reliable prediction of future situations. Figure 1 gives an overview of this approach.

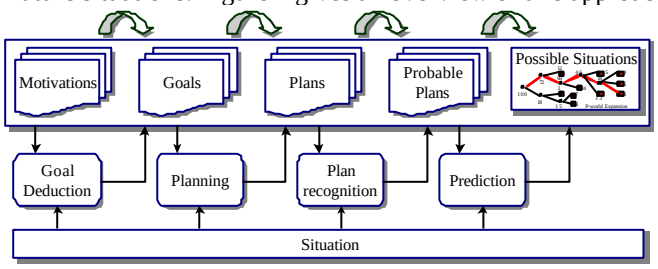


Figure 1 Approach to behavior recognition and prediction

Plan recognition is one important aspect but early discovery of conflicts in plans of two or more vehicles that can lead to critical situations require also reliable prediction of situations in the future. Prediction as it is suggested here is performed in a possible

situation/scenario structure, where possible futures are expanded within a tree and each node that represents a possible future is associated with a probability that is gained by the combination of the plan probabilities given by the plan recognition modules. This process is repeated for every vehicle in the scene until a probability has been assigned to each plan. The fusion of the most probable plans of all cars is then used to generate the possible situations - each of those situations is connected to a specific probability value.

The expanded possible situations are the basis of the situation analysis. Basically, situation analysis looks for relevant situations in the future that may affect the overall information, warning and control strategy of the assistance function. If the probability of a critical situation observed in the possible situations structure exceeds a certain threshold, the assistance system responsible for handling this situation becomes active and initiates a precautionary action in form of a warning or vehicle control.

1.2. System architecture

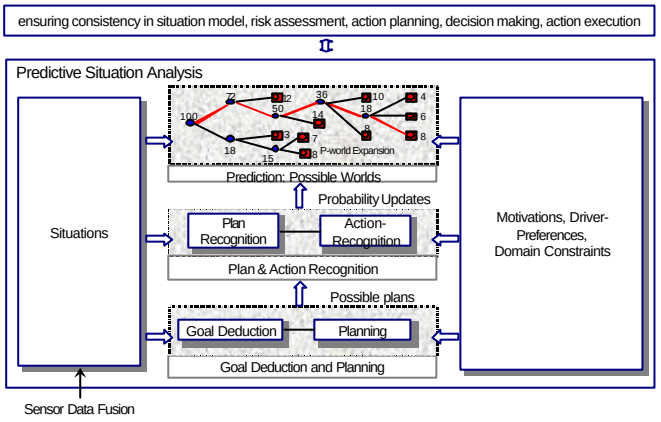


Figure 2 Architecture overview

Figure 2 shows the resulting software architecture: Situations and Motivations are stored in a global database. The whole world representation consists of a history of situations, motivations, goals, plans and possible worlds. The main component of the system is a heuristic planner that can cope with the variety of situations by exploiting heuristic search methods. Plans are created online according to pre-defined heuristics derived from motivations, the driver model and domain constraints. The plan recognition module takes the current set of possible plans and assigns probability hypotheses based on the observation of physical actions of vehicles. In order to make the prediction more efficient, prediction is focused on future situations resulting from combination of plans rather than considering each possible action. Furthermore, paths in the possible situations structure that are assigned a higher probability are expanded further into the future than less probable paths. The results (possible future situations) serve as basis for situation analysis. Please refer to [Dagli et al. 02] for a more detailed illustration (see Figure 2 Architecture overview).

The action recognition module that is discussed in the following is a self-contained unit that is responsible for the recognition of a single action within a plan description.

This is done by observation of the physical parameters of the vehicle. The result of the action recognition module is a probability assignment for each possible action which is fed into the plan recognition module.

2. Modeling principles

The following sections provide an introduction to the concepts and techniques which are the foundation for the realization of the action recognition model in chapter 3.2. Firstly, an overview of the used domain knowledge is given. Secondly, the used representation formalism - namely dynamic belief networks (DBN) - is introduced, to illustrate the methodologies behind the model.

2.1. Behavior Models

The notion of predictive[1] action recognition in traffic is based on the idea that actions in traffic are initiated by typical driving behaviors, and hence, even though afflicted with uncertainty, can be predicted.

The following sections introduce vehicle following and lane change models supported by experimental investigations of actions in traffic that form the basis for modeling action recognition with DBNs. The key concept in the probabilistic network is the representation of the (local) situation in terms of time measures. This form of representation is chosen mainly because of the lack of scalability of DBNs. The representation of physical parameters like distance, (relative) velocity and acceleration in time measures saves random variables in the belief network and causal links which reduces the statespace of probabilistic inference. The following measures are used in the dynamic belief network in section 3.2: net-time-gap (T_N) and time-to-collision (T_{TC}) concept which are defined as follows:

Definition 1

The net-time-gap (T_N) is defined as the time interval between two vehicles regarding an absolute position x_0. After the front vehicle (i-1) crosses the point x_0 it takes T_N for the following (ego i) vehicle to cross x_0, assuming that the physical parameters of i do not change during this interval:

$$T_{N,i} = \frac{-v_i \pm \sqrt{v_i^2 + 2\Delta x_i a_i}}{a_i} \qquad (1)$$

where Δx_i is the free space between both vehicles, v_i and a_i are the velocity and acceleration of the ego vehicle, respectively.

Definition 2

The time-to-collision (T_{TC}) is the time that is needed by vehicle (ego i) to reach (or collide with) the front vehicle (i-1), assuming that physical parameters of both vehicles do not change during this interval:

$$T_{TC,i} = \frac{-\Delta v_i \pm \sqrt{\Delta v_i^2 + 2\Delta x_i \Delta a_i}}{\Delta a_i} \qquad (2)$$

[1] The term predictive is related to the fact, that the aim is to recognize the intention to an action before it actually occurs.

where Δx_i *is the free space between both vehicles,* Δv_i *and* Δa_i *are the relative velocity and relative acceleration, respectively*

2.1.1. Vehicle following

The optimum velocity model (OVM)

In [Bando et al. 95] a microscopic vehicle following model, called Optimum Velocity Model (OVM [2]), is presented where the following behavior is stated with a simple differential equation:

$$a_i = k\left(V_{i,optimal}\left(\Delta x_i\right) - v_i\right) \qquad (3)$$

The parameter *k* reflects the sensibility and must be adjusted to the specific driver (see [Bando et al. 95] or [Manstetten et al. 97] for further detail). The optimum velocity $V_{optimal}$ is dependent on the distance and is given by a hyperbolic function:

$$V_{i,\,optimal}\left(\Delta x_i\right) = c_1\left(\tanh\left(c_2\left(\Delta x_i - c_3\right)\right) + c_4\right) \qquad (4)$$

In [Manstetten et al. 97] the initial model for Japanese highway traffic is adapted to city traffic in Germany, by the adjustment of the parameters c_1, c_2, c_3 and c_4 [3]. Several tests with this adjusted model that where performed to tune the parameters of the DBN have shown that typical values of T_N are between 1.3 and 1.4 seconds where the time-to-collision T_{TC} oscillates at high levels (>50sec).

The vehicle following model according to Wiedemann

A frequently cited vehicle following model is given in [Wiedemann 74], which considers thresholds in human perception and reaction. The model explicitly considers inaccuracy and resolution of human perception for distances and relative velocity.

The author defines four states for vehicle following scenarios:

1. *Unaffected:* Front vehicle is too far and there is no rapprochement observable. The driver drives at desired speed.
2. *Consciously affected*: The driver recognizes the rapprochement and starts braking.
3. *Unconsciously affected:* For $\Delta v_i \approx 0$ the driver can not recognize whether the distance increases or decreases. The driver keeps the last chosen velocity, which leads to a hysterisis effect.
4. *Aversion of danger:* If the distance falls below the minimum following distance, the driver brakes harder than in case 2.

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[2] The model assumes an optimal velocity for vehicle following. The introduced control equation seems to be dependent only on this "*optimal velocity*" (the names origin). Since this optimal velocity is also dependent on the distance, over another equation, the control strategy considers both: the distance and the relative velocity. In which sense the optimal velocity is optimal is not stated.

[3] Manstetten et. al. define c1 = 7.84; c2 = 0.184; c3 = 10.4 and c4 = 0.913. The desired velocity for driving without front vehicle is the desired velocity which is V ($\Delta x \rightarrow \infty$) = 15m/s for the defined parameters.

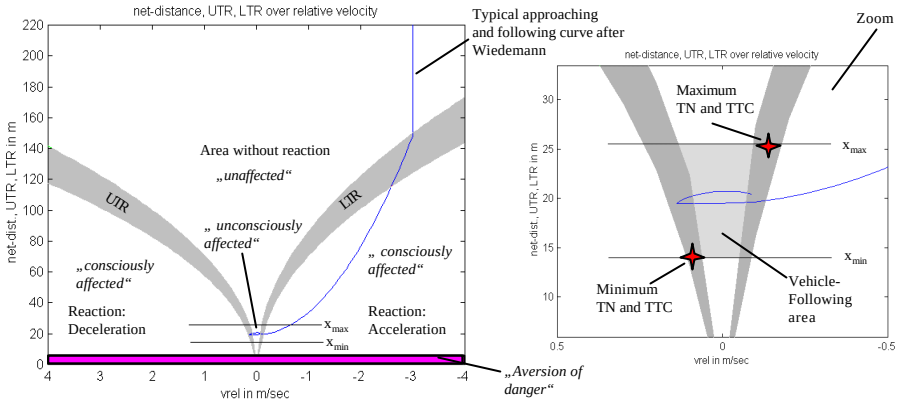


Figure 3 Vehicle following model after Wiedemann, [Wiedemann 74]

The interesting states are those which arise in the stationary vehicle following state – consciously and unconsciously affected. Here, the relative velocity and distance oscillate within certain bounds that are defined as follows:

Definition 3

UTR is the threshold where the following vehicle decelerates:

$$UTR: \Delta x = \sqrt{k_2 \Delta \dot{x}} \text{ for } \{\Delta \dot{x} \leq 0\} \quad (5)$$

LTR is the threshold where the following vehicle accelerates:

$$LTR: \Delta x = \sqrt{k_3 \Delta \dot{x}} \text{ for } \{\Delta \dot{x} > 0\} \quad (6)$$

$\Delta x_{\min}$ *is the minimum following distance and is given by where* Δx_s *is the distance to stop*

$$\Delta x_{\min} = \Delta x_s + \sqrt{k_1 \Delta \dot{x}} \quad (7)$$

The maximum following distance $\Delta x_{\max}$ *is roughly twice the minimum distance.*

$$\Delta x_{\max} \approx 2\Delta x_{\min} \quad (8)$$

The properties that have to be satisfied in the stationary vehicle following (VF) state can be derived from the above statements, which leads to:

$$\exists i: \Delta x_i > \Delta x_{i,\min} \wedge \Delta x_i < \Delta x_{i,\max} \wedge \left(\Delta x_i < \sqrt{k_2 \Delta \dot{x}_i} \wedge \Delta \dot{x}_i \leq 0 \vee \Delta x_i < \sqrt{k_3 \Delta \dot{x}_i} \wedge \Delta \dot{x}_i > 0\right) \rightarrow VF(i) \quad (9)$$

As shown in Figure 3, typical values for maximum and minimum T_N and T_{TC} can be concluded from this equation. Simulations with adapted parameters show T_N in the range of 1.45-1.55 seconds for the stationary case and T_{TC} oscillates at high levels like in the OVM model. Figure 3 depicts the results for adapted parameters[4] gained by simulation.

Experimental results

Experimental results given in [Hiller 99] and [Kienzle 00] show that T_Ns and T_{TC}s tend to be smaller as those gained by simulation with the models above. The authors identify a maximum of roughly 1 second for T_N. The authors further claim that drivers accept foreseeable risk, e.g. very small T_Ns are given in scenarios where the front vehicle changes its lane or the following vehicle intends to overtake.

[4] k_1=10sm, x_s=2m, k_2= 0.75 10^4 and k_3=-0.5 10^4

2.1.2. Lane change models

Most lane change models divide the lane change process in phases, [Fastenmaier et. al. 01], [Ehmanns 01]:

- The decision process of a lane change, where this process can be further sub-divided in phases (see below).
- The initiation and announcement of a lane change.
- The realization of a lane change.
- The end of a lane change.

The last two points are important for prediction as defined in 1.2 and play a minor role for action (intention) recognition and will not be discussed further. Interested readers can refer to [Fastenmaier et. al. 01].

Lane change desire and decision

[Ehmanns 01] sub-divides the decision process for lane change in further phases:

1. Perception of the situation
2. Evaluation of satisfaction on lane→lane change desire
3. Determine feasibility of lane change →lane change decision

Synthesis of lane change desire:

There can be many motivations leading to a lane change intention, [Dagli et. al. 02]. Following a certain route or overtaking slower vehicles are two named examples. Moreover, reactive behavior can also motivate lane changes, e.g. if a fast vehicle approaches from behind. [Ehmanns 01] defines a measure that summarizes the lane change desire: contentment on lane. This approach is the basis for modeling action recognition with DBNs, where contentment is expressed in terms of T_Ns and T_{TC}s.

Feasibility of lane change:

The feasibility of a lane change can be expressed in terms of T_Ns and T_{TC}s to the nearest neighbors, as done in the experimental investigations of [Ehmanns 01] and [Fastemaier et. al 01].

	Minimum Value	Maximum Value
T_n behind	0,3 sec	1,7 sec
T_n ahead	0,3 sec	3,0sec

Table 1 Minimal and maximal time gaps for lane change, aus [Ehmanns 01]

[Fastenmaier et. al. 01] introduces subjective values T_N=0.6sec and T_{TC}=3sec, where most drivers categorize the lane change as dangerous. Those values show that the evaluation of the feasibility of a lane change and also the lane change decision are driver (and also traffic type) dependent, which is an issue for the DBN model.

Lane change initiation

Action intention recognition requires the evaluation of typical behavior that initiates the action. Hence, the following variants for the initiation of a lane change will be exploited in the DBN model in section 3.2.

- In most European countries the initiation of a lane change using a turn indicator is prescribed by law. Unfortunately, this is not applicable for vehicles around because reliable detection of the vehicle turn signal is unsolved and a major issue in environment perception. Assuming inter-vehicle communication the turn

signal can be transmitted to concerning vehicles, but can not be the single source of evidence.

- In many cases, the obligation to initiate a lane change by using a turn indicator signal is omitted. A second source of evidence, that can be used in the DBN, is the offset and also the relative velocity to the center of the lane.
- Further evidence can be collected by evaluating the acceleration and decelerations processes of the vehicle. As shown in the preceding section there is a relation between T_Ns and T_{TC}s to the target lane that influences the lane change decision. The thesis utilized here is that the probability for a lane change increases if the conditions for vehicle-following models are fulfilled for the neighboring lane.

2.1.3. Summary

Models and experimental results presented so far are the basis for designing an action recognition model for driver assistance systems. As a matter of fact human driving behavior is subject to variances, and hence predicting driver-vehicle interactions is afflicted with uncertainty. The approach presented here consists of applying concepts and techniques of probability theory to tackle the uncertainty in sensor data acquisition and behavior models.

2.2. Dynamic Belief Networks (DBN)

Belief networks are directed, acyclical graphs, which illustrate the causal dependencies between probabilistic variables. An associated inference engine provides the necessary adjustment of each variable's probability distribution including the dependencies and possible a priori knowledge, called evidence. Many time-series models, e.g. Hidden-Markov-models or Kalman-filters, are examples of dynamic belief networks. The precondition for such models is, that an event at *t-1* might result in an event at *t* but never vice versa. A simple one-state Markov-Model illustrates such a precondition in statement (10).

$$P(X_1, X_2, X_3, \Lambda\ , X_t) = P(X_1)P(X_1 \mid X_2)P(X_2 \mid X_3)\Lambda\ P(X_t \mid X_{t-1}) \qquad (10)$$

This precondition provides a great reduction of possible events X_{t+1} and makes the whole concept feasible. The order of the models can be adapted, i.e. more than two time-steps can be included in such a model.

A first order dynamic belief network is composed of two stationary models for each time step and a time transition model comprised of links describing the dependencies between two time steps. The resulting model can be seen as nothing more than a new stationary model.

Please refer to [Spiegelhalter et. al. 93] and [Pearl 88] for a more detailed discussion on belief networks. The inference engine used in this work is described in [Kjaerulff 92].

3. Action model and Action recognition

3.1. Action Model

Elementary (atomic) actions represent non-dividable operations at the planning level and also realistic activities that a driver can perform. Unlike discrete, fully observable and deterministic domains, as in user interfaces, an action in traffic at the physical

level represents a process that requires time and can only be determined with uncertainty, because these physical processes are subject to variances. Hence, an action model for traffic must satisfy requirements raised by the planning level algorithms (see [Dagli et al. 02]) and also by the peculiarities of the traffic domain.
Several action model concepts have been proposed in the context of autonomous vehicles and driver assistance systems, see [Moeck-Hecker 94], [Zeller 96] and [Forbes et al. 00]. The dynamic (online) planning approach for plan recognition has additional requirements, so that a slightly different model will be proposed here.
The model satisfies the following requirements:

- Actions represent physical processes that continuously change the vehicle (and situation) state. These processes, even though afflicted with uncertainty, must be observable through sensors.
- The completion of an action leads to a change in the discretely represented situation model at the planning level.
- Actions are univocally distinguishable in the formulation and the degree of abstraction from higher level concepts as motivation, goal and plans.

In [Dagli et al. 02] an action model is introduced in the context of search-based action planning for highway traffic. The model depicted in Figure 4 excels by the chosen level of abstraction that facilitates efficient planning. The model is based on the considerations in section 2.1. Hence, the two actions beginning with the term *Remain* represent the vehicle following intention (if a vehicle in front exists). Therefore, evidence for lateral or longitudinal action which is intended to stabilize the vehicle, either to adjust the offset to the center of the lane or adjust the speed and distance to a vehicle in front, are seen as evidence for the *Remain* actions. Moreover, there is always a plan generated for plan recognition and also a goal or motivation, which is expressed through the *Remain* actions. The following definitions illustrate the properties of the action model.

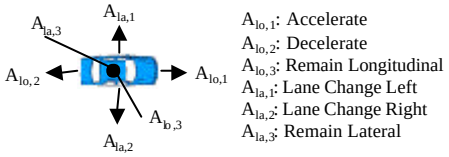


Figure 4 Action model for action recognition

The following definitions illustrate additional properties of the action model.

Definition 4

The actions are grouped in longitudinal (lo) and lateral (la) actions. Actions within a group are exclusive, i.e. if an action in a group is recognized and belongs to the evidence set E, then all other actions in the same group are not a member of E.

$$\exists i : A_{g,i} \in E \rightarrow \bigwedge_{i \neq j,\, g \in \{lo,la\}} A_{g,j} \notin E \qquad (11)$$

Definition 4, means e.g., that an accelerating car cannot break simultaneously or a lane change to the left cannot take place while the car changes lane to the right. This definition also means that sum of probabilities of a group is always 1.

Definition 5

Actions belonging to different groups may be executed at the same time or observe a certain time relation. These relations can be qualitatively formulated with 13 time relations, [Allen 84][5]

$$A_{g,i}\ op\ A_{f,j}\ \text{for}\ \{g, f \in \{lo, la\} \mid g \neq f\};\ i \in g;\ j \in f;\ op = \{<, >, =, m, mi, o, oi, d, di, s, si, f, fi\} \quad (12)$$

Definition 5 explains time relations between specific actions; e.g. $A_{lo,1}\ m\ A_{la,2}$ defines a period of acceleration followed by a lane change to the right. Definition 4 is reflected in the structure[6] of the DBN, the latter plays a role in the expansion of the possible future situations. Regardless of time dependencies, there are dependencies between actions from different groups, for e.g. a lane change to the left is mostly associated with an acceleration action. Dependencies between groups are modeled in the dependency graph (see section 3.2).

3.2. Action Recognition

The emphasis of the DBN illustrated in the following is early recognition of driver actions (intended actions of the driver) which is possible by considering time gaps to the nearest neighbors of the vehicle and also by expanding this static relationship over a number of time steps (prediction[7]).

The model in Figure 5 is not expanded over time for the sake of readability. The dashed links represent the time transition model that links the stationary models while the solid links represent the causal connections of the network.

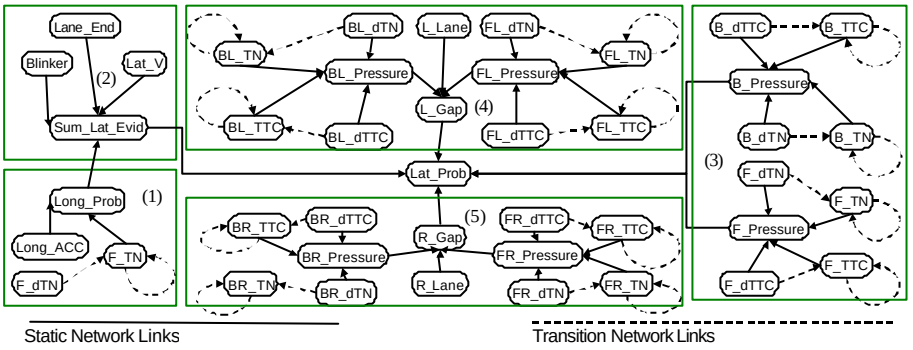


Figure 5 Resulting DBN

This model can handle traffic on roads with more than two lanes. Information is only needed and gathered as evidence from the neighboring lanes to the left and to the right.

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[5] Allen defines 7 time relations: $op = \{<, =, m, o, d, s, f\}$, corresponding to smaller, equal, meets, overlaps, during, starts, finishes. A total number of 13 arises by considering also the inverses $op = \{>, =, mi, oi, di, si, fi\}$.

[6] Actions within a group are allocated to one node in the probabilistic network. This ensures that the sum of probabilities within a group is always 1.

[7] Prediction here refers to the short term prediction of an action and must not be confused with prediction as defined in section 1.2.

In Figure 5 the nodes' names consist of certain abbreviations. The first letter(s) indicates what neighboring car is the source of possible evidence; e.g. the node FR_TN represents a probability distribution over the net-time-gap to the vehicle which is right and ahead of the concerned vehicle as does B_TTC for the time-to-collision in respect to the vehicle in the back. The nodes X_dTTC represent the change of the time-to-collision in respect to the vehicle X. The X_PRESSURE nodes sums up the evidence concerning the neighboring vehicle X and represents the pressure that this car emits. The pressure a neighboring car emits increases the closer the car is to the current position of the ego car and the higher its relative velocity is.
The nodes Lat_Prob and Long_Prob represent query variables which indicate the action probabilities for the action model in section 3.1. The following table explains the nodes of the network:

Node	Description
X_TTC	Time-To-Collision values to the vehicles of the same and neighboring lanes. The abbreviations B, F stand for back, front and R, L for right, left, respectively.
X_TN	Net-Time-Gap values to the vehicles. Same as X_TTC.
X_Pressure	These nodes are introduced to reduced the amount conditional probabilities within the CPT (see equation 13 below). The abstract measure summarizes the T_n and T_{tc} and their derivations to a single boolean value.
L_Gap, R_Gap	The two pressure values regarding the neighboring lanes are again summarized to a L_Gap and R_Gap value
Blinker	Evidence node representing the turn signal indicator state. This signal is only available for the vehicle equipped with the system.
Lane_End	This node states whether the lane on which the concerning vehicle ends, and if it ends, in which direction the vehicle has to perform merging. This evidence is only available if appropriate navigation information is provided by (GPS) sensors.
Lat_Evid	The lateral offset of the vehicle together with the relative velocity relative to the center (time to lane crossing as a derived measure) of the lane are incorporated in this value.
Long_Evid	Similar as Lat_Evid, but for the longitudinal actions. Here, the acceleration or deceleration of the vehicle is taken as node value.
Sum_Lat_Evid	Summarizes the lateral evidences (except the derived pressure values) for a lateral action within one node. This reduces the amount of conditional probabilities that have to be specified.
Long_Prob	Query node that state whether the vehicle performs a motivated acceleration or deceleration process. Motivated in this context means that, e.g. an acceleration of a vehicle to adjust the gap to the front vehicle is taken as evidence for the Remain_Long action.
Lat_Prob	Query node that states the probability distribution over the lateral actions.

Table 2 Description of the nodes

In the following the network is further divided in 5 subnets as depicted in Figure 5. The subnets and their functions are explained in the following.

1. The `Long_Prob` node is causally dependent on the time gap (`F_TN`) and also on the evidence given by the sensed longitudinal acceleration (`Long_ACC`). The acceleration is evaluated with respect to the time gap which is an indication for the vehicle following intention. Acceleration or deceleration to adjust the gap to the front vehicle is taken as evidence for the vehicle following intention and hence for the `Remain_Long` action.
2. This subnet summarizes the evidence for a possible lane change: the turn indicator signal (`Blinker`), the lateral velocity (`Lat_V`), longitudinal action evidence (`Long_Prob`) and the lane information (`Lane_End`).
3. This subnet models the contentment on lane as introduced in chapter 2.1.2: The little the time gaps on the same lane the less the contentment is and a lane change becomes more probable, where small T_Ns and T_{TC}s to the back increase the probability for a lane change to the right and small T_Ns and T_{TC}s to the front increase the probability for a lane change to the left. The pressure (`F_PRESSURE`) emitted from the car in front is determined by the net-time-gap (`F_TN`) and the time-to-collision (`F_TTC`) as well as their variation over the last time steps (`F_dTN, F_dTTC`). The same approach is taken for the car in the back.
4. The `Lat_Prob` is causally dependent on time gaps and also T_{TC}s on the neighboring lanes, where the models given in section 2.1 are expressed in the conditional probability table of the nodes. The more the vehicle following model expressed in terms of T_Ns and T_{TC}s is satisfied for a particular lane, the more likely a lane change is in the corresponding direction. This works well for free traffic but in the case of crowded traffic these conditions are satisfied without being an indication for a lane change. Therefore, the T_Ns and T_{TC}s can not be the single source of evidence for a lane change, so that the evidence provided in subnets 2 and 3 is also needed.

   The subnet works just like subnet 3 but for the lane left of the occupied lane. The pressure each car emits is generated using knowledge about the relevant time gaps. Again the car in front and in the back on the specific lane are the ones monitored. The key values are the net-time-gaps (`BL_TN, FL_TN`) and time-to-collision (`BL_TTC, FL_TTC`) and their respective derivatives (`BL_dTN, FL_dTN, BL_dTTC, FL_dTTC`).
5. Same as subnet 4 for lane change to the right.

The time transition model applies only for continuos nodes representing T_Ns and T_{TC}s. The network is expanded over time whereby T_Ns and T_{TC}s are recalculated for each step with the aid of the derivations of the time gaps and TTC and fed into the network as new evidence for the next time step. With this, a small horizon prediction can already be performed within the model, based on the assumption that the physical parameters of the vehicle will not change significantly within a short period of time.

All other nodes (except evidence and query nodes) represent intermediate nodes that are included to reduce the amount of assignments in the conditional probability tables. This beneficial property of belief networks is due to the conditional independence

assumption inherent to those models which states that any node is independent of all ancestors given its parents, which results in following relationship[8]:

$$P(X_i \mid X_{i+1}, \mathrm{K}\ , X_n) = P(X_i \mid Parents(X_i)) \qquad (13)$$

One remaining issue is adaptability of the model to drivers and traffic flow types, where an adaptability for the driver is only applicable for the driver of the own vehicle. In fact two approaches have been taken for adaptation of the network: Bayesian learning and re-instantiation with adapted and predefined parameters.
The first approach exposed to be infeasible because of the required learning data sample size and the inherent computational complexity in learning algorithms which makes real-time online learning infeasible. Further investigations of bayesian learning will be conducted as soon the required learning data is available. The second approach provides good results, when the parameterization of the network is tuned according to predefined driver and traffic types.
The following points are contemplating the properties of the model:

- DBNs are not scalable[9], and therefore reducing complexity in models is a major issue in designing such networks. Hence, the physical parameters distance, velocity, acceleration that are relevant are expressed in terms of "compressed" physical parameters of time.
- Representing the situation in terms of nearest neighbors reduces complexity and is sufficient for early action recognition based on physical parameters of vehicles and vehicle relations.
- DBNs provide concepts and techniques that can be used for short horizon prediction. The approach here proposes a continuation of physical parameters (T_Ns and T_{TTC}s) that facilitate reasoning about future beliefs.
- The adaptation of the network for different driver and traffic types is done by re-instantiation of the network with different parameters. Nevertheless, the major aim is to apply learning algorithms for the adaptation of the network shown here. Major benefits are expected regarding parameterization of the network when representative data for driving behavior is collected and used for learning.

4. Simulation results

Simulations have been carried out for various highway scenarios and the applicability to future assistance systems has been assessed. Figure 6 shows an excerpt of the results gained for overtaking scenarios. The prediction horizon in the DBN is set to 3 time steps where one time slice is 0.5 seconds. The figure shows that a probability of 0.8 is assigned to the change left action roughly 1.5 seconds before the actual lane change is performed. This is because before a lane change (or a turn indicator) is observed, the time gaps to the neighbors on the target lane must be adjusted, which provides additional evidence for early action recognition.
More important is the fact that the T_Ns and T_{TC}s are predicted within the 1s prediction horizon. This means the probability distributions within the T_N and T_{TC} nodes are recalculated by probabilistic inference given the assumption that the derivations of

[8] Please refer to introductory texts in [Dean 95], [Russel 96] that provide a comprehensive illustration of this topic.
[9] Inference in belief networks is NP-Hard

T_Ns and T_{TC}s do not change within the short prediction horizon. With that, the probability distribution of the `Lat_Prob` node for the predicted T_Ns and T_{TC}s can be extracted from the network. Further investigations have shown that a prediction horizon larger than 2s is not feasible because of the inherent assumption that the change of the T_Ns and T_{TC}s over each time step will not change within the prediction interval (the hypotheses become to inaccurate, when the behavior if the driver changes).

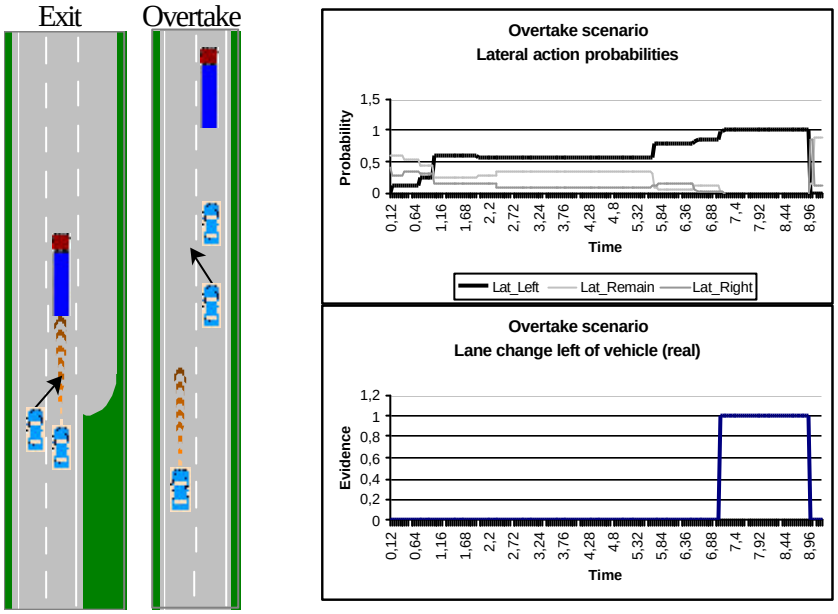


Figure 6 Highway scenarios and results of lane change probabilities for overtake scenarios. The prediction horizon is 3 time steps.

The advantages of the early recognition of a single action are twofold: Firstly, employing this approach to the general scheme introduced in chapter 1 enables early and reliable updates of the plan probabilities in the plan recognition module and enhances the prediction process. And secondly, the action (driver intention) recognition module can be used as self-contained unit and applied without realizing the whole framework, because the short horizon prediction achieved here can already bring enhancements for driver assistance systems. For instance, applying the approach to a lane change assistant would mean that necessary warnings can be identified earlier so that the reaction time of the driver can be bridged.

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5. Conclusion and outlook

Next generation assistance systems as adaptive cruise control (ACC) or lane change assistants should be able to perform predictive situation analysis to increase comfort and safety. The important aspect which makes up the quality of an assistance system is the interference strategy which determines when and how the assistance system informs, warns or even actively controls the vehicle. Without reasoning about driver intentions and predicting future situations this issue can hardly be solved.

The general scheme introduced at the beginning provides a framework for predictive situation analysis where action (intention) recognition is one major part. The approach for action recognition could give significant improvements to today's assistance systems (without applying the whole framework), especially to those coping with the driver in the loop. An appropriate information and warning strategy e.g. for a lane change assistant is conceivable, if the lane change intention of the driver can be determined with a certain probability. Hence, designing such a system requires looking beyond reactivity and control.

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