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Learning the Relevant Percepts of Modular Hierarchical Bayesian Driver Models using a Bayesian Information Criterion

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Abstract. Modeling drivers' behavior is essential for the rapid prototyping of error-compensating assistance systems. Various authors proposed control-theoretic and production-system models. Based on psychological studies various percepts and measures (angles, distances, time-to-x-measures) have been proposed for such models. These proposals are partly contradictory and depend on special experimental settings. A general computational vision theory of driving behavior is still pending. We propose the selection of drivers' percepts according to their statistical relevance. In this paper we present a new machine-learning method based on a variant of the Bayesian Information Criterion (BIC) using a *parent-child-monitor* to obtain minimal sets of percepts which are relevant for drivers' actions in arbitrary scenarios or maneuvers.

Keywords: Probabilistic Driver model, Bayesian Autonomous Driver model, Mixture-of-Behavior model, Bayesian Real-Time-Control, Machine-Learning, Bayesian Information Criterion, Hierarchical Bayesian Models

1 Introduction

The Human or Cognitive Centered Design of intelligent transport systems requires computational models of human behavior and cognition [1, 2]. Particularly the modeling of drivers' behavior is essential for the rapid prototyping of error-compensating assistance systems [1]. Based on psychological studies [3, 9-11, 13, 20, 21] various percepts and measures (angles, distances, time-to-x-measures) have been proposed for such models. These proposals are partly contradictory and depend on special experimental settings. A general computational vision theory of driving behaviour is still pending.

Due to the variability of human cognition and behavior*, the irreducible lack of knowledge about underlying cognitive mechanisms, and irreducible incompleteness of*

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knowledge about the environment [1] we conceptualize, estimate and implement models of human drivers as probabilistic models: Bayesian Autonomous Driver (BAD) models. In contrast to [21], BAD models don't need to be programmed like traditional simulation software but are condensed and abstracted in an objective manner using machine-learning techniques from human behavior traces.

2 Bayesian Autonomous Driver Mixture-of-Behaviors Models

In earlier research [14] we developed a BAD model with Dynamic Bayesian Networks based on the Bayesian Programming approach [1] and on the assumption that a *single* skill is sufficient for lateral and longitudinal control. Later, we realized that for modeling the *complex* competence of human drivers a *skill hierarchy* is necessary. We modified the simple BAD model architecture to a hierarchical modular probabilistic architecture to construct driver models by decomposing complex maneuvers into basic behaviors and vice versa: Bayesian Autonomous Driver Mixture-of-Behaviors (BAD MoB) models [5, 6, 15, 16].

BAD MoB models consist of *Gating*-, *Behavior-Classification*-, and *Action*-models. Their functional interaction allow the generation of context dependent driver behavior by sequencing and mixing pure basic behaviors [5, 6] (Fig. 1).

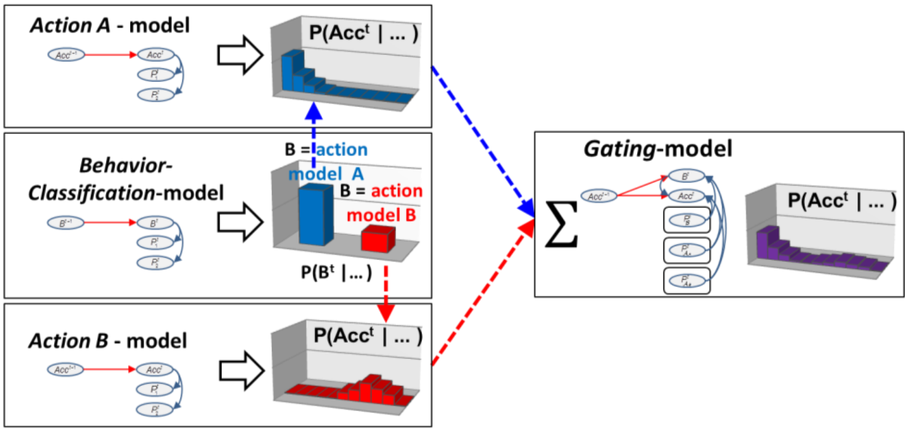


Fig. 1. Exemplary mixing of behaviors in a BAD MoB model assembled from two *Action*-models, one *Behavior-Classification*, and one *Gating* model. The *Gating*-model calculates a weighted sum over the answers of the two *Action*-models, according to the appropriateness of their corresponding behaviors, respectively their probabilities or mixing coefficients, inferred by the *Behavior-Classification*-model.

Based on a skill hierarchy, partitioning complex scenarios into maneuvers and maneuvers into simpler behaviors (cf. Fig. 2), each behavior is modeled by an *Action*-model. This is implemented by a dynamic Bayesian network that realizes the sensor-motor schema of the desired behavior. It can be utilized to infer the conditional probability distribution (CPD) of the actions given the former actions and the current percepts: $P(Actions^t|Actions^{t-1},Percepts^t)$. For each complex scenario (or maneuver) in the skill hierarchy a *Behavior-Classification*-model is used to infer the appropriateness of the corresponding simpler maneuvers (or behaviors). A *Gating*-model computes a weighted sum over the inferred CPDs of the *Action*-models by using the appropriateness of their corresponding behaviors, inferred by the *Behavior-Classification*-models in the form of mixing coefficients (Fig. 1). By calculating weighted sums over the mixture distributions BAD MoB models are able to combine mixture distributions in a hierarchically manner. Thus these models allow the combination of pure behaviors into more complex maneuvers and maneuvers into scenarios.

BAD MoB models sample random values $Actions^t = actions^t$ from the inferred CPD $P(Actions^t|Actions^{t-1},Percepts^t)$ every 50ms. These are used as motor commands to autonomously control (simulated) vehicles.

2.2 Skill hierarchy

For an experimental BAD MoB in the racing simulation TORCS[3], we defined a skill hierarchy of three hierarchical layers. The *Racing Scenario* was partitioned into the three *maneuvers LaneFollowing*, *CarFollowing* and *Overtaking*. *LaneFollowing* was partitioned into the *behaviors* for driving on a straight segment (*Straight*), through a wide curve (*Wide*) and through a sharp curve (*Sharp*), etc. pp. (Fig. 2).

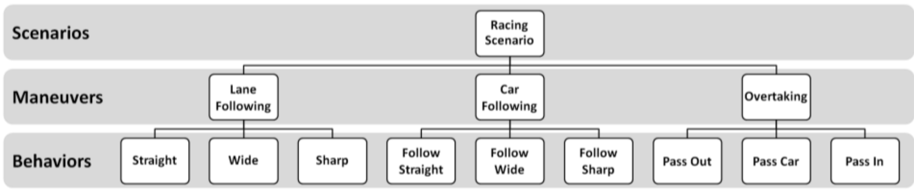


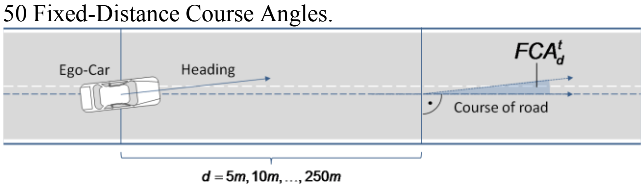
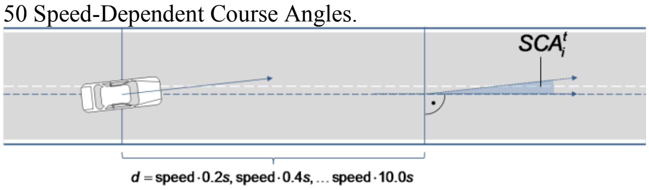
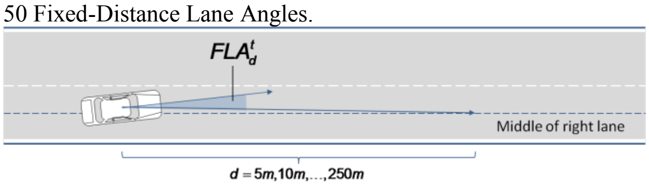
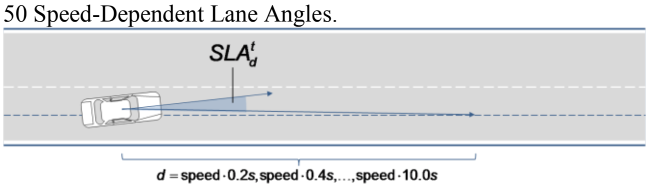
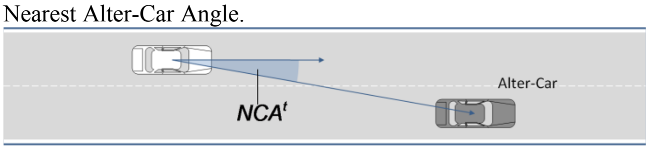
Fig. 2. Skill hierarchy for a racing scenario with three hierarchical layers.

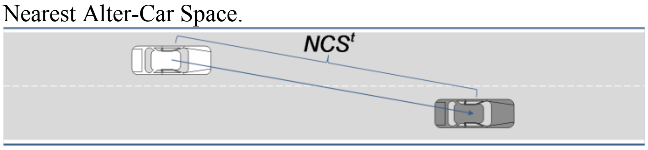
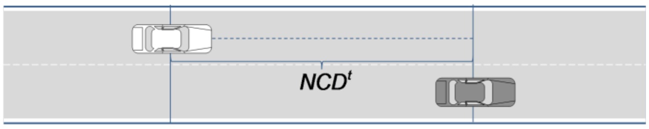
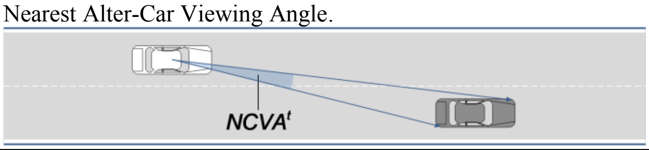
2.1 Training Phase

The learning of a BAD MoB model requires time series of human behavior traces. These were obtained from a single driver, who drove several laps on two different racing courses in the TORCS simulation. We recorded approximately 15000 data samples. Each time-stamped data record contained values for 211 discrete random variables (Table 1): two action-variables Acc^t and $Steer^t$, denoting the position of a combined acceleration and braking pedal and the steering wheel angle, four behavior-variables representing the partitioning of the task hierarchy (Fig. 2) and a set of 205 time-independent (estimates of distances and angles) and time-dependent percept-variables (TDPs), similar but not identical to Lee's time-to-x (tau) measures [12, 13, 17].

[3] http://torcs.sourceforge.net/ (last retrieved 2011-01-31)

Table 1. Overview of the two action-variables, four behavior-variables and 205 percept-variables defined for the foveal and ambient visual channel of the driver [7].

Variable	Range	Description
Acc^t	{0,…,14}	Position of a combined acceleration and braking pedal. Ranges from full braking (0) to full acceleration (14).
$Steer^t$	{0,…,29}	Steering wheel angle. Ranges from full turning to the right (0) to full turning to the left (29).
B^t_{Sc}	{0,…,2}	Represents the maneuvers *LaneFollowing*, *CarFollowing* and *Overtaking* that compose the *Racing Scenario*.
B^t_{LF}	{0,…,2}	Represents the *LaneFollowing* behaviors *Straight*, *Wide* and *Sharp*.
B^t_{CF}	{0,…,2}	Represents the *CarFollowing* behaviors *FollowStraight*, *FollowWide* and *FollowSharp*.
B^t_{OT}	{0,…,2}	Represents the *Overtaking* behaviors *PassOut*, *PassCar* and *PassIn*.
LS^t	{0,…,20}	Longitudinal speed of the ego-car.
FCA^t_{5m}, FCA^t_{10m}, …, FCA^t_{250m}	{0,…,20}	50 Fixed-Distance Course Angles. 
$SCA^t_{0.2s}$, $SCA^t_{0.4s}$, …, $SCA^t_{10.0s}$	{0,…,20}	50 Speed-Dependent Course Angles. 
FLA^t_{5m}, FLA^t_{10m}, …, FLA^t_{250m}	{0,…,20}	50 Fixed-Distance Lane Angles. 
$SLA^t_{0.2s}$, $SLA^t_{0.4s}$, …, $SLA^t_{10.0s}$	{0,…,20}	50 Speed-Dependent Lane Angles. 
NCA^t	{0,…,20}	Nearest Alter-Car Angle. 

NCS^t	{0,…,20}	Nearest Alter-Car Space. 
NCD^t	{0,…,20}	Nearest Alter-Car Distance. 
$NCVA^t$	{0,…,20}	Nearest Alter-Car Viewing Angle. 

2.3 Learning of Relevant Peephole Percepts

Until now the structures of skill hierarchies have to be created manually. But both the graph-structure of *Action*- and *Behavior-Classification*-models and the parameters of their (conditional) probability distributions can be obtained by machine-learning methods from time series of human behavior traces. To completely cover the skill hierarchy (Fig. 2) nine *Action*- and four *Behavior-Classification*-models have to be learnt [5, 6]. The structure of four complimentary *Gating*-models can then be derived automatically from the structure of the *Action*- and *Behavior-Classification*-models.

To ensure efficiency for the real-time control of a BAD MoB model, we constrain the structure of *Action*- and *Behavior-Classification*-models to dynamic (first order markov) naïve Bayesian Classifiers. For *Action*-models we further assume the action-variables Acc^t and $Steer^t$ to be independent given both of the former actions Acc^{t-1} and $Steer^{t-1}$, and that a percept must not be conditioned on *both* Acc^t and $Steer^t$. These assumptions allow the boosting of the inference performance by splitting the intended CPD $P(Acc^t,Steer^t|Acc^{t-1},Steer^{t-1},Percepts^t)$ into two independent distributions $P(Acc^t|Acc^{t-1},Steer^{t-1},Percepts^t)$ for longitudinal and $P(Steer^t|Acc^{t-1},Steer^{t-1},Percepts^t)$ for lateral control.

Our BAD MoB models rest on the assumption that there is considerable uncertainty about the relevant percepts for realization and classification of *natural* driving behaviors. So the relevant percepts should be identified during the modeling process. We rely on a step-wise structure-learning technique that exploits the probabilistic foundations of Bayesian driver models and determines the 'peephole' percepts from a universe of hypothetical possible or available percepts based on the *Bayesian Information Criterion* (BIC) [4, 8, 18].

2.3.1 The Parent-Child Bayesian Information Criterion

The BIC rewards how well a model fits the data while penalizing the model complexity. Let δ denote a set of n data rows associated with the behavior to be generated by an *Action*-model π_A or the mixture of behaviors to be classified by a *Behavior-Classification*-model π_B, $L(\delta|\pi)$ denote the likelihood of δ given a model π, and size(π) denote the size or complexity of a model π (we define as the number of edges in the DBN of the model) then the BIC for an *Action*-model π_A is defined as

$$\begin{aligned}&\log L(\delta \mid \pi_A) - \frac{size(\pi_A)}{2}\cdot\log n\\ &= \sum_{i=1}^{n}\left[\log P\left(actions^i, actions^{i-1}, percepts^i \mid \pi_A\right)\right] - \frac{size(\pi_A)}{2}\cdot\log n\end{aligned} \tag{1}$$

and the BIC for a *Behavior-Classification*-model π_B is defined as

$$\begin{aligned}&\log L(\delta \mid \pi_B) - \frac{size(\pi_B)}{2}\cdot\log n\\ &= \sum_{i=1}^{n}\left[\log P\left(behavior^i, behavior^{i-1}, percepts^i \mid \pi_B\right)\right] - \frac{size(\pi_B)}{2}\cdot\log n\,.\end{aligned} \tag{2}$$

To focalize on the intended purpose of *Action*- and *Behavior-Classification*-models, we evolved a version of the BIC, which we refer as the *Parent-Child BIC* (PCh-BIC), where the likelihood is replaced by a *parent-child-monitor* [4]. Following the foregoing definition, the PCh-BIC for an *Action*-model π_A is defined as

$$\sum_{i=1}^{n}\left[\log P\left(actions^i \mid actions^{i-1}, percepts^i, \pi_A\right)\right] - \frac{size(\pi_A)}{2}\cdot\log n \tag{3}$$

while the PCh-BIC for a *Behavior-Classification*-model π_B is defined as

$$\sum_{i=1}^{n}\left[\log P\left(behavior^i \mid percepts^i, \pi_B\right)\right] - \frac{size(\pi_B)}{2}\cdot\log n\,. \tag{4}$$

2.3.2 Learning Procedure

As the learning procedure of pertinent percepts doesn't differ between *Action*- and *Behavior-Classification*-models, it will be described for the learning of *Action*-models only: Starting with an initial *Action*-model π_A without any percepts (Fig. 3), new percepts are included in a step-wise manner.

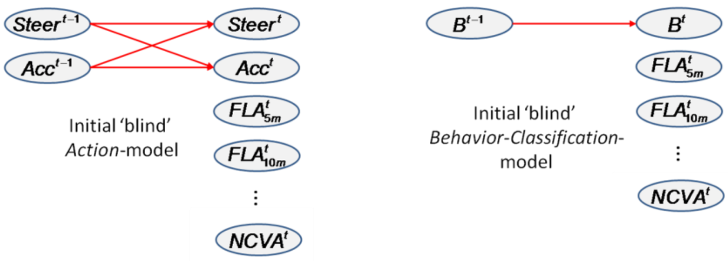


Fig. 3. DBN of an initial or blind *Action*-model and *Behavior-Classification*-model without any used percepts.

By now, a simple *greedy*-heuristic is used. For each one of the available percepts, the PCh-BIC is calculated for the initial model extended by an edge from the action-variable Acc^t to the respective percept. Using the intended inference for longitudinal control $P(Acc^t|Acc^{t-1},Steer^{t-1},Percepts^t)$ as the parent-child-monitor, the PCh-BIC is calculated by:

$$\sum_{i=1}^{n}\left[\log P\left(acc^i \mid acc^{i-1}, steer^{i-1}, fca^i_{5m},\ldots,ncva^i,\pi_A\right)\right]-\frac{size(\pi_A)}{2}\cdot\log n\,. \qquad \textbf{(5)}$$

The percept leading to the best PCh-BIC (Fig. 4) can be seen as the most pertinent percept of the given possibilities for longitudinal control and is permanently included in the model.

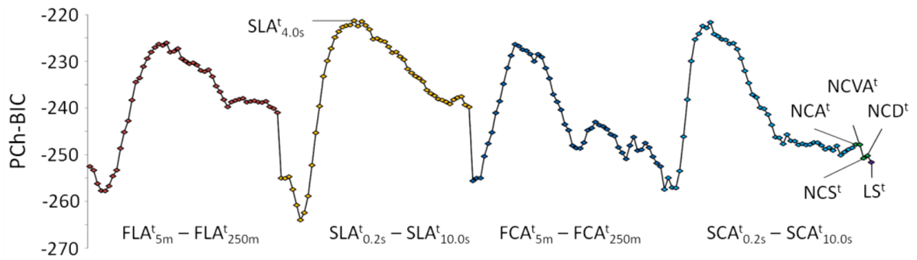


Fig. 4. Plot of PCh-BICs computed for an *Action*-model selecting one of 205 possible percepts for longitudinal control at a time. The PCh-BIC is maximized for a time-dependent percept $SLA^t_{4.0s}$, revealing it as the most pertinent percept of the given possibilities for longitudinal control.

Next, for each of the remaining percepts, the PCh-BIC is calculated for the improved model extended by a new edge from the action-variable $Steer^t$ to the respective percept. Using the intended inference for lateral control $P(Steer^t|Acc^{t-1},Steer^{t-1},Percepts^t)$ as the parent-child-monitor, the PCh-BIC is calculated by:

$$\sum_{i=1}^{n}\left[\log P\left(steer^i \mid acc^{i-1}, steer^{i-1}, fca^i_{5m},\ldots,ncva^i,\pi_A\right)\right]-\frac{size(\pi_A)}{2}\cdot\log n\,. \qquad \textbf{(6)}$$

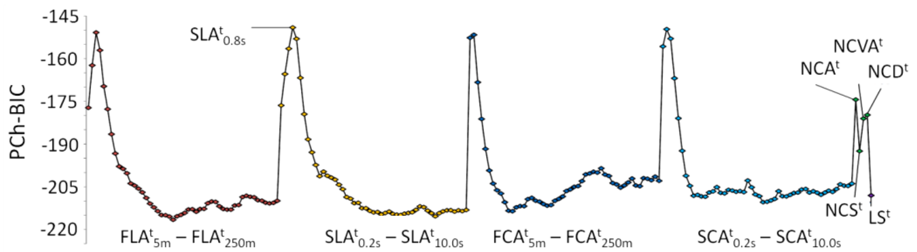


Fig. 5. Plot of PCh-BICs computed for an *Action*-model using one of 204 remaining possible percepts for lateral control at a time. The PCh-BIC is maximized for a time-dependent percept $SLA^t_{0.8s}$, revealing it as the most pertinent percept of the given possibilities for lateral control.

The percept leading to the best PCh-BIC (Fig. 5) can be seen respectively as the most pertinent percept of the given possibilities for lateral control and is likewise included permanently in the model.

The procedure will then be repeated with the new model. In this step-wise manner percepts are added until the PCh-BIC can't be improved any longer for any percept conditioned by Acc^t or $Steer^t$. As a result the learning procedure selects a minimal set of *peephole* percepts.

3 Results and Discussion

Using the learning procedure we revealed the most relevant peephole-percepts for all the nine *Action*-models and four *Behavior-Classification*-models of the skill hierarchy (Fig. 2). Learning the *Action*-models, 15 peephole percepts could be revealed as pertinent for longitudinal control, with the speed LS^t and the time-independent percept FLA^t_{5m} being the two most frequent ones (Table 2).

Table 2. Summary of the most relevant 15 peephole percepts used for longitudinal control.

Nr.	Percept	Times used	Relevant for longitudinal control in the
1	FCA^t_{40m}	1	PassCar *Action*-model
2	FCA^t_{80m}	1	FollowSharp *Action*-model
3	FCA^t_{110m}	1	FollowWide *Action*-model
4	FCA^t_{135m}	1	Sharp *Action*-model
5	FCA^t_{225m}	2	FollowStraight and PassIn *Action*-model
6	FLA^t_{5m}	3	Wide, Sharp and FollowWide *Action*-model
7	$SCA^t_{0.4s}$	1	PassIn *Action*-model
8	$SCA^t_{3.2s}$	1	Wide *Action*-model
9	$SLA^t_{4.0s}$	1	Straight *Action*-model
10	$SLA^t_{8.4s}$	1	FollowStraight *Action*-model
11	$SLA^t_{9.0s}$	1	PassOut *Action*-model
12	LS^t	4	Straight, Sharp, FollowStraight and PassOut *Action*-model
13	NCA^t	1	FollowSharp *Action*-model
14	NCD^t	1	FollowWide *Action*-model
15	$NCVA^t$	1	FollowSharp *Action*-model

For lateral control 22 pertinent percepts could be revealed, with the time-independent percept FCA^t_{5m} and the time-dependent percept $SLA^t_{0.8s}$ being the most frequent ones (Table 3).

Table 3. Summary of the most relevant 22 peephole percepts used for lateral control.

Nr.	Percept	Times used	Relevant for lateral control in the
1	FCA^t_{5m}	4	Straight, Sharp, FollowStraight and PassOut *Action*-model
2	FCA^t_{65m}	1	PassIn *Action*-model
3	FCA^t_{75m}	1	Sharp *Action*-model
4	FCA^t_{175m}	1	Sharp *Action*-model
5	FCA^t_{190m}	2	Straight and FollowWide *Action*-model
6	FLA^t_{5m}	1	PassOut *Action*-model
7	FLA^t_{10m}	1	FollowSharp *Action*-model

8	FLA^{t}_{15m}	1	FollowWide *Action*-model
9	FLA^{t}_{75m}	1	PassIn *Action*-model
10	FLA^{t}_{135m}	1	FollowWide *Action*-model
11	FLA^{t}_{185m}	1	Wide *Action*-model
12	FLA^{t}_{225m}	1	FollowStraight *Action*-model
13	$SLA^{t}_{0.2s}$	2	FollowWide and FollowSharp *Action*-model
14	$SLA^{t}_{0.8s}$	3	Straight, Wide and Sharp *Action*-model
15	$SLA^{t}_{1.2s}$	1	FollowSharp *Action*-model
16	$SLA^{t}_{1.6s}$	1	Sharp *Action*-model
17	$SLA^{t}_{2.0s}$	1	PassCar *Action*-model
18	$SLA^{t}_{8.8s}$	1	PassOut *Action*-model
19	$SLA^{t}_{9.6s}$	1	FollowSharp *Action*-model
20	$SCA^{t}_{0.4s}$	1	Wide *Action*-model
21	$SCA^{t}_{0.6s}$	1	FollowStraight *Action*-model
22	NCD^{t}	1	PassOut *Action*-model

Table 4 shows a summary of all used peephole percepts pertinent for classification of appropriate maneuvers or behaviors in the four *Behavior-Classification*-models.

Table 4. Summary of the most relevant 11 peephole percepts used for behavior-classification.

Nr.	Percept	Times used	Relevant for classification of driving behavior in the
1	FCA^{t}_{30m}	1	LaneFollowing *Behavior-Classification*-model
2	FCA^{t}_{60m}	1	LaneFollowing *Behavior-Classification*-model
3	FCA^{t}_{205m}	1	Racing Scenario *Behavior-Classification*-model
4	FLA^{t}_{5m}	2	CarFollowing and Scenario *Behavior-Classification*-model
5	FLA^{t}_{200m}	1	CarFollowing *Behavior-Classification*-model
6	FLA^{t}_{240m}	1	CarFollowing *Behavior-Classification*-model
7	$SCA^{t}_{0.2s}$	1	Overtaking *Behavior-Classification*-model
8	$SCA^{t}_{0.6s}$	2	LaneFollowing and CarFollowing *Behavior-Classification*-model
9	$SCA^{t}_{8.2s}$	1	LaneFollowing *Behavior-Classification*-model
10	NCA^{t}	1	Overtaking *Behavior-Classification*-model
11	NCD^{t}	1	Racing Scenario *Behavior-Classification*-model

Using only the 41 different peephole percepts that could be revealed during the learning process, the resulting BAD MoB model is able to drive on different racing courses in the TORCS simulation environment while overtaking slower vehicles (videos are available at http://www.lks.uni-oldenburg.de/46350.html).

For validation purposes we classed each of the models with a ranking of each five theoretical models of equal structure ranging from a totally uninformed model, solving the intended parent-child monitors (cf. (5) and (6)) with $P(searched|known) = 1/\lfloor searched \rfloor$ (a probability equal to randomness), to a perfect model, solving it with $P(searched|known) = 1$ (a probability equal to certainty). Based on these rankings, the Racing Scenario *Behavior-Classification*-model is the best, while the Overtaking *Behavior-Classification*-model is the worst of the four *Behavior-Classification*-models, though all of them show very great results. The *Action*-models allow a greater space for future improvement, with the PassCar *Action*-model being the best and the Sharp *Action*-model being the worst of all nine *Action*-models. As a next step, the percepts obtained should be validated by experiments with human drivers [16].

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