Mixture-of-Behaviors and Levels-of-Expertise in a Bayesian Autonomous Driver Model

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ABSTRACT

Traffic scenario simulations and risk-based design require Digital Human Models (DHMs) of human control strategies. Furthermore, it is tempting to prototype assistance systems on the basis of a human driver model cloning an expert driver. We present the model architecture for embedding probabilistic models of human driver expertise with sharing of *behaviors* in different driving *maneuvers*. These models implement the sensory-motor system of human drivers in a *mixture-of-behaviors (MoB)* architecture with *autonomous and goal-based attention allocation* processes. A Bayesian MoB model is able to decompose complex skills (*maneuvers*) into basic skills (*behaviors*) and vice versa. The Bayesian-MoB-Model defines a probability distribution over driver-vehicle trajectories so that it has the ability to *predict* agent's behavior, to *abduct* hazardous situations, to *generate* anticipatory plans and control, and to *plan* counteractive measures by *simulating*

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counterfactual behaviors or actions *preventing* hazardous situations.

Keywords: Bayesian models of human driver behavior and cognition, probabilistic driver model, Bayesian autonomous driver models, mixture-of-behavior model, visual attention allocation, prediction and abduction of behavior, anticipatory plans and control, counteractive measures, risk and hazardous prevention

INTRODUCTION

The Human or Cognitive Centered Design (HCD) of intelligent transport systems requires digital Models of Human Behavior and Cognition (MHBC) which are *embedded*, *context aware*, *personalized*, *adaptive*, and *anticipatory*. A special kind of MHBC is the *driver model* which is used mainly in traffic scenario simulations and risk-based design (Cacciabue, 2007).

Modeling drivers is a challenging topic because no well established psychological theory about driving is at hand. Even simple maneuvers like *braking* are not well understood empirically. With the need for smarter assistance the *problem of transferring human skills* (Xu, 2005) without having a well-founded skill theory becomes more and more apparent.

The conventional approach for driver modeling is the *handcrafting* of MHBC. An *ex post* evaluation of their human likeness or empirical validity and revision-evaluation cycles is obligatory. We propose as a *machine-learning* alternative the estimation of Bayesian MHBCs from human behavior traces. The learnt models are empirical valid by construction. An *ex post* evaluation of *Bayesian Autonomous Driver (BAD)* models is in principle not necessary when the statistical relations and conditional independencies between the pertinent variables in the data are mapped into the model.

The advantage of probabilistic models is their robustness facing the *irreducible incompleteness of knowledge* about the environment and the underlying psychological mechanisms (Bessiere, 2008).

A BAYESIAN MIXTURE OF BEHAVIORS MODEL

BAYESIAN AUTONOMOUS DRIVER MODELS

BAD models (Möbus et al., 2008; 2009a; 2009b, 2009c) are developed in the tradition of Bayesian expert systems (Pearl, 2009) and Bayesian (robot) Programming (Lebeltel et al., 2004, Bessiere et al., 2003, 2008). They describe phenomena on the basis of the joint probability distribution (JPD) and their factorization into conditional probability distributions (CPDs) of the observable pertinent variables. This is in contrast to models in cognitive architectures (e.g. ACT-R) which try to simulate latent or hidden cognitive algorithms and processes on a finer granular basis.

A BAD Mixture-of-Behaviors (BAD-MoB) model is a *Bayesian Program (BP)*, which is able to decompose complex skills (scenarios, maneuvers) into basic skills (= behaviors, actions) and vice versa. The basic *behaviors* or sensory-motor schemas could be shared and reused in different *maneuvers*. Context dependent complex driver behavior will be generated by mixing the pure basic *behaviors*. The BAD-MoB-Model is embedded in a dynamic Bayesian network (DBN). If its template (Fig. 5) is rolled out (Fig. 6, 7) it defines a probability distribution over driver-vehicle trajectories so that it has the ability to *predict* agent's behavior, to *abduct* hazardous situations (what could have been the initial situation), to *generate anticipatory plans and control*, and *to plan counteractive measures* by *simulating* counterfactual behaviors or actions *preventing* hazardous situations.

BAYESIAN PROGRAMS AND DESCRIPTION COMBINATION

A *BP* is defined as a mean of specifying a family of probability distributions (Bessiere et al., 2003, 2008; Lebeltel et al., 2004). On the basis of a BP it is possible to construct a BAD-MoB-model, which can effectively control a (virtual) vehicle.

As Bessiere (2008) points out it is possible to combine or select single descriptions (= BPs) by a *probabilistic if-then-else*. "*Description combination* appears to implement naturally a mechanism similar to *Hierarchical Mixture of Experts* (Jordan and Jacobs, 1994) and is also closely related to mixture models … From a programming point of view, description combination can be seen as a *probabilistic if-then-else* construction. H is the condition. If H is known with certainty, then we have a normal branching structure. If H is known with some uncertainty through a probability distribution, then the two possible consequences are automatically combined using weights proportional to this distribution." (Bessiere, 2008).

We embedded description combination (Lebeltel et al., 1999, 2004; Bessiere et al. 2003) in our DBN-based BAD-MoB-model. The *condition* variable H is a generalized *case-statement* like a Lisp *cond* and *one* of the root variables in our template model (Fig. 5), especially the variable *Behaviors*. The marginal probability distribution $P(Behaviors^0)$ or $P(Behaviors^{t-1})$ corresponds to the weighting or mixing coefficients of the *description combination*. The number of CPDs *P(Action | behavior, States, Percepts)* equals to the cardinality *Behaviors* variable. For each *behavior* we have to establish a local CPD *P(Action | behavior, States, Percepts)*. The collection of these local CPDs is the envisioned behavior library summarized in the total CPD *P(Action | Behaviors, States, Percepts)*.

LEVELS OF EXPERTISE AND MIXTURES OF BEHAVIORS

BAD-MoB-models are *dynamic Bayesian networks (DBNs)* which can be considered as a subtype of a *Bayesian Program (BP)* (Bessiere, 2003). Under the assumption of stationarity their *template models* are specified as *2-time-slice*

Bayesian networks (2-TBNs). The template model can be unrolled so that their *interface variables* (Koller and Friedman, 2009) *Behaviors* and *State* are glued together producing an unrolled DBN over T time slices (T-TBN) like the 3-TBN in Fig. 6, 7. Learning data are time series of the pertinent domain-specific variables *goals*, *behaviors*, *actions*, observable *states*, and *actions* combined with *posthoc annotations* of maneuvers and scenarios. Information can be propagated within the T-TBN in various directions. When working *top-down*, goals emitted by higher cognitive layers of the agent activate a corresponding *behavior* which propagates *actions*, relevant *areas of interest* (AoIs), and expected *perceptions*. When working *bottom-up*, percepts trigger *AoIs*, *actions, behaviors*, and *goals*. When the task or goal is defined and there are percepts, evidence can be propagated *simultaneously* top-down and bottom-up, and the appropriate *behavior* can be activated.

Our DBN-based MoB model is influenced by the *visual attention allocation* model of Horrey et al. (2006) and the *Bayesian filter and action selection* model of Koike (2008). The BAD-MoB-model we present here is tailored to a virtual highway scenario assuming a hierarchy of driving skills or expertise.

A Virtual Highway Scenario

For the proof of concept we developed a 2-TBN for a simple scenario with three areas of interest (AoIs) and maneuvers (Fig. 1-3) (Möbus, et al., 2009c). The driver is sitting in the *ego* vehicle (ev). Sometimes an *alter* vehicle (av) or the *roadside* is occupying the AoIs depending on the *state* of the car (State = left, middle, or right lane).

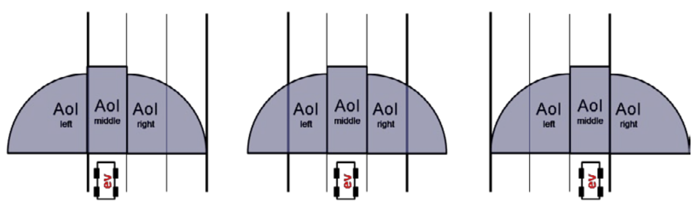

FIGURE 1. Areas of Interest (AoIs) and Ego Vehicle Positions

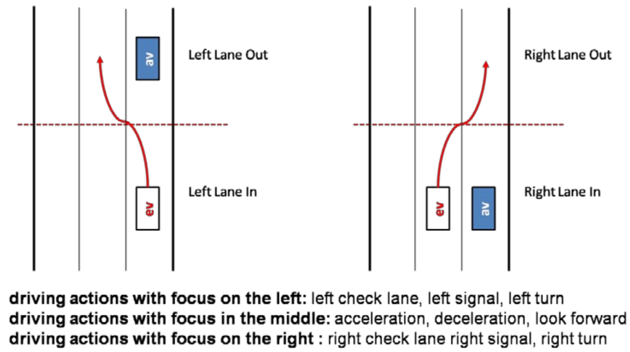

FIGURE 2. Driving Maneuvers LeftLaneChange LLC (left) and RightLaneChange RLC (right) with two sequences of Driving Behaviors each (above, below)

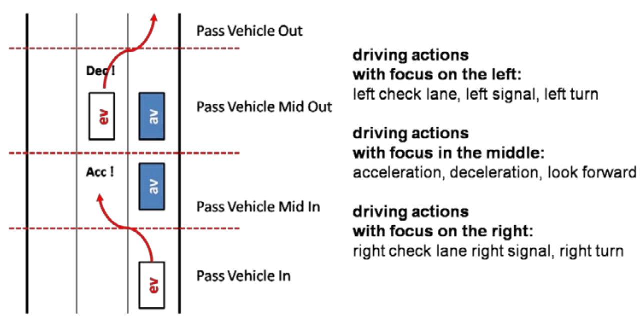

FIGURE 3 Pass Vehicle Driving Maneuver with a sequence of 4 Driving Behaviors

The levels of expertise, the model components (layer, sequence) and a partial grammar of expertise are shown in Fig. 4.

Levels of Expertise	Model Component	Hierarchy of Skills, Levels of Expertise
Skills		**Skills** = {…, drivingScenarioSkills, …}
Scenario Skills		**DrivingScenarioSkills** = { highway, countryRoad, city }
Driving **Maneuver** Skills	Driving **Maneuver** *Sequence* (horizontally distributed)	**highway.Maneuvers** = { leftLaneChange (lLC), rightLaneChange (rLC), passVehicle (pV), newManeuver }
Driving **Behavior** Skills	Driving **Behavior** *Layer*	**Behaviors** = { leftLaneIn (lLI), leftLaneOut (lLO), passIn (pI), passMidIn (pMI), passMidOut (pMO), passOut (pO), rightLaneIn (rLI), rightLaneOut (rO), newBehavior } e.g.: **leftLaneChange.Behaviors** = {leftLaneIn, leftLaneOut }
Driving **Action** Skills	Driving **Actions** *Layer*	**Actions** = { leftCheckLane (lCL), leftSignal (lS), leftTurn (lT), middleAcceleration (mA), middleDeceleration (mD), middleLookForward (mLF), rightCheckLane (rCL), rightSignal (rS), rightTurn (rT) } e.g.: **leftLaneIn.Actions** = {lCL, mD, mLF, lS, lT, mA}

FIGURE 4 Levels of Expertise, Model Components, and part of Expertise Grammar

Dynamic Reactive BAD-MoB-model

For our BAD-MoB-model we propose *partially inverted* dynamic Bayesian networks (DBNs) of the 2-TBN-type (Fig. 5). We call the model *Dynamic Reactive MoB Model*. The model is *reactive* because AoIs *directly* influence actions. The model embeds two naïve Bayesian classifiers: One for the *Behaviors* and one for the *States*. This simplifies the structure of the architecture. Time slices are selected so that in each new time slice a new *behavior* is active. A *sequence* of behaviors implements a single *maneuver*. When we replace the reactive submodel for the *Actions* variable in Fig. 5 by a *third* classifier we can simplify the model and reduce the number of parameters by 79%.

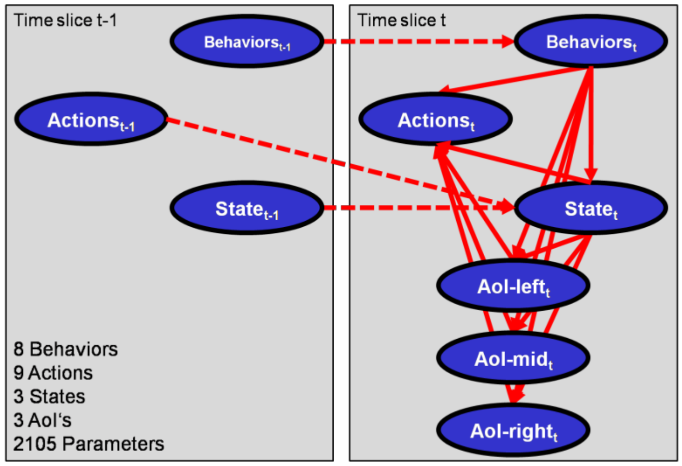

FIGURE 5 *Dynamic Reactive* BAD-MoB-model with *Behavior* and *State* Classifiers

The top layer consists of *behavior* nodes. There are behaviors for each main part of a *maneuver* (Fig. 2-4): *left_lane_in,…*. The next layer describes the *actions* the model is able to generate: *left_check_lane,…*. Below that appears the node *state* of the vehicle (*is_in_left_lane*, …). Then there are three bottom layers contain nodes for the three *AoIs* with values *is_occupied and is_empty*.

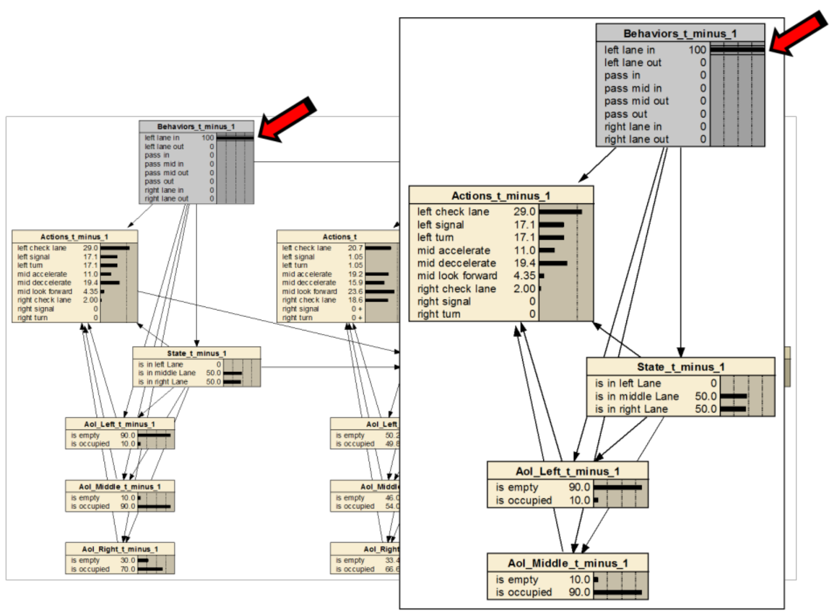

FIGURE 6 Expected behavior of the 3-TBN model with the goal behavior *left_lane_in* (the left-upper part of time-slice t-1 is expanded on the right of the figure)

An implementation in NETICA with artificial but plausible data is shown in Fig 6. When the model is urged to be in the *left_lane_in behavior* by e.g. goal setting from a higher cognitive layer, we expect in the *same* time-slice primarily that the *left lane is checked* and that the driver *decelerates the vehicle*. For the AoIs we expect that the middle AoI *is occupied* and the left AoI *is empty*. For the *this* time slice we expect the vehicle *in the right* or *middle lane*. The expected *behavior* changes between the time-slices. So the expected behavior in time-slice t is the *left_lane_out behavior*. We have higher beliefs in *acceleration*, *attention forward* and in *checking the left and right lane*.

When the state is known (e.g. *State* = *is_in_middle_lane*) we can include this as a single evidence in the model and infer the appropriate expectations (e.g. *left and right lane check*, *looking forward*, and both *(ac|de)celerations*).

When the model perceives a combination of AoI evidence, we can infer the *behaviors*. For instance, when the left AoI *is empty* and the middle and right AoI *is occupied*. We expect that the vehicle *is in the middle* or *right lane*, that the *behaviors left_lane_in* and *pass_in* are ambiguous, and that their appropriate *mixed* behavior (*left_lane_check*, *deceleration*) is activated. In the case, when all AoIs are occupied the model *is decelerating* with main attention to the middle AoI (*middle_straight_look*).

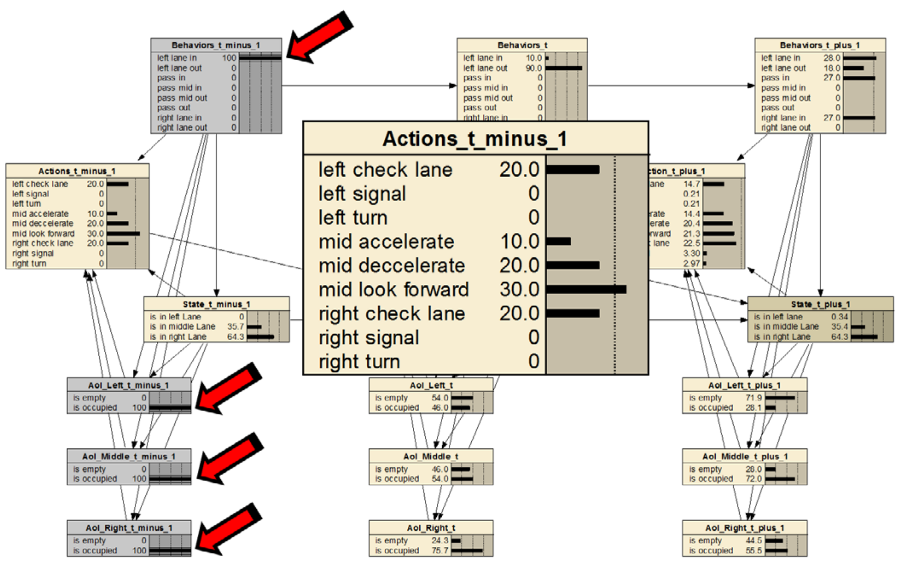

FIGURE 7 Conditional distributions in *Dynamic Reactive MoB Model* when receiving a combination of *Behavior* (goal) and *blocking AoI* evidence (Action-node expanded)

What will happen, if a goal is blocked? In Fig. 7 this is modeled by the appropriate evidence. The *lane-in behavior* is activated as a goal and at the same time the perception in the *left* and *middle* AoIs is set to *is_occupied*. This situation blocks the *left lane in* and the *pass vehicle in behaviors*. The expected actions are *looking forward*, *checking left and right lanes*, and *deceleration*. These are typical behavioral indicators for helplessness and stress.

This architecture has the ability to *predict* agent's behavior, to *abduct* hazardous situations (what could have been the initial situation), to *generate anticipatory plans and control*, and *to plan counteractive measures* by *simulating* counterfactual behaviors or actions *preventing* hazardous situations. For these applications we have to provide the model with appropriate evidence and questions.

For instance when *planning counteractive measures* by *simulating* counterfactual behaviors or actions *preventing* hazardous situations we need a 3-step procedure (Pearl, 2009): (1) *abduction* of a hazardous situation backwards with the *full* state-based BAD-MoB-model, (2) *mutilate* the full model to a *reduced* model, that is able to *predict intervention* effects, (3) experiment with counterfactual actions (= countermeasures) by *providing action* evidence in the *reduced* model and *predicting* the action effects.

FIRST MODELING RESULTS WITH REAL DATA

BAD-models with Mixed Behaviors are expressive enough to describe and predict a wide range of phenomena. In Möbus & Eilers (2009a) we presented a BAD model for lateral and longitudinal control *without* behavior mixing. The model showed nearly perfect behavior on the Aalborg course in the racing simulation game TORCS, though some suboptimal driving maneuvers could be observed. This is due to the fact that we used a *fixed* set of parameters in our model on a track with different segments like hair-needle curve, straight line segments etc. We modified the BAD-model architecture introducing concepts of the theory of ambient vision (Horrey et al., 2006). This led to a slightly simplified version of a BAD-MoB-model with two *behavior* and *steer-action* classifiers (Fig. 8).

The results are very promising as can be seen from Figs. 9 and 10. In Figure 9 the driver is driving in a right bended curve. His ambient vision field is sampled by 20 sensors (Fig. 9, left). Provided this perceptional evidence the conditional distribution for the *action* variable *Steer* (= steering angle) and the *behavior* variable *Behaviors* (= Experts) are inferred (Fig. 9, middle, right). As can be seen only the right-turn *behavior* (expert) is recognized and the corresponding angle of the steering-*action* is inferred. Sampling a concrete steering *action* from this conditional probability distribution gives the generated *action* of the BAD-MoB-model. Leaving the right-bended curve (Fig. 10) activates actions which are a mixture of the two *behaviors* (experts) straight and right (Fig. 10, right).

CONCLUSION AND OUTLOOK

We demonstrated that the DBN-based BAD-MoB-model has the ability to *predict* agent's behavior, to *abduct* hazardous situations (what could have been the initial situation), to *generate* anticipatory plans and control, and to *plan* counteractive measures by *simulating* counterfactual behaviors or actions *preventing* hazardous situations. In Eilers and Möbus (2010) we present an efficient implementation. The next research steps will work on the vertical refinement of models interfacing single *actions* with more concrete *behaviors*.

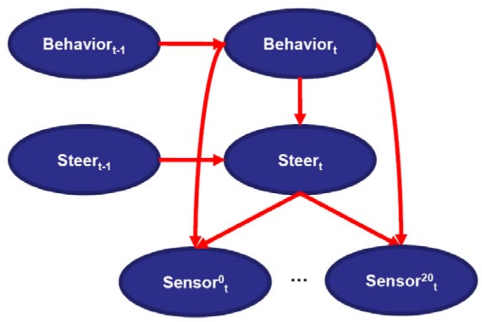

FIGURE 8 *Dynamic* BAD-MoB-model with Bayesian Classifiers *Behavior* and *Steer*

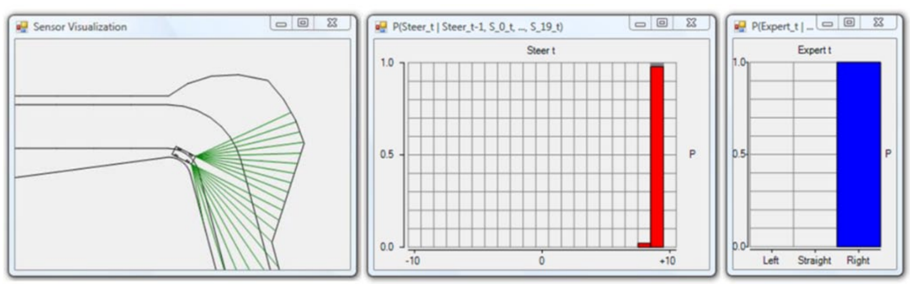

Fig. 9 Ambient perceptional evidence (left) and conditional distributions (middle, right) in *Dynamic Partial Inverted* BAD-MoB-model with 2 Bayesian Classifiers when driving in a right bended curve

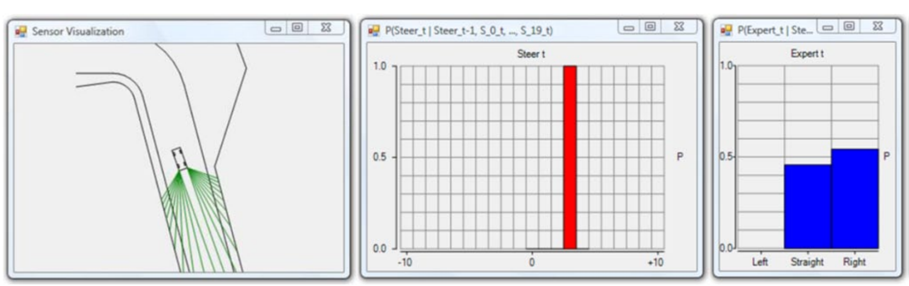

Fig. 10 Ambient perceptional evidence (left) and conditional distributions (middle, right) in *Dynamic Partial Inverted* BAD-MoB-model with 2 Bayesian Classifiers when leaving a right bended curve

REFERENCES

Bessiere, P. (2003). Survey: Probabilistic Methodology and Techniques for Artifact Conception and Development, Rapport de Recherche, No. 4730, INRIA

Bessiere, P. Laugier, Ch. and Siegwart, R. (eds.) (2008). *Probabilistic Reasoning and Decision Making in Sensory-Motor Systems*, Berlin: Springer, ISBN 978-3-540-79006-8

Cacciabue, P.C. (ed). (2007). *Modeling Driver Behaviour in Automotive Environments*, London: Springer, ISBN-10: 1-84628-617-4

Eilers, M. and Möbus, C. (2010). Learning of a Bayesian Autonomous Driver Mixture-of-Behaviors (BAD MoB) Model, (this proceedings), invited Special Interest Group: Möbus, C. & Bessiere, P., Models of Human Behavior and Cognition in the Bayesian Programming Framework, 1st International Conference On Applied Digital Human Modeling, 17-20 July, 2010, Intercontinental, Miami Florida, USA

Horrey, W.J. et al. (2006). Modeling Driver's Visual Attention Allocation While Interacting With In-Vehicle Technologies, J. Exp. Psych., 12, 67-78

Koike, C.C. Bessiere, P., and Mazer, E. (2008). Bayesian Approach to Action Selection and Attention Focusing, in Bessiere et al., (Eds.), Probabilistic Reasoning and Decision Making in Sensory-Motor Systems, Berlin: Springer, 177- 201

Koller, D., Friedman, N. (2009). Probabilistic Graphical Models, Cambridge, Mass.: MIT Press, ISBN 978-0-262-01319-2

Lebeltel, O. Bessiere, P. Diard, J. and E. Mazer (2004). Bayesian Robot Programming, Advanced Robotics, 16 (1), 49-79

Möbus, C. and Eilers, M. (2008). First Steps Towards Driver Modeling According to the Bayesian Programming Approach, Symposium Cognitive Modeling, p.59, in: L. Urbas, Th. Goschke & B. Velichkovsky (eds) *KogWis 2008*. Christoph Hille, Dresden, ISBN 978-3-939025-14-6

Möbus, C. Eilers, M. (2009a). Further Steps Towards Driver Modeling according to the Bayesian Programming Approach, in: *Conference Proceedings, HCII 2009, Digital Human Modeling*, pp. 413-422, LNCS (LNAI), Springer, San Diego, ISBN 978-3-642-02808-3

Möbus, C. Eilers, M. Garbe, H., and Zilinski, M. (2009b). Probabilistic and Empirical Grounded Modeling of Agents in (Partial) Cooperative Traffic Scenarios, in: *Conference Proceedings, HCII 2009, Digital Human Modeling*, pp. 423-432, LNCS (LNAI), Springer, San Diego, ISBN 978-3-642-02808-3

Möbus, C. Eilers, M. Zilinski, M. Garbe, H. (2009c). Mixture of Behaviors in a Bayesian Driver Model, in: Lichtenstein, A. et al. (eds), Der Mensch im Mittelpunkt technischer Systeme, p.96 and p.221-226 (CD), Düsseldorf: VDI Verlag, ISBN 978-3-18-302922-8, ISSN 1439-958X

Pearl, J. (2009). Causality – Models, Reasoning, and Inference, 2nd ed., Cambridge University Press, ISBN 978-0-521-89560-6

Yangsheng Xu, Ka Keung Caramon Lee, and Ka Keung C. Lee, *Human Behavior Learning and Transfer*, CRC Press Inc., (2005)