MÖBUS, C. & EILERS, M., *Integrating Anticipatory Competence into a Bayesian Driver Model*, in: P. C. Cacciabue et al. (eds.), Human Modelling in Assisted Transportation, DOI: 10.1007/978-88-470-1821-1_24, Springer-Verlag Italia Srl 2011

Integrating Anticipatory Competence into a Bayesian Driver Model

Claus Möbus[1], Mark Eilers[2]

Learning and Cognitive Systems / Transportation Systems

C.v.O University / OFFIS, Oldenburg, Germany

http://www.lks.uni-oldenburg.de/

claus.moebus@uni-oldenburg.de, mark.eilers@offis.de

Abstract: We present a probabilistic model architecture combining a layered model of human driver expertise with a cognitive map and beliefs about the driver-vehicle state to describe the effect of anticipations on driver actions. It implements the sensory-motor system of human drivers with autonomous, goal-based attention allocation and anticipation processes. The model has emergent properties and combines reactive with prospective behavior based on anticipated or imagined percepts obtained from a Bayesian cognitive map. 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 countermeasures preventing hazardous situations.

Keywords: Anticipatory planning, Bayesian cognitive map, probabilistic driver model, Bayesian autonomous driver model, mixture-of-behavior model, visual attention allocation, anticipatory plans and control, reactive and prospective behavior, risk and hazardous prevention

Introduction

Driving is a skill with high inter- and intraindividual variation [1]. So, the human or cognitive centered design of intelligent transport systems requires digital models of human behavior and cognition (MHBC) which are *embedded*, *context aware, personalized, adaptive,* and *anticipatory*.

[1]project Integrated Modeling for Safe Transportation (IMOST) sponsored by the Government of Lower Saxony, Germany under contracts ZN2245, ZN2253, ZN2366

[2]project ISi-PADAS funded by the European Commission in the 7th Framework Program, Theme 7 Transport FP7-218552

MÖBUS, C. & EILERS, M., *Integrating Anticipatory Competence into a Bayesian Driver Model*, in: P. C. Cacciabue et al. (eds.), Human Modelling in Assisted Transportation, DOI: 10.1007/978-88-470-1821-1_24, Springer-Verlag Italia Srl 2011

We present a probabilistic model architecture combining a layered model of human driver expertise with a cognitive map and beliefs about the driver-vehicle state to describe the effect of anticipations on driver actions. It implements the sensory-motor system of human drivers in a psychological motivated *mixture-of-behaviors (MoB)* architecture with *autonomous*, *goal-based attention allocation* and *anticipation* processes (Horrey and Wickens, 2006; Koike et al., 2008; Pezzulo et al., 2008).

Our Bayesian autonomous driver mixture-of-behaviors (BAD-MoB) model offers sharing of behaviors in different driving maneuvers and is able to decompose complex skills into basic skills and to compose the expertise to drive complex maneuvers from basic behaviors (Möbus and Eilers, 2010a, b; Eilers and Möbus, 2010). The 2-time-slice template of the basic dynamic *reactive* BAD-MoB Model is shown in the left part and a 4-time-slice roll-out in the total view of Fig. 1. This roll-out is made under the Markov and the stationary assumption.

We call the basic model *reactive* because the Areas of Interest (AoIs) *directly* influence actions. The model embeds two naïve Bayesian classifiers: one for the *behaviors B* and one for the *states S*. 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*. The *basic* model was discussed in detail in (Möbus and Eilers, 2010a, b).

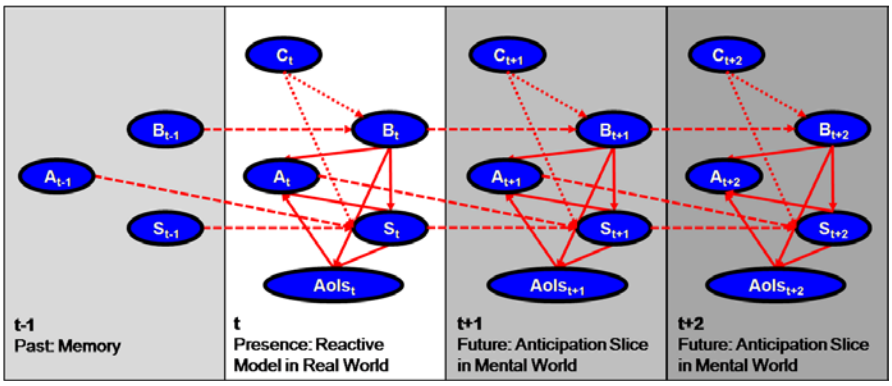

Fig. 1. 4-time-sliced (4-TBN) Anticipatory BAD-MoB Model

Time slices (t-1) and t are used for the dynamic *reactive* part of the model. This part uses percepts of the real world and some information from the most recent slice (t-1) to select appropriate behavior and actions for time slice t. It describes a driver who is driving a scenario the first time in a *visual* driving style, so that he can stop the car in the assured clear distance ahead. This driver has *no* imagination or anticipations about the course of the road beyond his vision field. The cognitive Bayesian map is represented in the model by adding model slices to the right according to the level of expertise or competence C augmenting the anticipation horizon into the future. Perception is then substituted by imagination obtained from the Bayesian cognitive map. This information is learnt by memorizing former drives. To get the parameters of the anticipatory model we need at least one replication of the training drive for each expertise level: at least 3 training drives for the model in Fig. 1.

Here, we give a proof of concept for the operating mode of the cognitive Bayesian map and anticipatory planning with plausible but artificial data. The model contains 2105 parameters. These have been hand-coded into the model to test the plausibility of the concept model. We demonstrate that a BAD-MoB model based on Dynamic Bayesian Networks (DBNs) shows some *emergent* competencies: 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 countermeasures *preventing* hazardous situations. The distinction between *prediction* and *anticipation* is defined by: *Prediction is a representation of particular future events. Anticipation is a future-oriented action, decision, or behavior based on a (implicit or explicit) prediction* [13].

Bayesian Autonomous Driver Mixture of Behaviors Models with a Bayesian Map Extension

BAD models [8 - 10] are developed in the framework of Bayesian (Robot) Programming [2, 7]. They describe phenomena and generate motor control on the basis of the joint probability distribution (JPD) of the variables of interest and their factorization into conditional probability distributions (CPDs).

A BAD-MoB model is able to decompose complex skills (scenarios, maneuvers) into basic skills (= behaviors, actions) and vice versa (Eilers and Möbus, 2010, Möbus and Eilers, 2010a, b). 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*. BAD-MoB models are embedded in DBNs. Under the assumption of stationary their *template models* (Fig. 1, left two slices) are specified as *2-time-slice DBNs* (2-TDBNs). The template model can be unrolled so that their *interface variables Behaviors* and *State* are glued together producing an rolled-out DBN over T time slices (T-TDBN) like the 4-TDBN in Fig. 1.

The degree of roll-out defines the anticipation horizon of the model. This is controlled by the level of the binary expertise or competence variable C_t. If $C_t = 1$, then the conventional transition probability matrices $P(B_{t+j} \mid B_{t+j-1})$ and $P(S_{t+j} \mid S_{t+j-1})$ are used. When $C_t = 0$, then all $C_{t+i} = 0$ $(i \geq 1)$ and the probability distributions $P(B_{t+j} \mid B_{t+j-1})$ and $P(S_{t+j} \mid S_{t+j-1})$ are replaced by static distributions $P(B_{t+j})$ and $P(S_{t+j})$. Hence, C_t can be seen as a switch to activate and deactivate anticipatory time slices.

Learning data are time series of the pertinent domain-specific variables *percepts, AoIs*, *goals*, *behaviors*, *actions*, *observable states*, and *actions* combined with *posthoc annotations* of maneuvers, scenarios, and the replication number of

MÖBUS, C. & EILERS, M., *Integrating Anticipatory Competence into a Bayesian Driver Model*, in: P. C. Cacciabue et al. (eds.), Human Modelling in Assisted Transportation, DOI: 10.1007/978-88-470-1821-1_24, Springer-Verlag Italia Srl 2011

the training drive.

Information can be propagated within the T-TDBN in various directions. When working *top-down*, goals emitted by higher cognitive layers of the agent activate a corresponding *behavior* which propagates *actions*, relevant *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. Furthermore, evidence can be propagated for *predictions* from the past to the future and vice versa for *abductions*. This flexibility is used for *anticipatory planning* (Fig. 3-5).

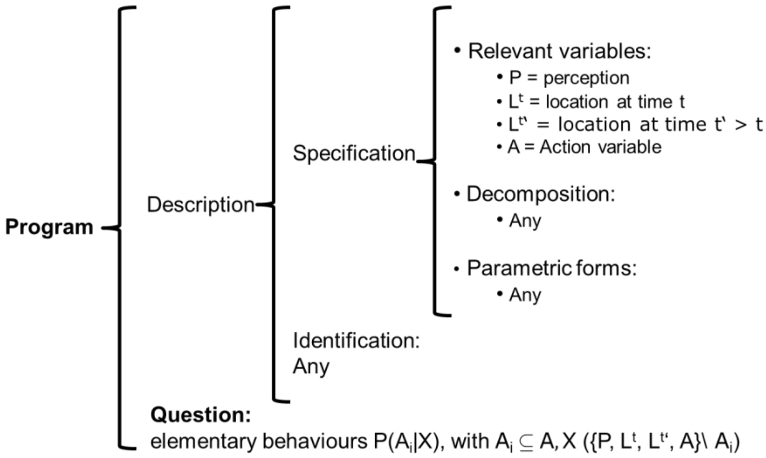

Fig. 2. The Bayesian Map model definition expressed in the Bayesian (Robot) Programming (BRP) formalism (Diard and Bessiere, 2008, p.165)

The BAD-MoB Model (Fig. 1) implements a Bayesian Map (BM). The structure of a BM is defined in (Fig. 2). The location variable L is redefined in our model as the belief state S. The belief state of future slices defines the Bayesian cognitive map.

A BM is capable to answer three kinds of questions:

- Localization (Where am I, if I have percept P ?) : $P(L^t \mid P) = ?$
- Prediction (Where do I go, when I generate action A?) : $P(L^{t'} \mid A, L^t) = ?$
- Control (What actions should I generate, to reach/avoid $L^{t'}$?) :$P(A \mid L^t, L^{t'}) = ?$

MÖBUS, C. & EILERS, M., *Integrating Anticipatory Competence into a Bayesian Driver Model*, in: P. C. Cacciabue et al. (eds.), Human Modelling in Assisted Transportation, DOI: 10.1007/978-88-470-1821-1_24, Springer-Verlag Italia Srl 2011

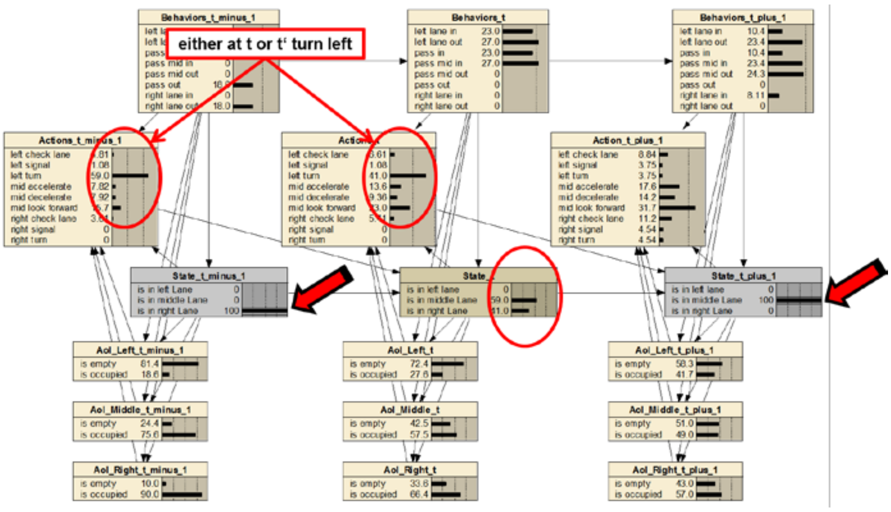

Fig. 3. The BAD-MoB gives an answer to the control question $\mathbf{P(A^{t-1},A^{t} \mid s^{t-1}, s^{t+1})}$

The model in Fig. 3 is a rolled-out version of our basic template (Fig. 1). It answers the control question P(Actions$_{t-1}$, Actions$_t$ | State$_{t-1}$ = is_in_right_lane, State$_{t+1}$ = is_in_middle-lane). The model recommends actions with P(Actions$_{t-1}$ = left_turn | State$_{t-1}$ = is_in_right_lane, State$_{t+1}$ = is_in_middle-lane) = 0.59 and P(Actions$_t$ = left_turn | State$_{t-1}$ = is_in_right_lane, State$_{t+1}$ = is_in_middle-lane) = 0.41 (circled in Fig. 3). If the spatial goal at time t+1 is changed to the *left lane* the corresponding conditional probabilities are changed to P(Actions$_{t-1}$ = left_turn | State$_{t-1}$ = is_in_right_lane, State$_{t+1}$ = is_in_left-lane) = 1.0 and P(Actions$_t$ = left_turn | State$_{t-1}$ = is_in_right_lane, State$_{t+1}$ = is_in_left-lane) = 1.0.

Anticipatory Planning of Countermeasures with our BAD-MoB Model

Generally, anticipatory systems are those that use their predictive capabilities to optimize behavior and learning to the best of their knowledge… Anticipatory behavior may be defined as: *[…] a process or behavior that does not only depend on past and present but also on predictions, expectations, or beliefs about the future. …While reactive systems can functionally be described with STIMULUS → ACTION (S-A) behavioral patterns, anticipatory systems have instead (STIMULUS +) EXPECTATION → ACTION (E-A) behavioral patterns, which is permitted by the explicit prediction of a stimulus or an action effect (STIMULUS → EXPECTATION (S-E), or STIMULUS, ACTION → EXPECTATION (S-A-E)).* (Pezzulo et. al, 2008, p. 24).

MÖBUS, C. & EILERS, M., *Integrating Anticipatory Competence into a Bayesian Driver Model*, in: P. C. Cacciabue et al. (eds.), Human Modelling in Assisted Transportation, DOI: 10.1007/978-88-470-1821-1_24, Springer-Verlag Italia Srl 2011

Our BAD-MoB model is an instance of an anticipatory system. The model in Fig. 3-5 uses partly perceptual and partly imaginary evidence. If perceptual evidence is included in time slice t or (t-1) the beliefs about the driver-vehicle state S will revise the beliefs based on pure imagination obtained from time slices t'>t.

The process of anticipatory planning consists of five steps (Figs 4, 5):

- Step 1: Anticipation and Prediction in (t-1) of Hazard and Collision for (t+1) and abduction of appropriate behaviors or goals in (t-1)

The model in Fig. 4 realizes in the current time step (t-1) that it is in the *belief State(t-1) = in_the_right_Lane* and that it will stay there including the future time slice (t+1) with the conditional probability *P(State(t+1) = in_the_right_Lane | ….) = 0.849*. This is an unfavorable state of affairs, because it "expects" at the same time, that only the left lane will be empty. These expectations are fed into the model as virtual evidence for t+1. The reason for this evidence has to be obtained from a higher cognitive layer of the model. Appropriate behaviors and goals could be inferred backwards by an abduction process: *left_lane_in*, *pass_in* in time slice t-1, etc.

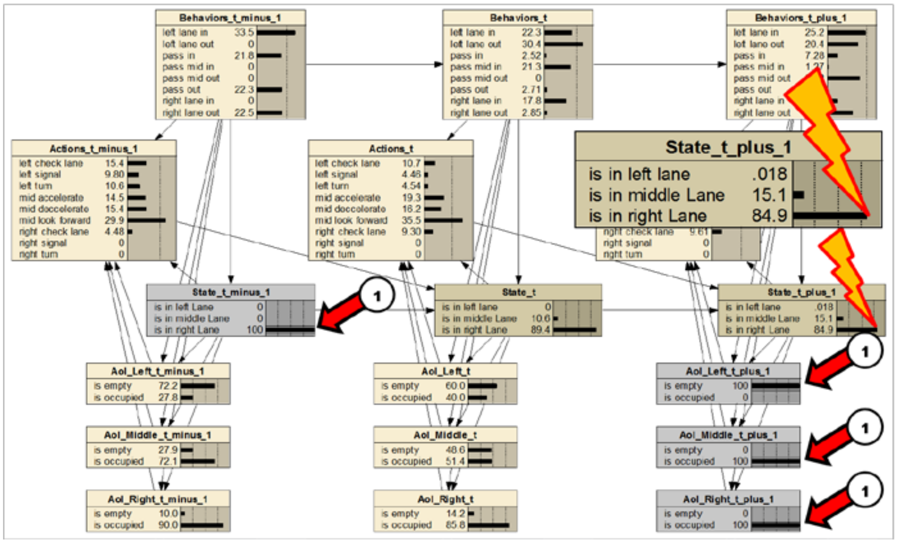

Fig. 4. 3-time-sliced roll-out of BAD-MoB model with belief state and Bayesian map with Anticipatory Planning Step 1 (NETICA implementation)

- Step 2: Proactive Goal Activation in (t-1) and Collision Prediction for (t+1)

The BAD-MoB model gets from a higher cognitive layer a goal activation for the *left_lane_change* maneuver. This maneuver starts with the *left_lane_in* behavior. This means that the goal *Behavior(t-1) = left_lane_in* is injected in the model as evidence for t-1. As a consequence the conditional probability drops down to *P(State(t+1) = in_the_right_Lane | …. Behavior(t-1) = left_lane) = 0.696*, which is far too high.

MÖBUS, C. & EILERS, M., *Integrating Anticipatory Competence into a Bayesian Driver Model*, in: P. C. Cacciabue et al. (eds.), Human Modelling in Assisted Transportation, DOI: 10.1007/978-88-470-1821-1_24, Springer-Verlag Italia Srl 2011

- Step 3: Proactive Action Selection in (t-1) and Crash Prediction for (t+1)

The model "knows" that some actions (like *signal left* or *look to the left*) do not change the belief state. So it activates and executes the state changing Action = *left-turn*. As a consequence the conditional probability drops down to *P(State(t+1) = in_the_right_Lane | …. Behavior(t-1)=left_lane, Action(t-1)=left_turn) = 0.000*. Because *P(State(t+1) = in_the_left_Lane | …. Behavior(t-1)=left_lane, Action(t-1)=left_turn) = 0.012* the model "decides" that the state of affairs will be still unfavorable.

- Step 4: Anticipatory Goal Activation for (t) and Collision Prediction for (t+1)

The models freezes the goal activation up to the next time slice with *Behavior(t) = left_lane_in*. As a consequence the conditional probability increases slightly to *P(State(t+1) = in_the_left_Lane | …. Behavior(t-1)=left_lane, Action(t-1)=left_turn, Behavior(t) = left_lane_in) = 0.031* which is still far too low.

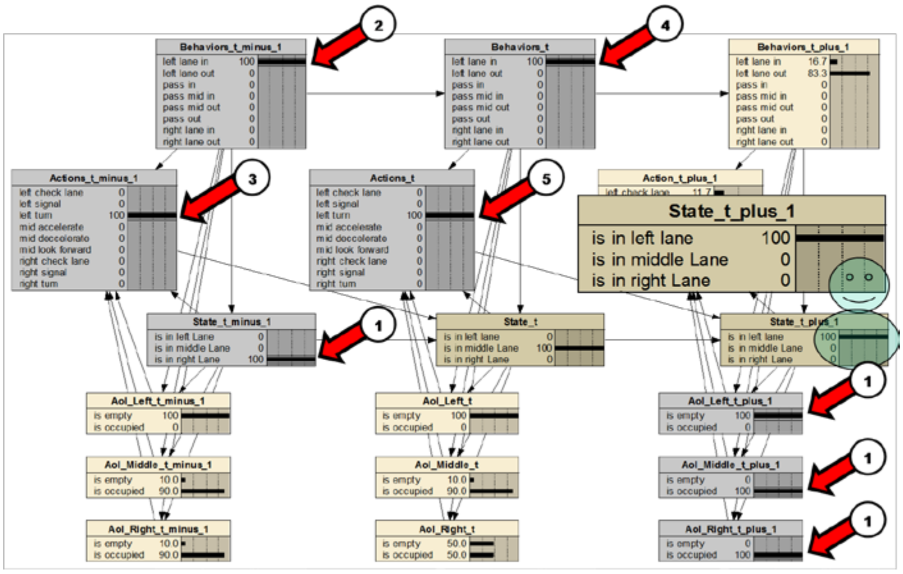

Fig. 5. 3-time-sliced roll-out of BAD-MoB model with belief state and Bayesian map with Anticipatory Planning Steps 1-5 (NETICA implementation)

- Step 5: Anticipatory Action Selection for (t) and Good Luck Prediction for (t+1)

This "motivates" the model to select the *Action(t)=left_turn* a second time (Fig. 5). Now the conditional probability increases to *P(State(t+1) = in_the_left_Lane | …. Behavior(t-1)=left_lane, Action(t-1)=left_turn, Behavior(t) = left_lane_in, Action(t)=left_turn) = 1.000*, which is a good state of affairs because it promises the avoidance of a collision.

Conclusions

We demonstrated that the Bayesian-Map-extended BAD-MoB model has the ability to *predict* agent's behavior, to *abduct* hazardous situations (what could have been the initial situation, what could be appropriate behavior), to *generate* anticipatory plans, and *control* countermeasures *preventing* hazardous situations. It was demonstrated that the selection of action and goal evidence has to be planned by a higher cognitive layer residing on top of the BAD-MoB model. An implementation with real expert and novice data has to follow this conceptual study.

References

1. Alms, R., et al., (2010), Generierung und Optimierung von Sollkursen mittels Expertenwissen und Heuristiken, in: Kolrep (Hrsgb), Fahrermodellierung, Düsseldorf: VDI-Verlag, (in press)
2. 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
3. Diard & Bessiere, Bayesian Maps: Probabilistic and Hierarchical Models for Mobile Robot Navigation, in: Bessiere, P., Laugier, Ch., and Siegwart, R. (eds), Probabilistic Reasoning and Decision Making in Sensory-Motor Systems, Springer, 2008, p.153 - 175
4. Eilers, M. and Möbus, C**.** (2010) *Learning a Bayesian Autonomous Driver Mixture-of-Behaviors (BAD-MoB) Model*, (paper accepted), 1st Intern.Conf. On Applied Digital Human Modeling, 17-20 July, 2010, Miami, USA
5. Horrey, W.J. et al. (2006). Modeling Driver's Visual Attention Allocation While Interacting With In-Vehicle Technologies, J. Exp. Psych., 12, 67-78
6. 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
7. Lebeltel, O. Bessiere, P. Diard, J. and E. Mazer (2004). Bayesian Robot Programming, Advanced Robotics, 16 (1), 49-79
8. 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
9. Möbus, C. Eilers, M. Garbe, H., and Zilinski, M. (2009b). Probabilistic and Empirical Grounded Modeling of Agents in (Partial) Cooperative Traffic Scenarios, in: *HCII 2009, Digital Human Modeling*, pp. 423-432, LNCS (LNAI), Springer, San Diego, ISBN 978-3-642-02808-3
10. 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
11. Möbus, C. & Eilers**,** M. (2010a) *Prototyping Smart Assistance with Bayesian Autonomous Driver Models*, in: Fulvio Mastrogiovanni & Nak-Young Chong (eds), Handbook of Research on Ambient Intelligence and Smart Environments, IGI Global publications, 2010 (in press)

12. Möbus, C. & Eilers, M. (2010b) *Mixture of Behaviors and Levels-of-Expertise in a Bayesian Autonomous Driver Model* (paper accepted), 1st Intern.Conf. On Applied Digital Human Modeling, 17-20 July, 2010, Miami Florida, USA
13. Pezzulo, G., Butz, M.V., and Castelfranchi, C. (2008) The Anticipatory Approach: Definitions and Taxonomies, p. 23-43, in.: G. Pezzulo, et al. (eds), The Challenge of Anticipation: A Unifying Framework for the Analysis and Design of Artificial Cognitive Systems, Heidelberg: Springer, LNAI 5225, ISBN 3-540-87701-0