Mixture of Behaviors in a Bayesian Autonomous Driver Model

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Abstract

The Human Centered Design (HCD) of Partial Autonomous Driver Assistance Systems (PADAS) requires Digital Human Models (DHMs) of human control strategies for traffic scenario simulations. We present a *probabilistic* model architecture for generating descriptive models of human driver behavior: Bayesian Autonomous Driver (BAD) models. They implement the sensory-motor system of human drivers in a psychological motivated mixture-of-experts (= mixture-of-schema) architecture with autonomous and goal-based attention allocation processes. Under the assumption of stationary behavioral processes models are specified across at least two time slices. Learning data are time series of relevant variables: percepts, goals, and actions. We can represent individual or groups of human and artificial agents. Models propagate information in various directions. When working *top-down*, goals emitted by a cognitive layer select a corresponding expert (schema), which propagates actions, relevance of areas of interest (AoIs) and perceptions. When working *bottom-up*, percepts trigger AoIs, actions, experts and goals. When the task or goal is defined and the model has certain percepts evidence can be propagated *simultaneously* top-down and bottom-up and the appropriate expert (schema) and its behavior can be activated. Thus, the model can be easily extended to implement a modified version of the SEEV visual scanning or attention allocation model of Horrey, Wickens, and Consalus. In contrast to Horrey et al. the model can predict the probability of attending a certain AoI on the basis of single, mixed, and even incomplete evidence (goal priorities, percepts, effort to switch between AoIs). In this paper we present the architecture and a proof of concept with plausible but artificial data.

1 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*. Models and prototypes we propose here are of that type. A special kind of MHBC is developed and used as *driver models* in traffic scenario simulations (Cacciabue, 2007). In current research projects their usefulness for proving safety assertions and supporting risk-based design is studied intensively (ISi-PADAS, 2009). In both cases it is assumed that the conceptualization and development of MHBCs and ambient intelligent assistance systems are parallel and independent activities. In the near future with the need for smarter and more intelligent assistance the problem of transferring human skills (Yangsheng, 2005) into the envisioned technical systems becomes more and more apparent. The conventional approach is the handcrafting of MHBC on the basis of human behavior traces. An ex post evaluation of their human likeness or empirical validity and revision-evaluation cycles is obligatory. We propose a machine-learning alternative: the estimation of Bayesian MHBCs from behavior traces. The learnt models are empirical valid by construction. We call these models *Bayesian Autonomous Driver (BAD)* models. An ex post evaluation of BAD models is not necessary.

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2 Probabilistic Models of Human Behavior and Cognition

A driver, a pedestrian or a biker is a human agent whose skills and skill acquisition process can be described by a three-stage model with the cognitive, associative, and autonomous stages or layers (Anderson, 2002). Accordingly various modeling approaches are adequate: production-system models for the *cognitive and associative* stage (e.g. models in a cognitive architecture), control-theoretic, or probabilistic models for the *autonomous* stage.

The advantage of probabilistic models is that they fulfill the above modeling criteria and above that especially robustness. This is a great advantage facing the irreducible incompleteness of knowledge about the environment and the underlying psychological mechanisms (Bessiere, 2008).

2.1 Bayesian Autonomous Driver (BAD) Models

Due to the variability of human cognition and behavior and the irreducible lack of knowledge about cognitive mechanisms it seems rational to conceptualizes, estimate and implement probabilistic models when modeling human traffic agents. In contrast to other models probabilistic models need not be idiosyncratically handcrafted but could be learnt objectively from human behavior traces. BAD models (Möbus, 2008; 2009a; 2009b) are developed in the tradition of Bayesian expert systems and Bayesian robot programming (Bessiere, 2003). They describe phenomena on the basis of the variables of interest and some conditional probability distributions (JPDs). This is in contrast to models in cognitive architectures (e.g. ACT-R) which try to simulate cognitive algorithms and processes on a finer granular basis which are difficult to identify even with e.g. functional magnetic resonance imaging (FMRI) methods.

In (Möbus, 2008) we described first steps to model lateral and longitudinal control behavior of single and groups of drivers with *reactive* Bayesian sensory-motor models. Then we included the time domain and reported work in progress with dynamic Bayesian sensory-motor models (Möbus, 2009a; 2009b). The vision is a dynamic BAD model which is able to decompose complex situations into basic situations and to compose complex behavior from basic motor schemas (experts). This new Mixture-of-Experts (MoE) model facilitates the management of sensory-motor schemas in a library. Context dependent driver behavior could be generated by mixing pure behavior from different schemas.

2.2 Basic Concepts of Bayesian Programs

A BP is defined as a mean of specifying a family of probability distributions. By using such a specification it is possible to construct a BAD model, which can effectively control a (virtual) vehicle. The components of a BP are presented in (Bessiere, 2003), where the analogy to a logic program is helpful.

An *application* consists of a (task model) description and a question. A *description* is constructed from preliminary knowledge and a data set. *Preliminary knowledge* is constructed from a set of pertinent variables, a decomposition of the JPD and a set of forms. *Forms* are either parametric forms or BPs.

The purpose of a *description* is to specify an effective method to compute a JPD on a set of variables given a set of (experimental) *data* and preliminary knowledge. To specify *preliminary knowledge* the modeler must *define the set of relevant variables* on which the JPD is defined, *decompose the JPD* into factors of CPDs according to CIHs, and *define the forms*. Each CPD in the decomposition is a form. Either this is a *parametric form* which parameter are estimated from batch data (behavior traces) or another *application*. Parameter estimation from batch data is the conventional way of estimating the parameters in a BAD model. The Bayesian estimation procedure uses only a small fraction of the data (cases) for updating the model parameters. This procedure is described below.

Given a description a *question* is obtained by partitioning the variables into *searched*, *known*, and *unknown* variables. We define a question as the CPD P(*Searched* | *Known*, *preliminary knowledge*, *data*). The selection of an appropriate action can be treated as the inference problem: P(*Action* | *Percepts, Goals, preliminary knowledge*, *data*). Various *policies* (Draw, Best, and Expectation) are possible whether the concrete *action* is *drawn* at random, chosen as the *best* action with highest probability, or as the *expected* action.

3 Mixture of Expert Model

3.1 A Psychological Motivated Model

Currently we are evaluating the suitability of static and dynamic graphical models. Dynamic models evolve over time. If the model contains discrete time-stamps one can have a model for each unit of time. These local models are called *time-slices* (Jensen, 2007). The time slices are connected through *temporal links* to give a full model. In the case of identical time-slices and temporal links we have a *repetitive temporal model* which is called *Dynamic Bayesian Network model* (DBN).

In our current research we strive for the realization of dynamic Bayesian Autonomous Driver model (Fig. 1). The model is suited to represent the sensor-motor system of individuals or groups of human or artificial agents in the functional *autonomous* layer or stage of Anderson (2002). It is a psychological motivated *mixture-of-experts* (= mixture-of-schema) model with *autonomous and goal-based attention allocation processes*. It is distributed across two time slices, and tries to avoid the *latent* state assumptions of HMMs. Learning data are time series or case data of relevant variables: percepts, goals, and actions. Goals are the only latent variables which could be set by commands issued by the *associative* layer.

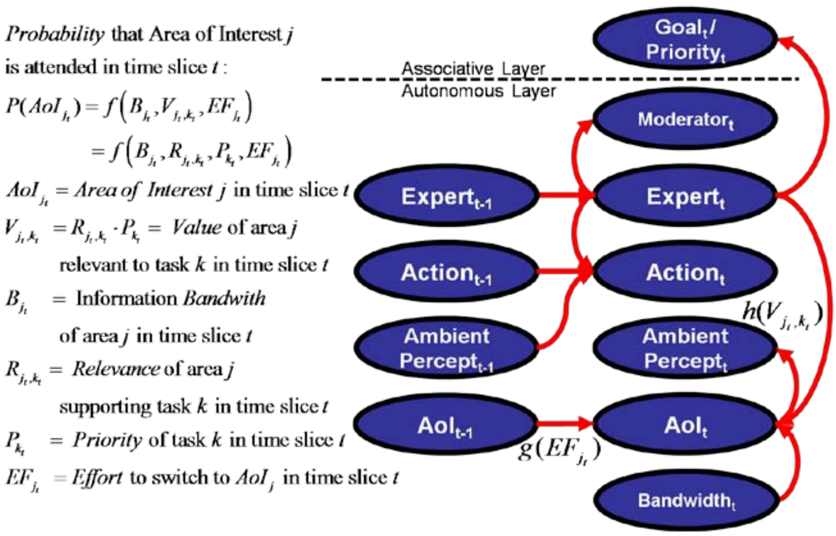


Fig. 1**:** Mixture-of-Experts (= Mixture-of-Schema) Model with Visual Attention Allocation Extension (mapping ideas of Horrey et al. (2006) into the Dynamic Bayesian Network modeling framework).

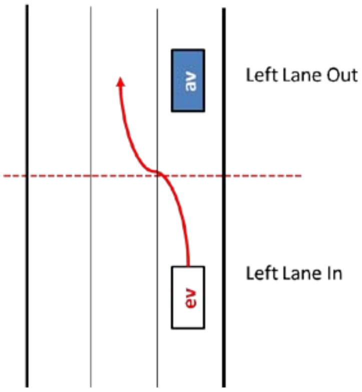
The model propagates information in various directions. When working *top-down*, goals emitted by the associative layer select a corresponding expert (schema), which propagates actions, relevance of areas of interest (AoIs) and perceptions. When working *bottom-up*, percepts trigger AoIs, actions, experts and goals. When the task or goal is defined and the model has certain percepts evidence can be propagated *simultaneously* top-down and bottom-up and the appropriate expert (schema) and its behavior can be activated.

Thus, the model can be easily extended to implement a modified version of the SEEV visual scanning or attention allocation model of Horrey, Wickens, and Consalus (2006). In contrast to Horrey et al. the model can predict the probability of attending a certain AoI on the basis of single, mixed, and even incomplete evidence (goal priorities, percepts, effort to switch between AoIs). In 3.2 we want to demonstrate that this architecture is feasible.

3.2 A Proof of Concept

In our current research we used partial inverted Markov models for modeling the sensory-motor system of the human driver. Now we want to discuss what kind of DBNs are worth to be considered next when driver state variables (e.g. *lateral and longitudinal (de|ac)-celeration*) are included and when a psychological motivated *mixture-of-experts* (= mixture-of-schema) model with *autonomous and goal-based attention allocation processes* is the ultimate goal.

For the proof of concept we develop a Bayesian model for a simple scenario with three maneuvers (Fig. 2 – 4) and three areas of interest (AoIs) (Fig. 5). The driver and the BAD model are sitting in the *ego* vehicle (ev). Sometimes there is an *alter* vehicle (av) or the *roadside* occupying the AoIs depending on the *state* of the car (State = left, middle, or right lane).



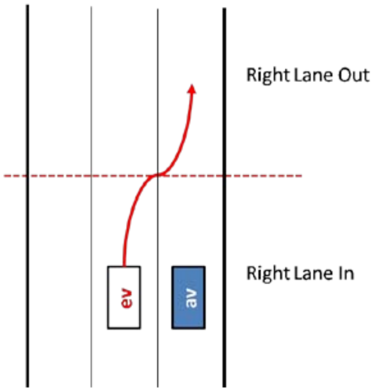
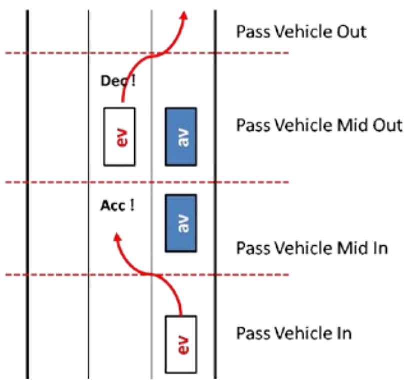


Fig. 2: Left Lane Change Maneuvre

Fig. 3: Left Lane Change Maneuvre



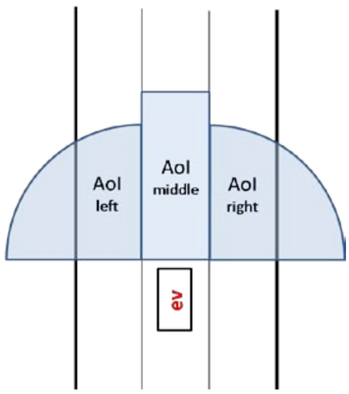


Fig. 4: Pass Vehicle Maneuvre

Fig. 5: Areas of Interest

We call the model *Reactive State-Based Expert-Role Model* (RSRM) (Fig. 7). This is due to the fact that AoIs directly influence actions. The model embeds two naïve Bayes classifiers: One for the *expert-roles* and one for the *states*. This simplifies the structure of the architecture. Time slices are selected that in each new time slice a new expert role is active.

Expert roles are contained in the top layer of nodes. We have experts for each main part of a maneuver (Fig. 2 - 4): *left_lane_in*, *left_lane_out*, *pass_in*, *pass_mid_in*, *pass_mid_out*, *pass_out*, *right_lan_in*, *right_lane_out*. The next layer of nodes describes the actions the model is able to generate: *left_check_lane*, *left_signal*, *left_turn*, *middle_straight_accelerate*, *mid-*

dle_straight_decelerate, *middle_straight_look*, *right_check_lane*, *right_signal*, *right_turn*. Below that layer a layer of nodes is describing the *state* (*is_in_left_lane*, *is_in_middle_lane*, *is_in_right_lane*) of the vehicle. These state nodes should be augmented in the future by states describing the driver. The three bottom layers contain nodes describing the activation of the three AoIs: *is_occupied and is_empty*.

When the model is urged to be in the *left_lane_in* role by e.g. goal setting from the associative 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 *next* time slice we expect the vehicle *in the left* or *middle lane*, The expected behavior is that of the *left_lane_out* expert. This role specific behavior in this next future time slice is a bit different than before. We expect more *acceleration*, more *attention forward* and more *checking the right lane*.

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

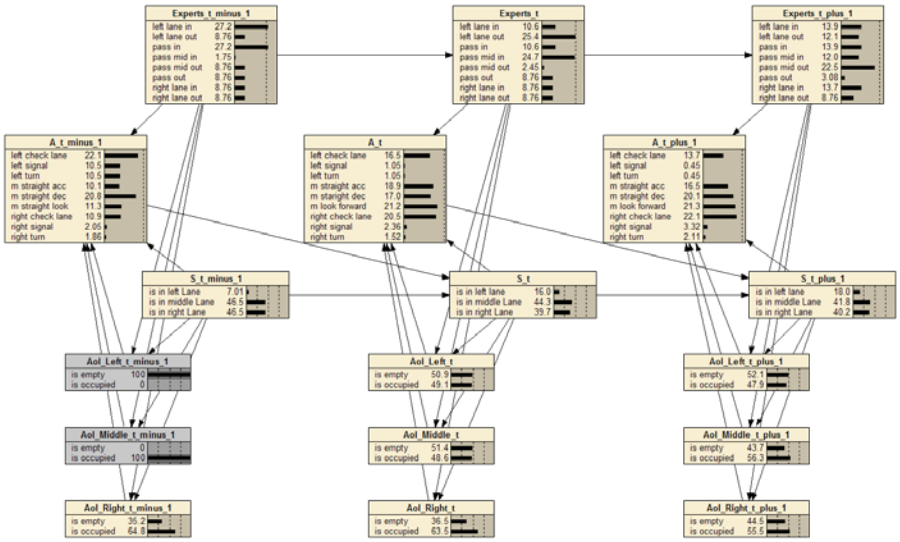


Fig. 7: *Expectations* when BAD RSRM model perceives a combination of AoI evidence

When the model is perceiving a combination of AoI evidence (Fig. 7), we can infer the maneuvers (= expert-roles). For instance, in Fig. 7 the left AoI *is empty* and the middle AoI *is occupied*. We expect that the vehicle *is in the middle* or *right lane* and that the expert-roles are *left_lane_in* and *pass_in* and their appropriate *mixed* behavior is activated. In the case, when all AoIs are occupied the model *is decelerating* with main attention to the middle AoI (*middle_straight_look*).

What will happen, if a goal (= expert role) is blocked? In Fig. 8 this situation is modeled by the appropriate evidence. The *lane-in* 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* maneuvers. The expected behavior is *deceleration* and *looking forward*.

4 Outlook

We believe that the proof of concept is convincing: Bayesian Driver Models with Mixed Experts are expressive enough to describe and predict a wide range of phenomena. In our future research we will implement the model with real driving data.

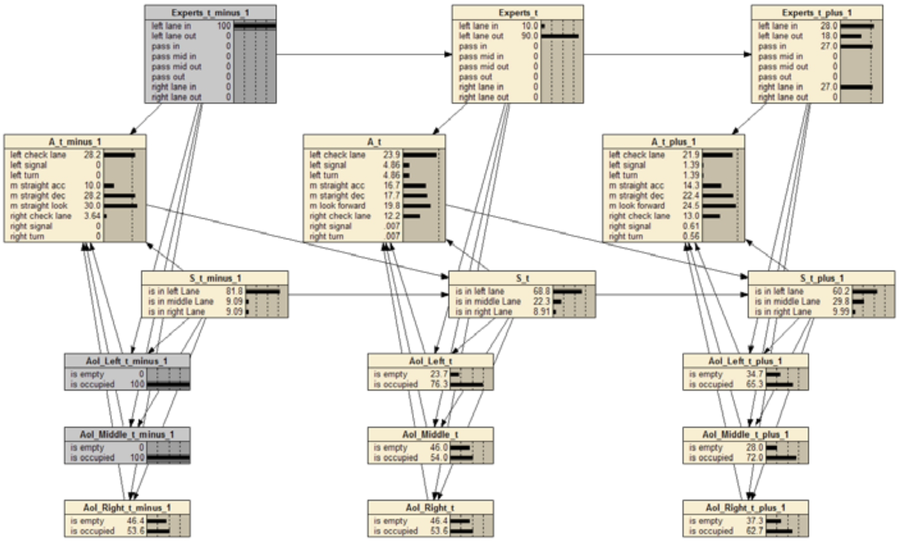


Fig. 8: *Expectations* when BAD RSRM model perceives a *blocking of goals or expert-roles* by a combination of *occupied* AoIs

5 References

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

ISi-PADAS, http://www.offis.de/projekte/v/240/isi-padas%20_e.php (visited 08.08.2009)

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

Anderson, J.R.: *Learning and Memory*, John Wiley, (2002)

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

Möbus, C. and Eilers, M., 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 (2008)

Möbus, C., Eilers, M., 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 (2009)

Möbus, C., Eilers, M., Garbe, H., and Zilinski, M.: 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 (2009)

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

Jensen, F.V. & Nielsen, Th.D.: *Bayesian Networks and Decision Graphs* (2nd edition), Springer, ISBN 0-387-68281-3 (2007)

Horrey, W.J., Wickens, Ch.D., and Consalus, K.P.: Modeling Driver's Visual Attention Allocation While Interacting With In-Vehicle Technologies, J. Exp. Psych., 2006, 12, 67-78