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ADAPTATION TO THE DRIVER AS PART OF A DRIVER MONITORING AND WARNING SYSTEM[1]

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Abstract—A driver monitoring and warning system called DAISY (Driver AssIsting SYstem) is presented, which adapts its warning messages to warning thresholds acceptable to the driver. This is achieved by the use of a model of the individual driving behaviour of the driver actually driving. Artificial neural networks based on the ART architectures were used for on-line learning to realize this model. Besides a brief survey of the main features of DAISY this paper emphasizes the modelling of the driving behaviour with ART networks. The way the ART networks are adapted to the problem is described. This includes the realization of a hierarchical ART structure and of a situation specific weighting of the components of the feature vector. The network parameters were adjusted through genetic algorithm optimization. © 1997 Elsevier Science Ltd.

Keywords—Man-machine interaction, Driver modelling, Driver behaviour, Driver assistance, Adaptive systems

INTRODUCTION

Monitoring and warning systems in road vehicles have been proposed for a long time. However, they usually lacked driver acceptance because of inadequate (i.e. neither situation-specific nor driver-adapted) warning thresholds. Michon (1993) gave a representative review of the investigations and development efforts in the past. However, none of them, including the GIDS (Generic Intelligent Driver Support) project described in Michon (1993) has gone beyond conceptual views for driver-adapted warning on the basis of the behaviour model of the actual person driving. Developments in new techniques for knowledge processing have produced autonomous functional capabilities like autonomous situation assessment which can be exploited to support the driver's situation awareness through situation-specific alert messages and warnings which are, at the same time, adapted to the individual demands of the driver. The Driver Assisting System (DAISY) has been developed to comply with these requirements. The development was mainly conducted within the European PROMETHEUS project. In its first version of implementation DAISY was designed for the freeway scenario. At present the development is extended to the highway and urban road scenario environment.

DAISY architecture

To satisfy these requirements a model based approach was used to implement the following main components of DAISY: To account for the required situation adaptivity DAISY contains the Situation Analysis Module (SA). This module performs an explicit analysis of the current objective traffic situation by classifying it from a driver's point of view on the basis of environmental data, i.e. looking at situation features which are relevant with regard to the actual driver tasks. The result is a symbolic description of the situation. This information is used to predict the average behaviour of the other vehicles in terms of a model for average driver behaviour (Kopf, 1994) and to determine objective action limits caused, for example, by other vehicles. The SA module is implemented on the basis of Petri-Nets. This methodology allows a modular implementation covering different aspects of the total traffic situation and combining them in a very flexible manner. Examples of implemented situation models are car following and lane keeping/overtaking.

The Model of the Actual Driver (MOAD) accounts for the adaptivity to the individual driver. Here the actual driver's normal driving style is extracted from observations of his behaviour during a learning phase. In the MOAD the driver objectives (e.g. desired driving speed) are determined first. Then

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the driver intent is recognized by use of a rule based model. In a trained condition the skill based driver control inputs can be predicted and the individual normal driving behaviour described by characteristic time reserve values can be extracted. A further processing step is the assessment of the current driver resources.

The Warning System (WS) combines the output of SA and MOAD to issue a situation-specific danger warning/alert in the case of a dangerous deviation from normal behaviour caused for example by distraction, degraded vigilance or driver overload. Thereby, the warnings/alerts have got the outstanding feature of being adapted to the specific situation including the individual driver's personal characteristics in driving behaviour. The dangers for freeway driving covered by the system are: collision with in-lane (preceding) objects; collision with out-of-lane objects because of unsuitable steering behaviour; collision with out-of-lane objects because of too high a velocity in curves.

The warning messages to the driver have been proven adequate when given haptically. Lateral control warnings are given through vibration signals on the steering wheel combined with a small constant steering wheel torque signal in the direction to be adopted by the driver. Longitudinal control warnings are provided through a vibration signal in the driver cabin floor at the location where the accelerator foot is resting. To detect the deviation from normal behaviour the time reserve is used as a danger measure. The time reserve reflects the driving behaviour of danger prevention on the time basis by a combination of certain parameters. It not only takes into account the actual situation but also includes potential driver actions and potential actions of other vehicles which could endanger the driver. The time reserve proved adequate in a number of experiments with the driver in the loop in a driving simulator and in a test vehicle. The test vehicle experiments have proved the feasibility of the concept in the real environment, in particular with regard to sensing for machine situation on the basis of computer vision (Kopf, 1994).

Figure 1 shows the whole DAISY system. In the following section the design of the behavioural driver model as an essential component of MOAD is described in more detail; the skill based modelling is emphasized.

DESIGN OF THE BEHAVIOURAL DRIVER MODEL

Description of the problem

Rassmussen (1983) has categorized human cognitive behaviour in three main levels: knowledge-based, rule-based and skill-based behaviour. The driving task can also be broken down into three levels to navigation, guidance and control. These levels match the Rassmussen scheme in the following manner. Guidance and navigation can be allocated to the rule-based behaviour, possibly in knowledge-based behaviour for certain cases; vehicle lateral and longitudinal motion control matches best with the traits of skill based behaviour (Donges, 1992). The task domain DAISY mainly has to deal with is typified by the rule-based and skill-based behaviour of the driver. Therefore, it was one of the main design tasks for DAISY to develop a model of the driver as to these behaviour levels and to achieve the ability to learn the individual driving behaviour on the skill-based level on-line.

When selecting an approach for driver modelling one has to pay attention to the following characteristics of the driving task: the driving behaviour is extremely situation specific; the driver perceives a lot of information at about the same time which influences his behaviour and driving behaviour is nonlinear.

These characteristics can be met by an approach based on artificial neural nets. To select a neural net paradigm for driver modelling technical requirements also have to be taken into account. Necessary requirements are: the learning module must have realtime processing capability; gathered knowledge about the driving behaviour must be stored (stability) and new knowledge must be incorporated in the system (plasticity). To meet all of these requirements Fuzzy ART was chosen for the modelling task.

METHODOLOGY

Basic ideas in the neural network literature

The following basic mechanisms which are useful for driver modelling are implemented in different paradigms of artificial neural networks: self organization; stability–plasticity trade off and association.

All ART networks were designed to operate in an environment that requires realtime capability by using self organization as a basic feature. They also incorporate the requirement of sufficient stability of learned patterns while always being able to acquire new knowledge (stability – plasticity trade off). In particular, Fuzzy ART allows to combine different analog sensor inputs to one feature vector and can be trained in realtime by a fast-commit, slow-recode option (Carpenter et al., 1991b). But Fuzzy ART primarily only performs classification of analog patterns. To build a driver model an association between the actual traffic situation and the anticipated driver reaction has to be made. In Carpenter et al. (1991a)

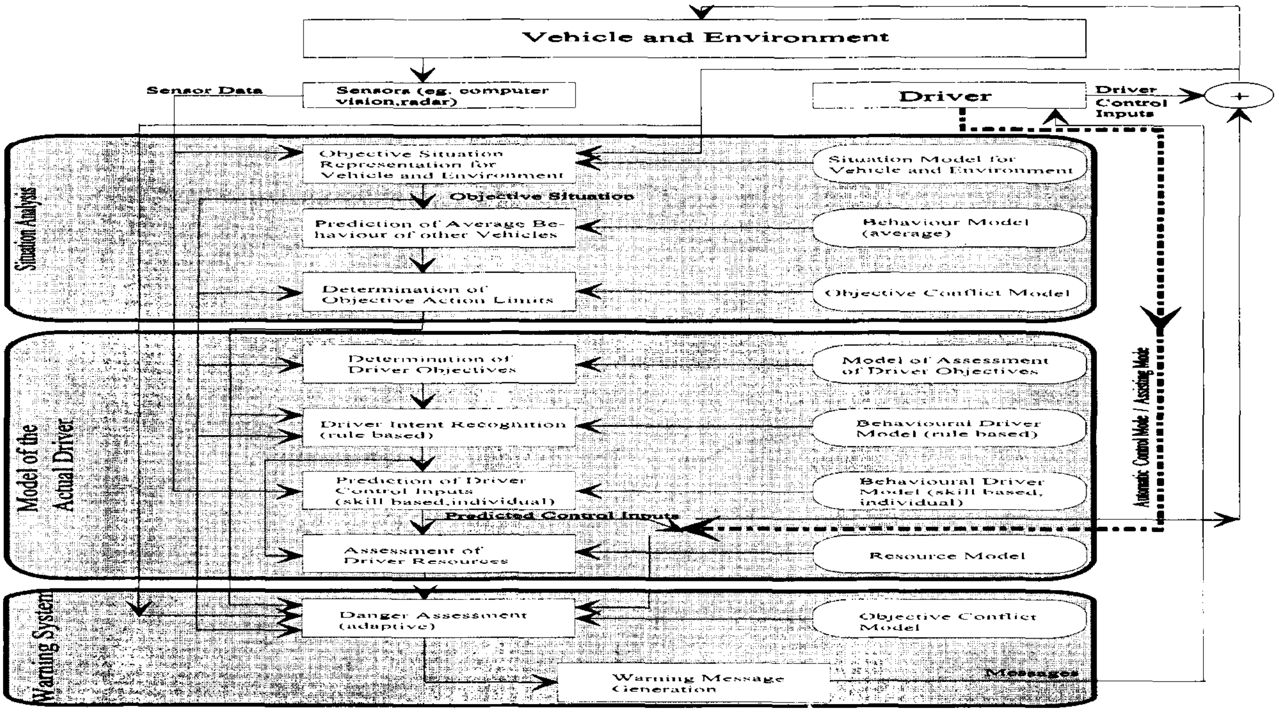

Fig. 1. DAISY architecture.

ARTMAP was published which consists of two ART-networks combined by an inter-art associative memory. Basically this topology combines two different feature vectors by association. An association mechanism is also implemented in the counter-propagation network (Hecht-Nielsen, 1988) and other network paradigms.

Adaptation of Fuzzy ART to the problem

The first adaptation step was simply to associate time series of driver reactions with classes of traffic situations. Traffic situations are represented as feature vectors which include sensoric measurements of the vehicle itself, street parameters and information about other vehicles. These vectors were complement coded. Driver reaction was sampled and the signals were combined to vectors of time series of entire reaction sequences. To model the driving behaviour for lateral control the steering wheel rate and for longitudinal control the break and gas pedal position were taken. After classification of the situation describing vector by the self organizing mechanisms of Fuzzy ART a vector containing sampled driver reactions is associated with the detected class during the learning phase. Refinement of this vector is done with the same learning rule which is part of the ART networks (Carpenter et al., 1991b). With this adaptation the driving behaviour can be learned by observation; this principle was used in a similar way but with a different neural network paradigm in Kraiss and Küttelwesch (1992).

The second adaptation step was to build a hierarchy of Fuzzy ART networks. The reason for this step was the realtime requirement but also to provide better model accuracy. The Fuzzy ART networks of the first level perform a coarse clustering process. For every class found for the first level a second clustering process with higher resolution is made. Every class found for the second stage is associated with the driver reaction sequences.

The third adaptation step was driven by the idea that different elements of the feature vector will have varying relevance in different traffic situations. Therefore a weighting of each element must be done. This was accomplished by introducing relevance parameters in the Fuzzy ART algorithm. In particular the category choice function (Carpenter et al., 1991b) was expanded with the component depending factors $\boldsymbol{k}_i$ (eqn (1)). These factors can be looked at as extra degrees of freedom compared to the basic algorithm which allows a situation specific weighting of the components of the feature vectors.

$$T_j = \frac{\sum_{i=1}^{M} |\boldsymbol{k}_i \cdot \min(\boldsymbol{I}_i, \boldsymbol{w}_{ij})|}{\alpha + \sum_{i=1}^{M} |\boldsymbol{k}_i \cdot \boldsymbol{w}_{ij}|} \tag{1}$$

$T_j \equiv$ matching value for category j
$\boldsymbol{w}_j \equiv$ M-dimensional weight vector of category j
$\boldsymbol{I} \equiv$ M-dimensional input vector
$\boldsymbol{k} \equiv$ M-dimensional relevance parameter vector
$\alpha \equiv$ choice parameter

Figure 2 outlines how the Fuzzy ART hierarchy is implemented in the MOAD module and its interaction with the SA. The symbolic description of the current objective situation is processed in a selection module which corresponds with the rule based Behavioural Driver Model to choose the ART-network covering the situation. Depending on the situation the input vector components and the ART-parameters are selected. All these sources of information are used in the Fuzzy ART hierarchy. In the trained condition driver specific outputs like time reserve values and control signals can be recalled. For driver adaptive warnings the actual time reserve values and the normal ones are compared in the WS. In DAISY at present 17 different Fuzzy ART hierarchies for longitudinal control are implemented; typical examples are car following or car approaching. For lateral control there are 24 Fuzzy ART hierarchies; typical examples are lane keeping and overtaking.

Optimization of network parameters

Designing an artificial neural network to solve a specific problem often means the selection of network

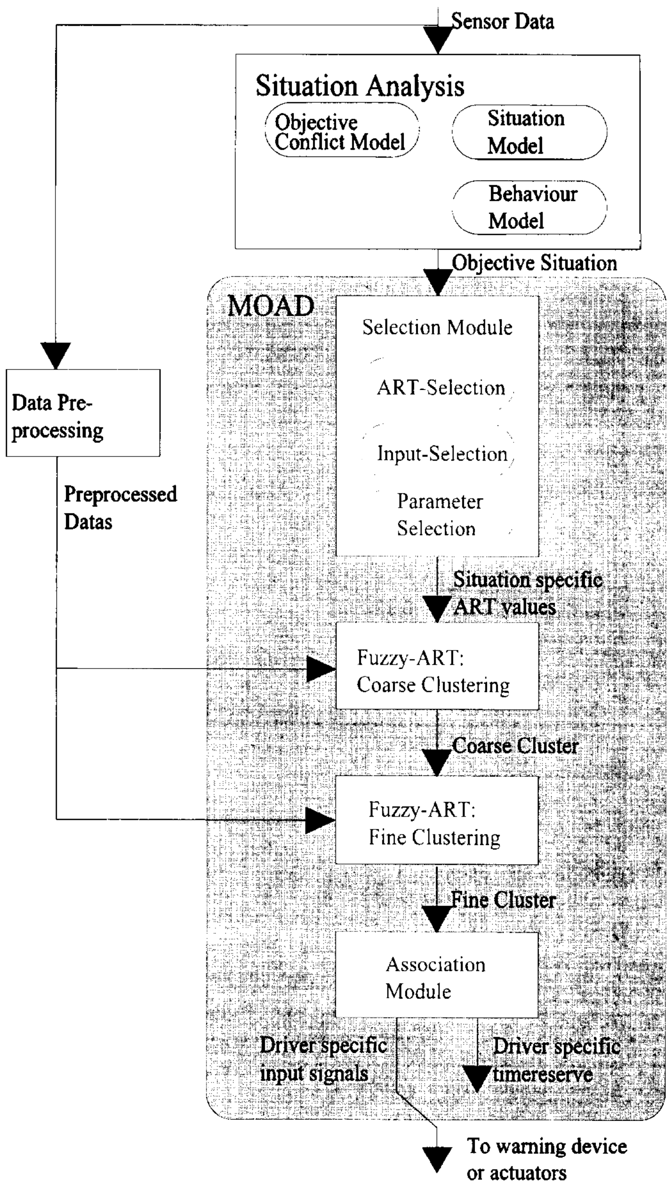

Fig. 2. The Fuzzy ART based MOAD module.

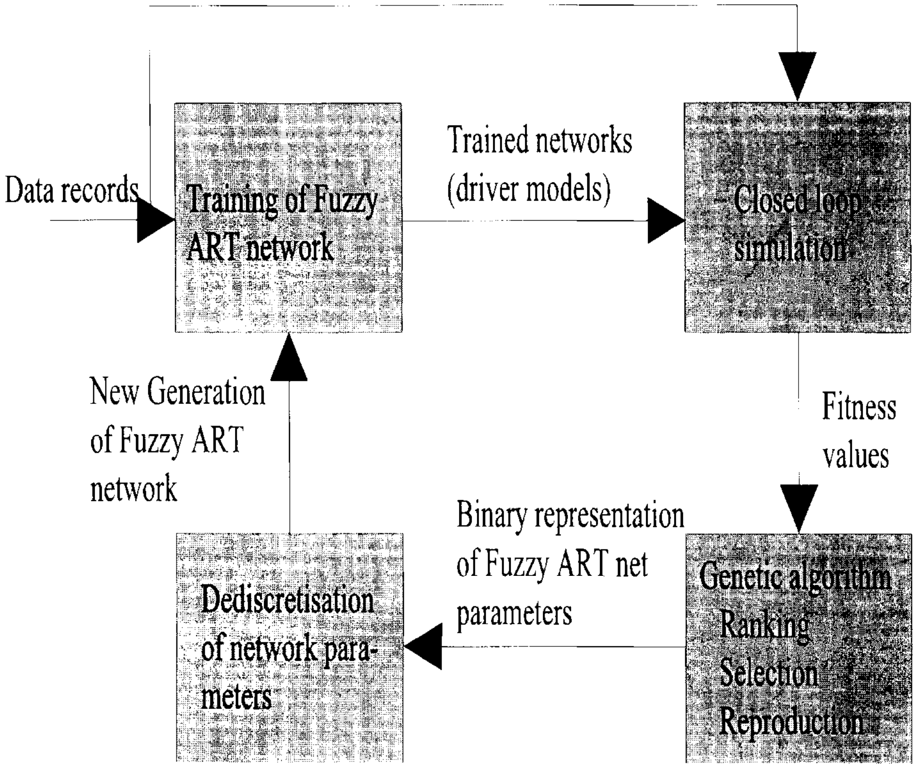

Fig. 3. Principle of network parameter optimization.

parameters by trial and error. At present, no analytical method is available which provides problem specific parameter values of a special neural network. This is also true for the above described Fuzzy ART approach for driver modelling. In this approach the two vigilance parameters for coarse and fine clustering but also the introduced parameters for situation specific weighting of the input vector components must be tuned to get accurate driver models.

Genetic algorithms have proven to be a very flexible and a generally useable method to solve search and optimization problems (Goldberg, 1989). They realize the trial and error process to find a good problem solution. This method was used to optimize the Fuzzy ART parameters off-line in the following way (Fig. 3). Recorded data from test trials which describe the driving behaviour of a particular driver are used to train a population of Fuzzy ART networks; each of these has its own set of parameters (e.g. vigilance parameters or relevance parameters). After training every network is used as a controller to drive a model of the used car. During this closed loop simulation car reactions and previously recorded data of the human driver are compared in order to calculate fitness values for the different network controllers. These values are used in the genetic algorithm to adapt the network specific parameters by use of genetic operators. A binary representation of the Fuzzy ART parameters is transformed in the floating

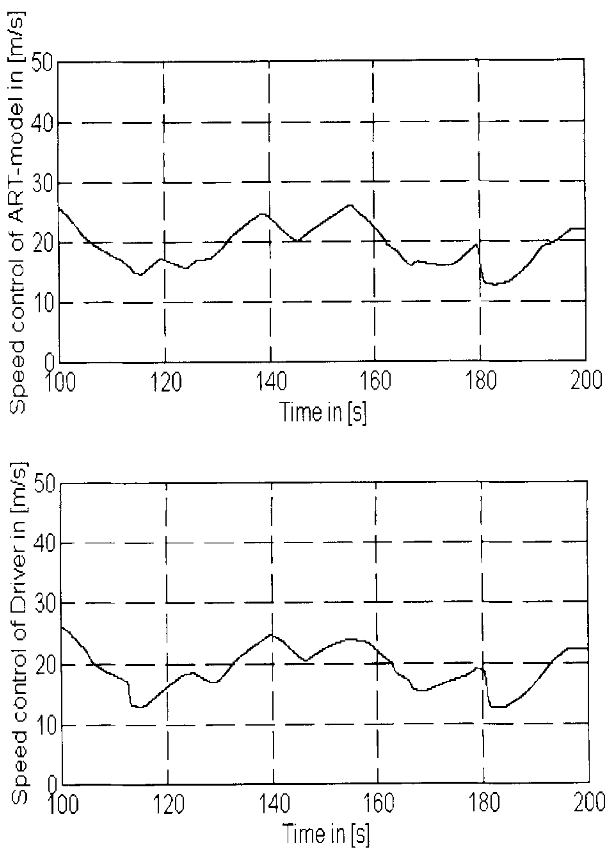

Fig. 4. Speed control: Driver - ART model.

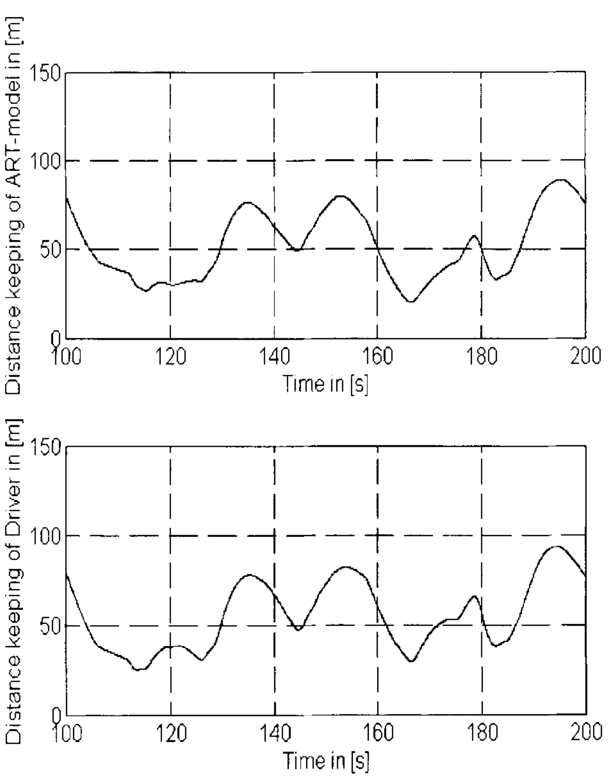

Fig. 5. Distance keeping: Driver - ART model.

point values of these parameters which are used for a new training cycle. This process is repeated until a satisfactory solution is found or a predefined number of generations is reached. After a parameter set is found this can be used to train drivers on-line in future. The procedure was used to first adapt the vigilance parameter set and then the relevance parameter set; it was done twice to stabilize the found parameters.

The main characteristics of the implemented genetic algorithm are: steady state reproduction without duplicates; 8 bit binary representation using grey coding; linear normalization as fitness technique; roulette wheel selection of individuals and operators; used operators: One-point crossover, two-point crossover, uniform crossover, one-bit mutation; population size: 16 and new children: 4. The concept of Pareto optimality was used because different fitness values were evaluated at the same time to describe the total fitness of the individuals (Goldberg, 1989).

RESULTS

First the use of a trained and optimized neural driver model as a human-like controller is shown for longitudinal control. Figure 4 shows a comparison of the driver and his trained network. The network works on an input feature vector describing the driving situation for approaching and following a preceding vehicle by the following parameters: actual speed of own vehicle; actual acceleration of own vehicle; actual difference in speed between own vehicle and preceding vehicle; actual headway distance to preceding vehicle; time-to-collision (TTC) with respect to preceding vehicle; anticipatory road curvature; and azimuth of own vehicle relative to the road. The driven speed in a car following situation is depicted for both in a typical sequence. In Fig. 5 distance keeping of driver and network in the same sequence is plotted. The network is stable and behaves very similar to the driver which is an indication that the model can imitate the driver.

As a sufficiently accurate human driver model is available this can be used in DAISY in different ways. Here the use for driver adaptive warnings for longitudinal control is outlined. The time reserve concept is well suited to define the warning threshold (Kopf, 1994). This measure can be used for objective as well as subjectively adapted hints and warnings. To realize situation adaptivity for each Fuzzy ART class-specific statistical values can be evaluated for the time reserve, e.g. the average value and standard deviation. Both values describe the situation-specific

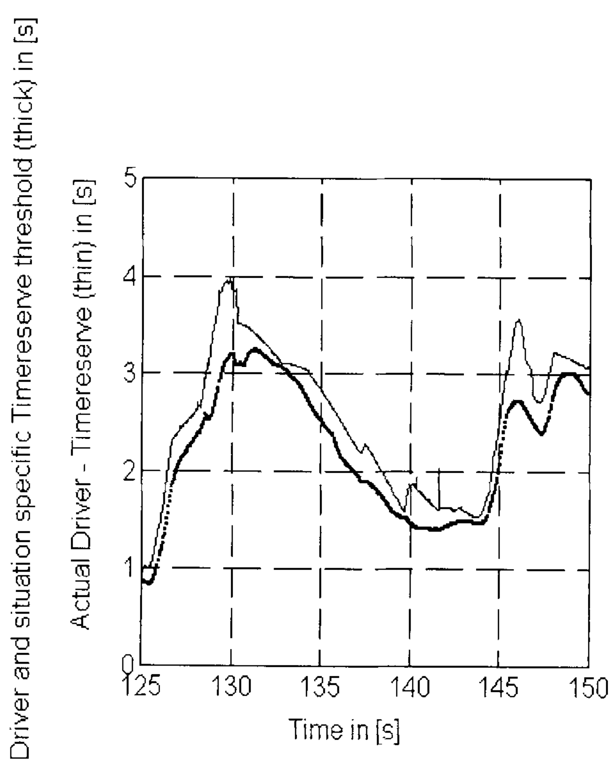

Fig. 6. Comparison of situation specific actual time reserve values during normal driving with the thresholds of normal behaviour region.

normal region of the driving behaviour. By comparing the actual time reserve value with the normal region, deviations from normal can be detected. These deviations are considered to be caused by abnormal driving behaviour which may have its deeper cause, for example, in a lack of vigilance. If the actual value of the time reserve falls below a certain level adapted to the normal driving behaviour, a warning is issued.

Figure 6 shows the actual time reserve values during normal driving compared to the situation specific threshold values of the normal driving behaviour region; as can be seen the driver does not leave the normal region during the entire sequence indicating that the driver behaves normally. Figure 7 shows the comparison of an imitated abnormal driving behaviour of the same driver with the learned normal behaviour region; in this case, the driver leaves his normal time reserve region all the time; this deviation can be taken as an indication of abnormal driving. Some kind of message should be issued to the driver to draw his attention to this behavioural change. The intensity of this message should be increased along with further departure of the normal driving behaviour, in particular with respect to the case, when the time reserve is approaching zero.

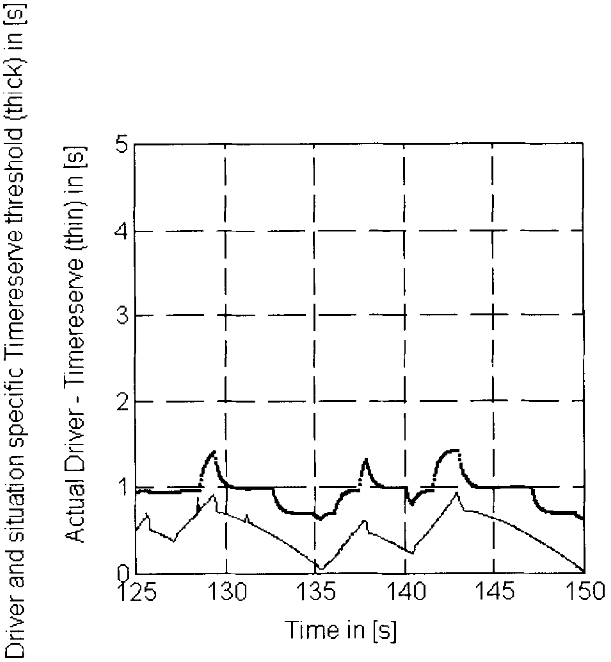

Fig. 7. Comparison of situation specific actual time reserve values during unnormal driving with the thresholds of normal behaviour region.

CONCLUSION

In this paper it was shown that realtime learning of driving behaviour can be accomplished by a neural net approach based on Fuzzy ART. ART specific parameters and the introduced relevance parameters were found by means of off-line optimization with genetic algorithms; once predefined, these parameter sets can be implemented in the on-line learning process to extract the normal driving behaviour by observation. The trained driver model can be used in a driver assistance system like DAISY in different ways. To satisfy the requirement of adaptiveness for messages and warnings it is possible to extract the driver and situation specific time reserve values to describe normal driving behaviour on a time basis. Deviations from these regions can be detected and used to issue driver adaptive warnings. It is also possible to use a trained neural network as a human-like controller. Other possible applications like driver intent recognition, assessment of current driver resources and driver identification are part of the current research work.

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