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Driver-Adaptive Assist System for Avoiding Abnormality in Driving

M.A.S. Kamal, T. Kawabe, J. Murata and M. Mukai

***Abstract*— Sometimes a driver deviates from his natural or normal driving style due to inadequate attention or faces abnormal situation caused by a number of psychological and physical factors. Such abnormalities often lead a driver to a mistake that may cause an accident. This paper presents a novel approach called driver-adaptive assist system to avoid such abnormalities in driving scenario as a preventive measure against occurrence of vehicle collisions, assuming that natural driving style of individual drivers is the safest style. Adaptive fuzzy system with statistics of recent fluctuations records are used to determine the driving behavior from noisy data. Another fuzzy reasoning section determines the level of abnormality in driving to notify or warn the driver so that he can pay back his full concentration in driving. Different simulated drivers with pseudo realistic styles in starting, stopping and car following are used to investigate performance of the proposed system. Empirical results show the ability of the system to recognize abnormality of drivers having different driving styles.**

I. INTRODUCTION

Increasing trend in traffic accidents has become a serious social problem all over the world. Traffic accidents are often caused by mistakes of human drivers. A large number of mistakes are due to drivers with inadequate attention in driving led by fatigue, tiredness, drowsiness, having drunk, etc. It is obvious that a warning systems could be effective in most rear-end crushes and other accidents.

Conceptual view of the driving process from a driver's perspective is shown in the Fig. 1. Based upon the basic assessment of range-clearance, velocity, etc. the driver decides on a course of control action that determine the acceleration-braking of the vehicle. The rear-end collisions are led by the situation when a vehicle's stopping distance is greater than the range-clearance from front vehicle or obstacle [6].

Researchers have been working to develop collision avoidance and steady following systems to avoid traffic collisions by providing automatic warning to the driver or braking the car in an emerged danger. Most of such systems use a similar algorithm to warn a driver when the inter-vehicle gap reduces to less than a critical distance. The critical distance for warning a driver is often determined heuristically based on the skill of an average driver in each of the systems [1], [2], [3]. Thus those warning systems provide the same type and the same level of assistance to all drivers, regardless of their driving behaviors, skills, ages and preferences. But it is believed that in reality the types and the levels of assistance desired by drivers vary widely according to their driving behaviors, because driving behavior of a beginner and an expert person, a young and an old person are completely different. So a typical assist system that assists all drivers in the same way may not be accepted widely due to mismatch with individual preference. This system may seem appropriate to only some drivers whereas it may seem noisy for providing unwanted advice to some other and may seem insufficient assistance to the others.

M. A. S. Kamal is with the Department of Mechatronics Engineering, International Islamic University Malaysia, Kuala Lumpur, Malaysia. Email:maskamal@iiu.edu.my

T. Kawabe, J. Murata and M. Mukai are with the Graduate School of Information Science and Electrical Engineering, Kyushu University, Fukuoka, Japan. Email:{kawabe, murata, mukai}@ees.kyushu-u.ac.jp

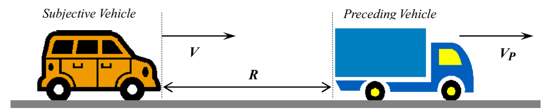

Fig. 1. Physical variables sensed in human-manual driving.

Since abnormality in driving leads a mistake that may cause an accident, a system of notifying abnormality in driving rather than only notifying at emerging collision probably produces a much more conducive outcome for reducing rear-end collisions. Some researchers have been working on the development of safety systems using different techniques based on physiological measures like brain waves, heart rate, pulse rate, respiration, etc. [15], [13], [14]. There are different methods that can be used to detect fatigue, drowsiness and other psychological facts in driving. But these techniques have the drawbacks since they require sensing-equipment (electrocardiogram, electromyogram, respiration, skin conductance, wristband etc.) to be attached to the drivers causing annoyance to them [15], [16]. The other techniques monitor eyes and gaze movement using complicated image analysis.

A driver's state of attention can also be characterized by comparing current driving behavior with his natural driving behaviors like the lateral position, variation in headway range, braking and acceleration characteristics, speed and range fluctuations, steering wheel movements, and time-to-line crossing. To cope with the actual inattentiveness in driving it is necessary to develop a non-intrusive system based on observation of indirect driving behavior of individual driver. Although, these methods seem a bit complicated due to variation in vehicle type, driver experience, road type, weather etc., it may be an efficient and widely accepted system, and contribute in reducing traffic accident due to mistakes greatly.

Here we propose a behavior based adaptive assist system to identify level of inattentiveness or abnormality in driving that reflects individual skills, preference, and other factors

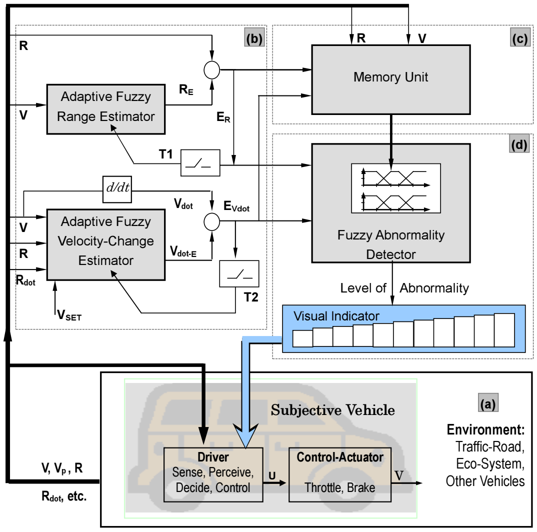

Fig. 2. The overall system consists of driving behavior model, abnormality detector, and human interface to notify the driver.

in driving and seems natural to the drivers as an effective accident-preventive measure. Block (a)-(d) in Fig. 2 show the general structure of the proposed system that is considered in this paper. It has a complete behavior model of the driver that can predict or estimate the ideal styles, such as range-clearance, acceleration-braking, etc., from any driving condition. Since a driver always fluctuates from usual (mean value) behavior in his natural course of driving, it is necessary to know the history of such fluctuations. So a sufficient behavior model should include the driving fluctuation history to represent overall driving behavior range of the driver. Once the behavior is known, it is easy to observe the driver whether he is deviated from his natural driving style. The deviation levels in different aspects can be used to determine degree of abnormality of the driving situations, and through the human interface the driver can be notified.

To investigate the proposed idea, in this paper, we have developed an adaptive fuzzy estimating system and a fluctuations recording memory unit to form a complete driving behavior model. Another fuzzy reasoning section determines the level of abnormality in driving to notify or warn the driver so that he can pay back his full concentration in driving. The system could learn the different driving patterns of corresponding drivers and generate effective abnormality indication based on the individual behavior when they deviate from their natural style or when the preceding car brakes suddenly.

II. DRIVER ADAPTIVE ASSIST SYSTEM

A. Adaptive Fuzzy Inference System

Adaptive fuzzy systems, the self tuning fuzzy inference systems, are suitable when a priori knowledge is not easy or possible to realize, specially for the conclusion of the rules. The input side of the adaptive fuzzy inference system in this work uses Gaussian membership functions, because of its simplicity in tuning and excellent approximation properties [7]. The membership degree of the fuzzy set F_i^l in state variable x_i is

$$\mu^{F_i^l}(x_i) = \exp\left[-\left(\frac{x_i - c_i^l}{\sigma_i^l}\right)^2\right] \tag{1}$$

where $l = 1, 2, ..., M$ is the rule number, c_i^l and σ_i^l are the center and radius of lth Gaussian function respectively. The IF-THEN rules of the fuzzy estimator for n-number of input varaibles can be expressed as

R_l :IF x_1 is F_1^l,..., and x_n is F_n^l THEN $u = w^l$.

The singleton output membership functions are used in the output side. The singletons are the simplest membership functions that are very commonly used in practical control applications [8], [9], [10], [11]. A fuzzy system modeled with singleton consequents is a special case of fuzzy system modeled with trapezoidal consequents, with membership value 1.0 at only one number from the real line and 0 everywhere else, and can do almost the same thing as modeled with trapezoidal consequents [12].

Consequently, the output value is

$$u = \frac{\sum_{l=1}^{M}\left[\left(\prod_{i=1}^{n}\mu^{F_i^l}(x_i)\right).w^{F^l}\right]}{\sum_{l=1}^{M}\left(\prod_{i=1}^{n}\mu^{F_i^l}(x_i)\right)} \tag{2}$$

where w^{F^l} is the position of the singleton w^l in rule R_l.

Such membership functions in the conclusion part provide a very simple tuning way to adjust their positions if the target output values are available. Initially, the position of the fuzzy singletons are set at approximated or random values. For certain input state values it estimates the output. Then it is compared with the target output of the system to find out the estimation error $E = [u_{target} - u]^2$. Finally, the positions of the output singletons are adjusted in proportion to the error, using gradient descent algorithm,

$$\Delta w^{F^l} = -\eta \frac{\partial E}{\partial w^{F^l}}. \tag{3}$$

The process continues for all the available data repeatedly with a very small learning rate η until the estimation error reduces to some threshold value. In case of the standard fuzzy system, where the rule base is derived from a priori knowledge, the adjustment of eq.(3) is omitted. This paper also used such fuzzy system with triangular membership function for generating abnormality signal.

B. Adaptive Model of Driving Behavior

There are a number of parameter based driving models that can represent typical driving pattern if a few things such as time headway, braking rate of preceding vehicle, etc., are known a priori. Although in most of such cases it is assumed that the range-clearance characteristic of a driver is linear, but in reality, it is a non-linear function of the vehicle velocity. In order to find a universal structure of the driving model here we propose a composite system to learn the complete driving model of individuals online.

A driver has visual capabilities for sensing range-clearance (headway distance) R, range changing rate $\dot{R} = V_P - V$, and the velocity V, Fig. 1. Based upon this basic assessment and desired or set velocity V_{set} the driver of the subjective vehicle decides the acceleration/ braking $\dot{V}$ of the subjective vehicle [5]. V_{set} is the speed that the driver chooses to go when range is large in the driver's view of situation. When a preceding vehicle is absent or the range is very large then the deciding factor is V_{set}. The desired velocity V_{set} of a driver varies due to a number of unknown psychological and physical factors such as road types, stormy-weather (snow, rain), turning in a crossing, running over curved road, overtaking, etc. In this work a constant V_{set} is considered assuming the observation is made on a straight single lane road in an ideal driving environment. Thus it is necessary to model the range-clearance and acceleration-braking styles of a driver to express his longitudinal driving behavior.

To represent the driving behavior model here two adaptive fuzzy estimators Fig. 2(b) and a memory unit Fig. 2(c) are proposed to learn and record individual driving style.

At steady following it is believed that a driver decides the range-clearance according to the current car-velocity. Here the fuzzy range estimator estimates R_E, the steady state range-clearance, from the current velocity V of the vehicle. It compares the estimated value R_E with the actual value R to determine $E_R = R - R_E$ the estimation error (or deviation of the driving style). It observes changes in V and R for a several seconds to confirm the steadiness of the vehicle. In such steady cases using this error E_R the position of fuzzy singletons in the output membership function are updated using eq.(3).

The proposed fuzzy velocity-change estimator estimates $\dot{V}_E$, acceleration-braking values from V_{set}, V, R and $\dot{R}$. It compares the estimated value $\dot{V}_E$ with the actual value $\dot{V}$ to determine $E_{\dot{V}} = \dot{V} - \dot{V}_E$ the estimation error (or deviation of the driving style). To avoid much computation, only after a few estimations the position of fuzzy singletons in the output membership function are updated.

Usually range-clearance, velocity control actions of a driver are not constant for a certain scenario. Instead there are some stochastic variations due to unknown psychological and physical factors. This variations seem noisy to the estimator, but they can learn the mean behavior values of the driver with small learning rates. The range and frequency of variations from the mean value differ from driver to driver. Thus the representation of the natural driving behavior requires learning the variations or range of usual deviation from the mean behavior of individual drivers. Here the memory unit is incorporated to count the frequency of variations at different range steps, and a forgetting factor is introduced in the counter so that the values reflect the recent behavior. Fig. 3 shows a typical values of range clearance error distribution over range error intervals of 1.0 in length. Here the range error is scaled as $\frac{R - R_E}{R_E}$. Thus this unit and fuzzy estimators together represent the natural driving behavior of a driver in longitudinal motion, Fig. 2(b) and (c).

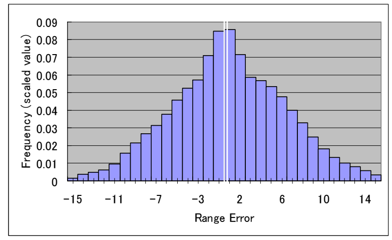

Fig. 3. Distribution of variation from mean range-clearance values.

C. Situation of Traffic Collisions

Generally a driver keeps approximately a constant time headway, which is the time taken by the subjective vehicle to reach the current position of the preceding vehicle. A constant time headway specifies an increasing range-clearance (distance headway), $R = V \times T_{headway}$, between the subjective and preceding vehicle as the speed of the subjective vehicle increases. Most of the rear-end collisions are led by the situation when a vehicle's stopping distance is greater than the range-clearance from front vehicle or obstacle (distance headway) [6]. Therefore, apparently it is important to maintain greater headway so that the vehicle can be stopped before a collision. Survey shows that the desired range-clearance or the time headway of drivers vary widely. Some drivers choose to keep a time headway of 1 sec or less, and some others prefer safer and longer time headway more than 3 sec [5]. This scattered patterns do not represent the possibility of an accident to some driver is much higher than the other. The drivers with short, medium or long headway preferences reflect their natural behavior in driving in which they have been continuing for the years safely. The skilled drivers with shorter time headway are habituated to act faster in their typical styles when the preceding vehicle brakes. On the other hand, the drivers, who are habituated to act slowly in a safer way, keep the time headway longer. They can easily avoid any collisions if they are steadfast in their own style regardless of their behavior-types except only those whose styles are inherently abnormal.

A number of human factors and physical factors cause the variation of time headway and increase the stopping distance [6]. The most vital cause of smaller headway is due to fast driving to reach the destination in short time. The drivers who want to reach the destination in shorter time reduce the time headway than their usual headway. Inadequate attention in driving may be caused by fatigue, lack of sleep, use of medication and other reasons. It affects the perception, reaction time, and control of throttle and brake that deviate a driver from his natural driving style. Some other physical situation may put the vehicle in abnormally dangerous condition.

D. Assistance in Abnormality

If the natural driving behavior of a driver is available, it is easy to compare his current behavior to know whether he is on the track of his own style. Whenever the driver deviates from his style beyond threshold levels a warning

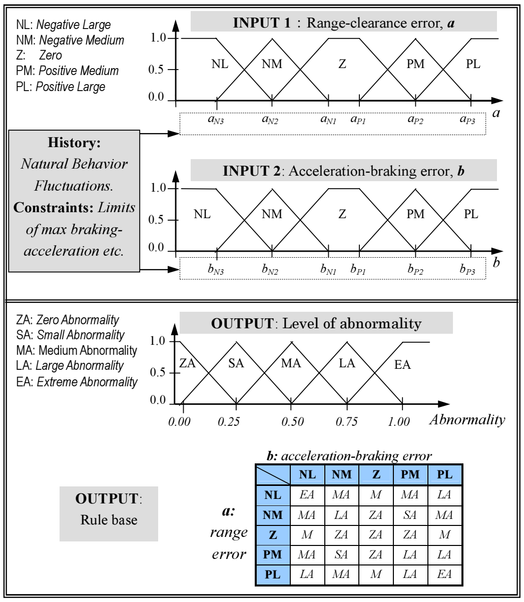

Fig. 4. Membership functions and decision table for abnormality level determination

should be provided through human interface, Fig. 2(d). The threshold should be soft and based on natural behavior so that frequent unwanted notices can be easily avoided. Here we propose a fuzzy system to generate such abnormality signal replacing the ordinary thresholds with soft fuzzy sets as in shown Fig.4. It is designed to produce a signal indicating level of inattentiveness based on the natural headway and instantaneous acceleration-braking behavior.

The inputs of the system are range-clearance error $a = \frac{E_R}{R_E}$, and error in acceleration-braking $b = \frac{E_V}{V_{mx}}$. An average error over 3.0 sec is consider to calculate a. The values of fuzzy linguistic variables are the corresponding range error magnitudes a_{N3} to a_{P3} in INPUT1, and the corresponding acceleration-braking error magnitudes b_{N3} to b_{P3} in INPUT2. These error values, that are derived from recent history database and physical constraints of the vehicle, constitute an adaptive structure of the membership functions.

To define the limits of zero abnormality, the frequencies of positive deviation and negative deviation as in Fig. 3 are considered separately. The point a_{P1} is selected in such a way that 90% values fall in the interval [0, a_{P1}]. If it exceeds the limit $0.05 \le a_{P1} \le 0.15$, then a_{P1} is set at the given max or min limit. The points a_{P2} and a_{P3} are analogous to the range-clearance error at the warning distance and critical braking distance of other collision avoidance systems [2], [3]. Here we set a_{P3}, the error in the critical distance at which the driver must apply full braking immediately to avoid the collision at that velocity, and a_{P2} is the midpoint of between a_{P1} and a_{P3}. The selection of the point a_{N1} is similar to that of the point a_{P1}, within the limit $-0.20 \le a_{P1} \le -0.05$. The a_{N3} is set at 1.0, which corresponds to the clearance being double of the usual, and a_{N2} is the midpoint between

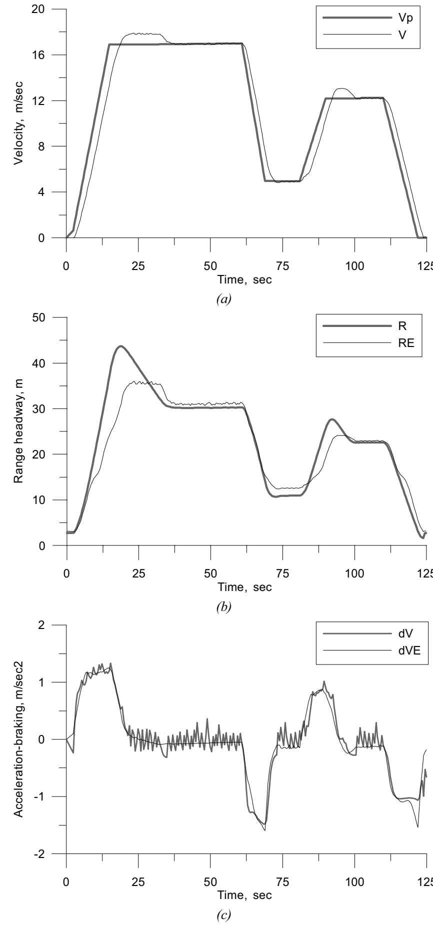

Fig. 5. Driving behavior in longitudinal motion and estimation (a) velocities of both cars, (b) range-clearance: actual (R) and estimated (RE) values, (c) acceleration-braking: actual (dV) and estimated (dVE) values.

a_{N1} and a_{N3}.

In the membership function of acceleration-braking error, the point b_{N1} and b_{P1} are decided from recent variations in acceleration-braking similar to the selection of the point a_{P1} but without a limit. The point b_{N2} are the average maximum values of braking when the car stops, and b_{P2} is the average maximum values of acceleration when the car starts from standstill. The point b_{N3} is the midpoint of b_{N2} and maximum possible braking, and b_{P3} is the midpoint between b_{P2} and maximum possible acceleration. Thus the two dimensional behavior errors are completely adaptive to individual driver's skills, his style and the physical braking limits of the car. The lower part of Fig. 4 shows the output membership function and decision table to generate abnormality signal.

III. TEST RESULTS

Recently proposed two pseudo realistic simulated driver models are taken, and a number of drivers are used to be assisted by the proposed system. These drivers have different non-linear range-clearance, fluctuations, acceleration-braking, action delays characteristics. The first one is a model of automatic driver implemented experimentally that is capable to start, stop and follow the preceding car by controlling both the brake and accelerator very similar to a human driver actions in generating complex control action [4]. The driver follows a constant time headway with a zero-speed range margin. The second one is based on modified Gibbs method in which a driver tries to adjust the headway gap and velocity [5], [17]. The acceleration/braking rate is generated in proportion to the headway range and range rate. Here, gain scheduling is used to deal with different relation of the range and range rate, so that for shorter range and negative range rate the controller reacts more aggressively. A number of effects of human factors such as reaction time, jerk in braking or acceleration, slight variation in headway time, etc. are introduced to both systems to make them close to real drivers.

The fuzzy behavior learner was initialized using typical driving pattern with 2.0 sec time-headway gap and a 2 m zero-speed range clearance. This initialization sets output fuzzy singletons of the fuzzy range and velocity-change estimators. During initialization, the typical driving model was simulated in different hypothetical situations subjected to states that would be dangerous in reality and hardly happen in a life of a driver. This ensures whenever a driver faces an extreme danger for the first time the system can support him by providing the abnormality information with respect to the ideal case (of initial driver) at least.

The initialized system is used to learn the behavior of different drivers whose desired range-clearance styles are completely different [4], [5], [17]. Their responses contain stochastic noise and random reaction delay. It is found that the estimators could approximate the mean values of range-clearance and response throughout the driving states of each driver properly. A typical pattern in Fig. 5 shows the comparison of the estimated values with the actual values in a typical scenario when the preceding car starts from its standstill position to a steady speed, then brakes to a lower speed, again speed up and finally stop. The subjective car follows the preceding car with desired time-headway of 1.8 sec and desired velocity of 18.0 m/sec. The system could estimate the steady range-clearance with less than 3.0% error. This error could be reduced further if there were no variation in driving style. In speed up and speed down of a car the actual range clearance is not the same as of its steady (or estimated) values. The acceleration-braking style is also estimated for the same driving scenario. Although the actual values are very noisy even in steady driving, the estimator could correctly approximate the mean values of acceleration-braking throughout the driving states. In the figures, RE and dVE indicates the ideal values (estimated values) of range-clearance and acceleration-braking rate of the driver.

A. Abnormality Detection

Fig. 6 shows the abnormality indication when the driver was inattentive for a while and the preceding car braked to down its speed at a lower level. At 22 sec the driver became inattentive and kept the car going at the same speed. But at 26 sec the preceding car braked down its speed, whereas at 31 sec the driver realized the fact and braked aggressively to compensate the braking delay. The abnormality changed from zero at 28 sec with a peak value at 31 sec when the driver started to act, and finally it became zero when the driver reached at steady state condition with new preceding car velocity.

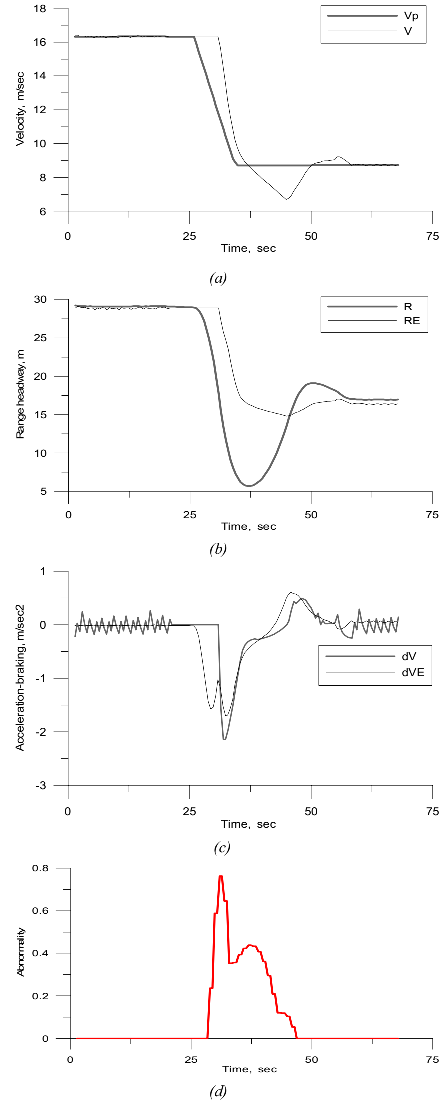

Fig. 6. Scenario in driving when the driver was inattentive for a few second and preceding car brakes, (a) velocities of both cars, (b) range-clearance: usual (RE) and current (R), (c) acceleration-braking: usual (dVE) and current (dV), (d) abnormality.

Fig. 7(c) shows the abnormality indication when the driver changed his driving style for the same velocity pattern of the preceding car of in Fig. 5. The suffix 1.8, 1.4 and 2.2 indicates the respective time-headway in sec of the driver who usually drives at time headway of 1.8 sec. The abnormality is almost zero when the driver drives as per his usual style

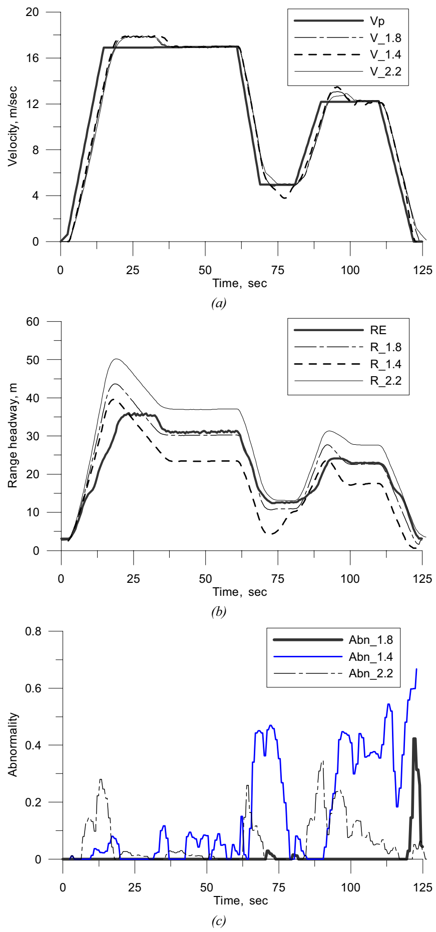

Fig. 7. Scenario when the driver, who usually follow approximately 1.8 sec headway, follows shorter (1.4 sec) and longer (2.2 sec) time headway, (a) velocities, (b) range-clearances (R) and usual range-clearance RE, (c) abnormality.

of keeping 1.8 sec time headway, with a variation of 10.0%. When the time headway decreased at 1.4 sec, the abnormality appeared and became very high while the preceding was car braking. While the same driver drived with a time headway of 2.2 sec, a much safer separation but causing traffic congestion, the abnormality indication appeared and became high in the time of the preceding car was speeding up. Thus the abnormality indicator provides a visual warning when the driver changes his style significantly.

IV. CONCLUSIONS AND FUTURE WORK

A. Conclusions

This paper has presented a novel approach of assisting a driver when he deviates from natural driving behavior as a preventive measure of accidents. It also notifies at the abnormal situations due to other vehicle or environmental causes in a non-intrusive manner. The simulation results showed that the assistance provided by the system is completely appropriate to an individual and reflects his need of assistance. The proposed driver-adaptive assist system matches with the preference of individual drivers, and it is expected to play significant role in reducing traffic accidents.

B. Future Work

The novel idea presented in this paper has opened a number of aspects to be investigated in future to implement it on a real system. The desired speed is considered constant for a driver in a typical road. But in reality the desired speed of the driver is completely unknown, and a system is to be developed to identify this. An online experiment is necessary to evaluate the reliability of the assist system taking feedback from individual drivers. The proposed stand-alone assist system can be enhanced by incorporating communication with other cars and road-transport infrastructure.

REFERENCES

[1] S. Nagiri, Y. Amano, K. Fukui and S. Doi, A Study of a Personally Adaptive Driving Support System Using a Driving Simulator,*Driver Behavior and Active Safety*, Special Issue R&D Reviw of Toyota CRDL, vol.39 no.2, 2004.

[2] A. Doi, T. Butsuen, T. Niibe, T. Yakagi, Y. Yamamoto and H. Seni, Development of a Rear-End Collision Avoidance System with Automatic Braking Control, *JSAE Review*, vol.15(4), pp.335-340, 1994.

[3] Y. Fujita, K. Akuzawa, and M. Sato, "Radar Brake System," in 1995 Annual Meeting of ITS America, vol. 1, pp.95-101, Washington D.C., 1994.

[4] J.E. Naranjo, C. Gonzalez, R. Garcia and T. Pedro, ACC+Stop&Go Manuevers with Throttle and Brake Fuzzy Control, *IEEE Trans. on Intelligent Transportaion Systems*, vol.7, no.2, 2006, pp.213-225.

[5] P. Fancher, Z. Bareket, H. Peng and R. Ervin, "Research on Dersirable Adaptive Cruise Control Behavior in Traffic Streams," Phase 2 Final Report, The University of Michigan Transportation Research Institute, 2003.

[6] K. Matsunaga, Combined Factors in Traffic Accidents and a Method of Education for Safe Driving, *Society of Automotive Engineers of Japan*, Vo. 54(7), 2000, pp.23-38.

[7] B. Liu and J. Si, The best approximation to C^2 function and its error bounds using regular-center Gaussian networks,*IEEE Trans. Neural Netw.* vol.5, no.5, 1994, pp. 845-847.

[8] M. Sugeno, H. Winston, I. Hirano, and S. Kotsu, "Intelligent control of an unmanned helicopter based on fuzzy logic," in Proc. Amer. Helicopter Soc., 51st Annu. Forum, Houston, TX, 1995, pp. 791-803.

[9] J. E. Naranjo, C. Gonzalez, R. Garcia, T. de Pedro, and R. E. Haber, Power steering control architecture for automatic driving, *IEEE Trans. Intell. Transp. Syst.*, vol. 6, no. 4, 2005, pp. 406-415.

[10] P. Salgado and J. B. Cunha, "Greenhouse climate hierarchical fuzzy modeling," *Control Eng. Pract.*, vol. 13, no. 5, 2005, pp. 613-628.

[11] G. Vachkov and T. Fukuda, Structured learning and decomposition of fuzzy models for robotic control applications, *J. Intell. Robot. Syst.*, vol. 32, no. 1, 2001, pp. 1-21.

[12] M. Sugeno, "On stability of fuzzy systems expressed by fuzzy rules," *IEEE Trans. Fuzzy Syst.*, vol. 7, no. 2, 1999, pp. 201.224.

[13] L. M. Bergasa, J. Nuevo, M. A. Sotelo, R. Barea and M. E. Lopez, Real-Time System for Monitoring Driver Vigilance, *IEEE Trans. on Intel. Trans. Syst.*, vol.7, no.1, 2006.

[14] M. Kaneda, H. Obara and M. Owada, "Study on a Method of Using Image Processing Technology to Detect Inattentive Driving," Conf. of JSAE, 1999.

[15] J. Healey, and R. Picard, "SmartCar: Detecting driver stress," in Proc. 15th Intl. Conf. Pattern Recognition, Barcelona, Spain, vol.4, 2000, pp.218-221.

[16] A. Kircher, M. Uddman and J. Sandin, Vehicle control and drowsiness, *Tech. Rep. VTI-922A*, Swedish National Road and Transport Research Institute, Linkoping, Sweden, 2002.

[17] Q. Xu, K. Hedrick, R. Sengupta and J. Vander Werf, "Effects of Vehicle-vehicle/ roadside-vehicle Communication on Adaptive Cruise Controlled Highway Systems," in Proc. of Vehicular Technology Conference, 2002, pp.1249-1253.