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Driver Behavior Classification Model based on an Intelligent Driving Diagnosis System

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***Abstract*—This paper considers the problem of characterize the way people drive applied to driver assistance systems and integrated safety systems without using direct driver signals. To make this, is proposed the design of a driver behaviors classifier based on a previous intelligent driving diagnosis system development by us [1]. This, take into account signals that can be acquired by a GPS data logging system: position, velocity, accelerations and steering angle. The classifier proposed, present the structure of an intelligent driver behaviors model based on neural networks and using as inputs statistical transformations of the driving diagnosis time signals: steering profiles, pedals uses, speeding and getting out of the lane and road. The validation of this classifier is developed in two applications: driver identification for security systems and to classify a driver into one of two categories, aggressive and moderate. The proposed approach has been implemented in real environment and its performance tested in simulation runs. Experimental results presented in this paper shows that our intelligent driving diagnosis system is able to classify different kinds of drivers with a high degree of reliability.**

***Index Terms*—driver behavior classification, driving diagnosis system, driver assistance systems, integrated safety systems, intelligent transportation systems.**

I. Introduction

ONE of the major problems of mortality rate, according to the World Health Organization, are traffic accidents that claims more than 1.3 million victims annually around the world and is ranked ninth in the list of causes of death. Factors contributing to this high rate of accidents and deaths are: health problems, people's skill to perform driving task, education and awareness by people who deliberately driving under psychoactive substances influence, for example drive under alcohol influence. This define different kinds of drivers: impaired, drowsy, teenage, aggressive and distracted.

The field of road safety and safe driving has witnessed rapid advances due to improvements in sensing and computation technologies. However, the US Department of Transportation (DOT) still classifies road safety as "a serious and national public health issue." In 2008, road accidents in the US caused 37,261 fatalities and about 2.35 million injuries [2]. This data suggests that driver assistance or warning systems may have an appropriate role in reducing the number of accidents, improving the safety and efficiency of human-driven ground transportation systems. Such systems typically augment the driver's situational awareness, and can also act as collision mitigation systems[3].

The main dangerous actions carried out by drivers can be identified specifically: mishandling steer and pedals, speeding and getting out of the lane and road.

Using simulation software called Dolphinity Racer [4] created by Ruud Van Gaal is possible to obtain highly reliable data on the physics of driving. This is a simulation software used in the scientific community for these purposes.

Characterizing the driving schemes and the analysis of the parameters obtained from the input signals, is a difficult process for regular algorithms, as it has to be independent as the road type, the driver profile, and the car physics model [5]. So, the proposed system is based on a soft computing technique that offers a robust processing, with the abilities of detect, approximate, and classify, with a high reject ratio for the noise, and work based on learned cases. Neural network based algorithms that are correctly trained, should work with those conditions [6].

The proposed system achieved in the first stage driving an erroneous driving diagnosis using neural networks [1]. The results show the feasibility and reliability in various driving situations. In this second stage, it is presented a classifier based on neural networks capable to classify whether a driver is aggressive or moderate, at the same time it can differentiate a driver of another (driving behaviors). The system can also identify areas on the road where driver had a high probability of accidents (high risky areas). Development, analysis, and application of this model using a driving simulator are described in this paper.

II. Related Work

The design of driver behavior classifiers includes a research in three areas: vehicle diagnosis systems, analysis of driver behaviors and intelligent techniques for modeling. In addition, the scientific community has taken the initiative to develop measurement tools for vehicles, as well as tools

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that seek to evaluate driver performance focusing on establishing the causes that may lead to an accident. Many studies have been conducted so far to identify these factors.

Regarding vehicle diagnostic systems, some hardware prototypes have been proposed as diagnostic systems, developed for automotive applications [7]. The methods used in these models promise to reduce hardware costs, implementing redundancy analysis software. Besides they do not require additional sensors, the diagnostic system enables high precision and low development costs by using information from multiple models.

Some other presented works showed an approximation of a self-diagnostic system to replace the human capacity for diagnostic, on a test of the durability of cars [8]. To achieve their goal they merged a control system of the vehicle with special diagnostic module to identify faults, which was implemented and tested with two artificial neural network topologies: Back Propagation (BP) and Learning Vector Quantization (LVQ). Better results were obtained with BP.

Erroneous driving analysis performed by video recording was successfully implemented. Thus, Jeffrey S. et al. [9] implemented a video-monitoring system to assess risk behaviors while commercial vehicles are being driven. Using video recording registers, they studied how to recognize dangerous maneuvers and behaviors from drivers that perform delivery and shipping services works driving a vehicle. By implementing this system risky behaviors were reduced. All these devices require a robust infrastructure. The software should not allow any kind of modification on the acquired signals. Researches focus on mathematical behaviors models design different techniques going from the use of soft computing techniques to probabilistic methods are been implemented.

A patent related to hardware devices for the diagnosis in the car was developed by Jerome H. Lemelson [10], which is a device for monitoring driving performance. The instantaneous acceleration and position of the vehicle are continuously sensed and stored in computer memory for performance variables. These variables are analyzed through an intelligent neuro-fuzzy system to evaluate how the vehicle is being driven. When patterns of erroneous and dangerous driving are detected, signals are generated to warn the driver and / or authorities.

One of the most important works related to driving diagnosis systems was proposed by Burger et al. [11]. They have developed an expert system for driving assistance. It consists on an intelligent system with a prior knowledge which can process data received from signals acquired by the sensors. With this system it is possible to identify drowsy drivers by using neural networks.

Another developed system for the driving diagnosis is the result of the work of Pomerleau A. Dean [12]. He focused his research in three areas, all of them applying neural networks in the domain of intelligent vehicles: traffic video monitoring, monitoring and control signals from the vehicle computer and the control of the lateral view. The author proposes that because of the simplicity and uniformity of neural network architectures and algorithms used for their operation, these have the potential to be implemented efficiently in hardware, which is commercially viable.

As mentioned, soft computing techniques have also been implemented for this work. C. Quintero et al. [1] propose an intelligent system based on neural networks that gives a percentage of erroneous driving after finishing a tour in a simulated environment. The main objective of this work is to assign a percentage number that may give an idea of how much affected is the driving capacity of the user. The unsafe behaviors of the drivers almost always show 4 types of faults: Exceeding the speed limits, or taking the road curves too fast; getting out of the road or the lane; over steering; and over pedaling.

The proposal aims to model driving behaviors. Then using this information the system will be able the to perform the identification of different types of drivers, and identify high risk areas on the road.

III. Proposed Approach

Vehicle telemetry is now possible thanks to the various sensors present in the electronic systems of modern vehicles. However, these signals can be obtained in a simpler way to perform diagnostics driving and vehicle tracking in real time.

Thus, this system seeks an intelligent diagnostic on board, and also with the ability to classify and identify a driver. Basically we propose to locate potential high risk areas on roads and driver identification based on the driving diagnosis signals: mishandling steer and pedals, speeding and getting out of the lane and road.

For classification process a neural network driver is engaged in the evaluation. Once the network is trained with different driver paths, classify as aggressive and moderate drivers in terms of mistakes committed are possible.

In addition to the driver identification process, several training runs for the neural network that performs recognition of the driver were performed.

The following figure shows an overview of the system.

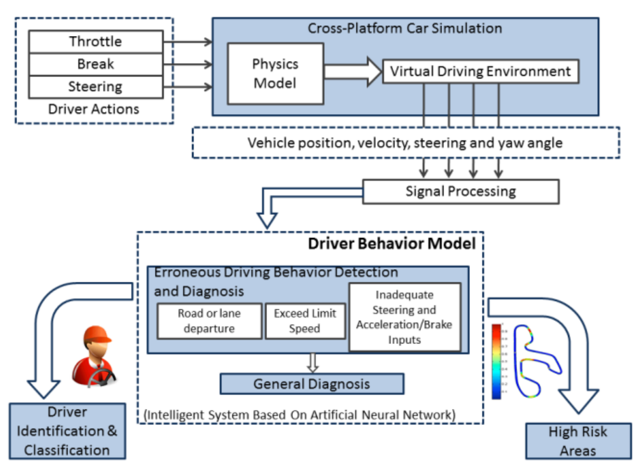

Fig. 1.Diagram of the implemented system.

In summary, we present a system that has the following faculties: intelligent erroneous driving diagnosis, evaluate and identify drivers, and finally identification of risky areas using driver diagnosis.

An intelligent system based on neural networks allows to the program to easily learn from the drivers who feed the network with training data. Besides, implementation is also simple and the results have a high confidence level.

On the other hand, positive results in the simulated system proposed in early stage, allows us to present in this paper a scheme of intelligent diagnosis based on Fuzzy Logic. System acquires telemetry signals via GPS. Then through internet communication, data travels to a database for future analysis on a web platform in which the intelligent system is housed. Using these signals: speed, acceleration, steering angle, vehicle satellite location, the analysis could be performed.The following figure shows the outline of the proposal for a real system.

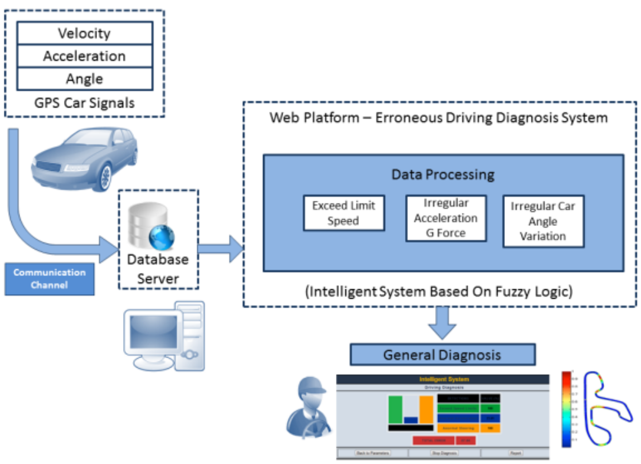

Fig. 2.Diagram of the real implemented system.

IV. Diagnosis System Implementation.

In the first stage of this research [1], develop an intelligent system for erroneous driving detecting was possible.

Now an intelligent system based on Neural Networks Feed-Forward type that has the ability to perform different analysis is presented below:

A. *Driver Identification*

Diagnostic software tool have seven diagnostic parameters of a driver:

- Final percentage for each detections signal. This is calculated using the average of the samples which detections indicate erroneous behavior (greater than 10%).
- Final percentage of erroneous driving, which is obtained by evaluating the above percentages at the end of each detection on the diagnosis network.
- Real time signals detections: out of the lane, out of the road, make sudden movements with the steering wheel and pedals.
- Historical record of diagnosis and histogram.

The goal is to use these parameters to characterize types of drivers. Achieve this characterization is one of the pioneering proposals on this paper, which can be used to classify a good driver from a bad driver, identify a driver from another, even characterization of drowsy drivers or under the influence of alcohol.

With the requirement to design an intelligent system based on artificial neural networks, able to learn different characterizations of drivers is necessary that input data to the neural network becomes representative parameters of different diagnosis time signals. To do this, we used the following statistical measures of central tendency:

- Range.
- Media.
- Standard deviation.
- Variance.
- Mean absolute deviation.

It is important to point what signals from the previous parameters were taken. Only diagnosis time signals, statistical measures using all samples in time were used. Erroneous behavior signals detections samples were used only if it had exceeded the limit from a selected experimentally threshold.

For these signals, the operating point was specified in 10% (range of 0 -100%, which was determined from neural networks training) using this percentage system indicates that the user has committed a wrong behavior while driving.

Thus, it actually gives a statistical analysis on the samples which have an erroneous driving rate. The equivalent corresponding detection signal in time for statistical analysis is obtained by removing all samples below 10% from original time signal. Furthermore, with this the new signal average it is a better representation of erroneous driver data that average signal over time.

This analysis is performed for all acquired signals and processed by sensor networks (Diagnosis, outside lane, off road, excessive speed, steering).

B. *Potential High Risk Areas on Road*

Once the networks have detected the driver's misconduct, road areas where an accident could be possible are displayed. This makes it possible to graphically display risky areas on the taken route, see Figure 3.These areas are viewed as the signal user want to evaluate (steer, pedals, speed, off-track, off-road). It is also possible monitoring each signal acquired for the diagnosis system on real-time. This information allows knowing what happened in a specific section of the road. Finally, the diagnosis system evaluates how the performance of the driver and the detection levels of the acquired signals were.

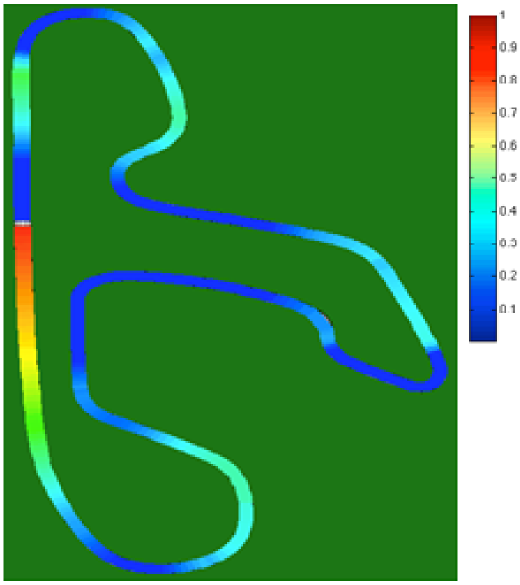

Fig. 3.Risky Areas Identification Graphic Simulated Environment.

C. *Real Environment Implementation*

Diagnosis is made with fuzzy logic. The inputs in this system are speed, acceleration and steering acquired by a GPS data logging system, see Figure 5. Once system has identified the inputs to the diagnostic system, fuzzy system makes the diagnosis based on quantitative driving rules and safe driving behaviors.

The designed system can also track real-time satellite vehicle views, while showing signals acquire, see Figure 4.

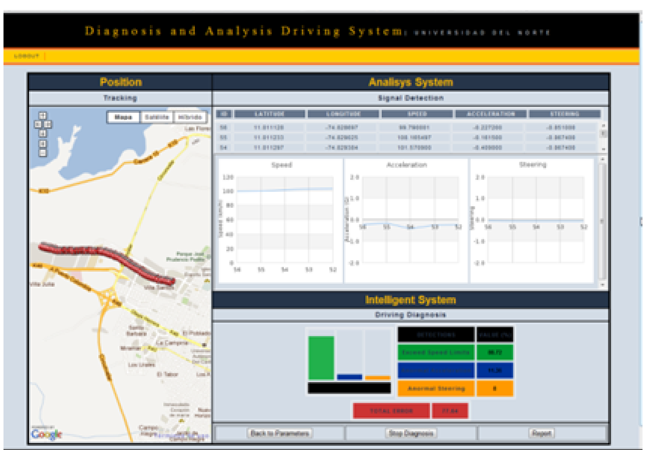

Fig. 4.Intelligent Driving Diagnosis System – Real Environment.

The fuzzy system is designed to receive as inputs 3 signals from a GPS connected to a vehicle. The three signals are: speed, acceleration and steering angle. These are inputs to the fuzzy system. a) Speed was classified into three levels: low, medium and high. Speed is normalized with respect to the speed limit on highway, which means 1 corresponds to the speed limit. b) The acceleration has 2 levels: Normal and irregular which means that accelerations values above ±0.3 (in G Force Units) are consider irregular. c) The steering has 2 levels: Normal and irregular. Steering corresponds to the rate of change between the previous sample and the next sample in the time that the data is taken. Membership functions are listed below. Notice that x-axis represent normalized variable value (steering, G Force Acceleration and speed) and y-axis represent degree of membership variable diagnosis.

Fig. 5.Hardware for Real Environment Implementation.

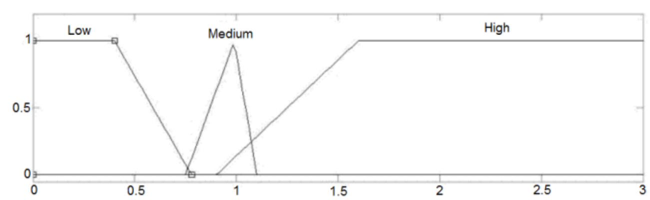

Fig. 6. Speed Signal - Membership Function.

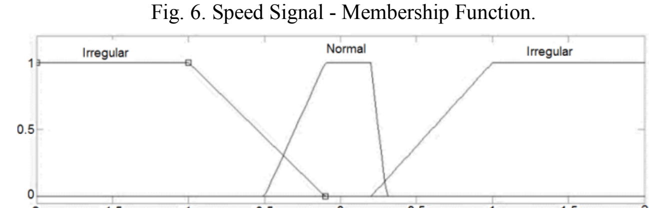

Fig. 7.Acceleration Signal - Membership Function.

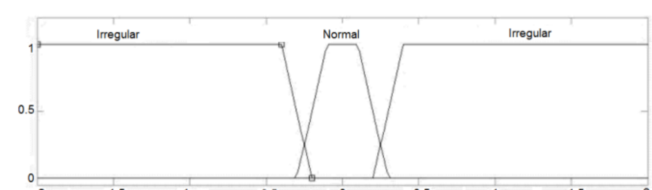

Fig. 8.Steering Signal - Membership Function.

To evaluate the output process in the system corresponding to the total error percentage, the designed membership function of total error percentage is classified into 6 possible states: Very high, high, medium, low, very low, and also a special condition called no error. Membership function is listed as follow:

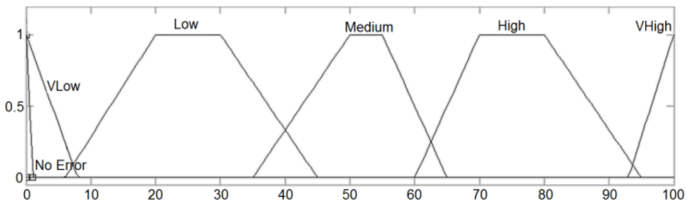

Fig. 9.Total Error Percentage - Membership Function.

V. Experiments And Results

The data used for intelligent driving diagnosis system identification were collected from a series of driving simulators tests on different cars and roads. The Racer Simulator (created by Ruud van Gaal) was used to conduct these experiments in the platform on Fig. 10.

Fig. 10. Driving platform for simulated experiments.

A. Moderate and Aggressive Driver Classification

All experiments were performed under laboratory conditions. Evaluated subjects were taken randomly but all of them had their own national driver license that certified their ability to drive. Specific routes which may simulate real driving situations in order to assess the abilities of the driver through this type of road were selected (eg, bends, straight lanes, intersections, two-way lanes and zigzag lanes).

Driver classification is made taking into account the results of diagnosis. It is classified as moderate (good) or aggressive (bad) driver.

304 routes were used taken by a group of 11 people in the same road and using different cars. The diagnosis of each route was analyzed subjectively under supervision, classifying the driver as good or bad, in terms of how many times they went off the road, the attitude of the driver at the time of making a mistake and corrects it, and overcome excesses the speed limit. Taking into account the above, 115 trips were classified as good and bad drivers 189.

The training data were subjected to an algorithm that finds the architecture of a neural network feed-fordward type that has the lowest number of accumulated errors in the output, alternating the number of neurons per layer (1 to 20) and functions transfer per layer (logsig, pureline, tansig). The best performing architecture was a two-layer neural network, logsig - tansig, with 9 neurons in the intermediate layer, 31 inputs and one output that indicates 0 if it is bad driver and 1 if it is a good conductor, which got an error to assess cumulative 1.9808 on the training data.

The following table shows an analysis of probability to a set of 500 different routes training. Using analyzed courses 190 were classified as good drivers and 310 as bad drivers. It is notes that just over 97% of drivers were described as a good driver, while the others were rated as poor driver.

TABLE I
User Classification

	Good driver	Bad driver
Good driver	0.9739	0.0261
Bad driver	0	1

B. Intelligent Driver Identification

The identification aims to identify the driver, as distinct from a potential thief. It works as anti-theft system.

172 courses were used, made by a group of 11 people in the same road and using different cars, of which 72 were performed by one user (José Oñate) and 100 distributed among 10 drivers.

The training data were subjected to an algorithm that finds the architecture of a neural network feed-fordward type that has the lowest number of accumulated errors in the output, alternating the number of neurons per layer (1 to 20) and functions transfer per layer (logsig, pureline, tansig).

The best performing architecture was a two-layer neural network, logsig - pureline, 2 neurons in the intermediate layer, 31 inputs and one output indicating 0 in the case of any other driver was into the car and 1 if the user José Oñate, was driving, which earned an accumulated error of 4.0107.

The following table shows an analysis of probabilities for a set of 500 different training routes. Of these, 210 are from user Oñate L., J. and 290 correspond to other drivers. It is observed that just over 97% of the routes taken by the user Oñate L., J. were classified as made by him, and 98% of all other drivers were classified as other drivers.

TABLE II
User Identification

	José Oñate	Other drivers
José Oñate	0.9722	0.0278
Other drivers	0.02	0.98

Once data were collected, the intelligent diagnostic using neural network is able to perform an evaluation of the driver at the same time the identification can be performed as shown in the figures 11 and 12.

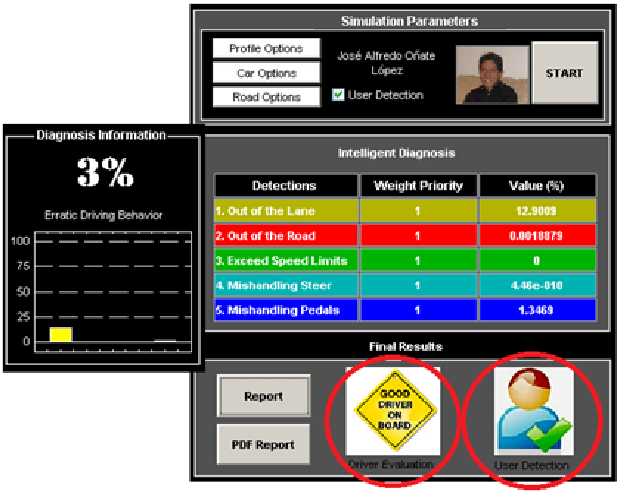

Fig. 11. Positive user identification.

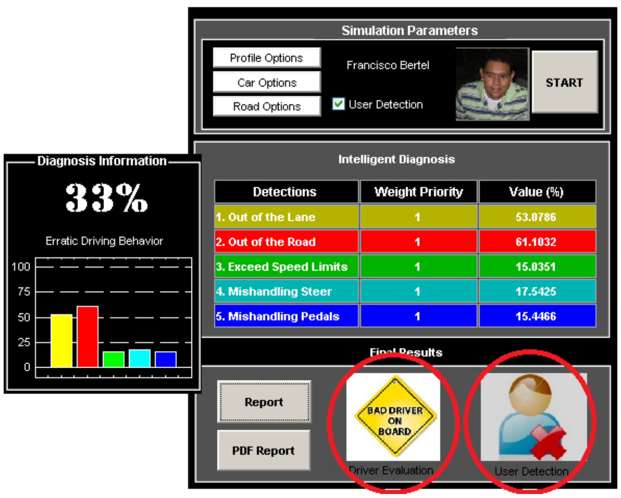

Fig. 12. Negative user identification.

VI. Conclusion

Topologies of feed-forward neural network algorithms trained with Back-propagation type are a useful tool for the design of intelligent diagnostic systems, offering a high learning ability, even with a relatively low amount of data [1]. Also, this technique is very useful and reliable for identification of drivers and driver performance evaluation.

Thus far, it has been possible to perform moderate and aggressive driver classification. So, it is possible to think for future works on the implementation of intelligent systems capable to detect drowsy drivers or drunk drivers.

It is becoming more and more interesting to build intelligent vehicle systems which have a knowledge base and process the received sensory data not only quantitatively but also qualitatively, i. e., interpret the data, compare it with other similar data from the past, in some case add this new data to the knowledge base, recognize patterns in the behavior of the driver and the environment (potential high risk areas on road).

It is very interesting that the system can detect driving errors although they are symptoms of alcohol consuming, or from somnolent drivers. It is noteworthy also that modern systems of GPS data logging, and other sensors offer an amount of data that, due to its quality, may be used to diagnose a very accurate driving level of an user. This is because most driving failures can be directly associated with one or more of the signals available from these devices.

It is hoped that intelligent systems are implemented for local driving diagnosis, which may serve as a tool to alert the user, and/or the authorities about the danger of erroneous driving. Based on this work, there may be a lot of applications designed to improve the road security.

However, future works may focus on real environments, real sensors and driving should be performed in roads with other vehicles, instead of simulated environments with no others cars in the road. Following that line of facts, the next step would be developing most powerful hardware/firmware for real applications.

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