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A Neuro-Fuzzy Application Proposal of an Individual Intelligent Driving Behavior Predictor Device

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ABSTRACT: Ever since automobiles evolved as the dominant transportation mode, road safety emerged as one of the governments' greatest concerns. A number of surveys highlight the fact that unpredictable reaction of drivers is one of the major accident reasons, especially on highways and major roads. Researchers have not made many efforts to tackle this issue, which leaves this a rather untouched problem requiring more research. Intelligent transport systems (ITS) technologies are increasingly being accepted by traffic authorities and people. This paper attempts to offer an ITS solution which can help to learn and predict drivers' behaviors which can be useful for predicting their actions and reactions during driving. This approach consists of three major phases: Learning, Modeling and Predicting. An artificial Neural Network (ANN) has been applied for learning phase and then the learned parameters are utilized in generating a fuzzy model of the driver behavior which can be a basis for the third phase which is prediction. In other words, this research uses a neuro-fuzzy approach to learn, model and predict a driver's behavior. Previously, researches have been conducted in providing safer roads by using intelligent systems and inter-vehicle communication. The aim is to implement this process in personal devices, each located in every car, which are inter-connected.

KEYWORDS: ITS, Neural network, Fuzzy systems, Neuro-fuzzy, Driving behavior simulation.

BACKGROUND:

There have been some efforts in providing safer roads by using intelligent systems and inter-vehicle communication as in [1-2]. There are also some materials on using a neuro-fuzzy approach toward driving simulation as in [3-6]. However these methods were limited to traffic simulations which can only be usable for traffic authorities and they do not provide a personal use. This research tries to propose a device which can be used in personal cars in order to increase roads' safety.

1 INTRODUCTION

Intelligent transport systems (ITS) technologies are being more and more accepted by traffic authorities [7]. ITS has even entered personal use domain; Advanced Transport Telematics (ATT) and Advanced Traveler Information Systems (ATIS), in particular, allow travelers to make informed travel decisions and are increasingly being recognized as a potential strategy for influencing driver behavior and improving traffic quality [3], [8].

There is a long list of reasons recognized as major causes of car accidents; however, in most studies 'distractions' and 'unpredictable actions of other drivers' are at the top of this list [9]. Distraction can be avoided, or at least reduced, by

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driving more carefully or being more cautious. But it is not easy, or even possible in some cases, to predict other drivers' actions and reactions! Such a prediction needs to be carefully derived from a driver's driving behavior and road condition. Obviously, this is a complicated analysis which cannot be easily managed by a driver's mind and requires a more intelligent mechanism to be taken care of. An intelligent traffic behavior simulator might be a good idea to ameliorate the number of accidents caused by this phenomenon; a device which can learn and model a driver's habits and warn other drivers by predicting his or her actions and reactions.

There have been a lot of materials discussing different approaches toward driver behavior modeling. Driver behavior models that can be used to dynamically estimate or predict the drivers behavior can be thought of as a classification problem where the inputs to the model comprise drivers' individual socio-economic characteristics and other variables that may influence their behavior; and the output a binary integer (1,0) representing whether drivers comply with travel rules or not, respectively. Two of the approaches available for developing such models include discrete choice models and artificial neural networks [10]. However, these models have major limitations:

- They cannot efficiently handle fuzziness of the phenomenon as they tend to result in crisp values
- They require inputs such as socio-economic characteristics which cannot be practically provided
- They require a large amount of resources for processing which makes them inefficient for individual uses
- They work better in large scales (e.g. modeling driving behavior of a society) rather than individual use

2 SIGNIFICANCE AND CONTRIBUTIONS OF PROPOSED MODELING APPROACH

This previous discussion shows that existing models lack the necessary features to allow for modeling driver behavior in the context of Advanced Traveler Information Systems. The desired models should have capabilities for modeling the behavior of individual drivers, the uncertainty inherent in driver decision making and the vagueness in information received from ITS devices and the road environment.

One benefit of fuzzy systems is that the rule base can be created from expert knowledge, used to specify fuzzy sets to partition all variables and a sufficient number of fuzzy rules to describe the input/output relation of the problem at hand [11-14]. However it usually requires high expert knowledge and the defined parameters may not be necessarily correct in all cases. To be more specific, in driving case, each driver has a different driving behavior which is formed by a series of factors such as experience, personality, expertise and etc. Accordingly it is somewhat impossible to define a model which is accurate for all driving types.

Fuzzy logic and artificial neural networks [15-16] are complementary technologies in the design of intelligent systems. The combination of these two technologies into an integrated system is a promising path toward the development of Intelligent Systems capable of capturing qualities characterizing the human brain [14], [17].

The neuro-fuzzy method is a way to create a fuzzy model from data which has been collected via some kind of learning process motivated by learning procedures used in neural networks. In other words, the neural part collects data via learning and the fuzzy part creates a fuzzy model using the alleged data. This application can be quite useful in this case as it can be integrated in a device which learns about the drivers' driving habits and notify other drivers about his or her possible actions or his dangerous driving behavior.

3 NEURO-FUZZY APPROACH FOR EXTRACTING DRIVER BEHAVIOR RULES

One technique which gained considerable acceptance in the design of complex transport algorithms is the use of artificial neural networks, these have been successfully used to overcome limitations of existing analytical approaches [18]. The main advantages of ANNs include the ability to deal with complex non-linear relationship; fast data processing; handling a large number of variables and fault tolerance in producing acceptable results under imperfect inputs [15], [19].

Given only a set of inputs and outputs during the training process, the neural network is able to determine all the rules relating input and output patterns based on the given data [20], [15]. In this paper, each driver is modeled as an agent with a set of preferences and knowledge about the environment. It is hypothesized that the use of neuro-fuzzy models, where fuzzy logic is coupled with neural networks, would be a viable approach for incorporating human decisions and capturing the uncertainty in drivers' behaviors [4]. In Figure 1 a general scheme of a neuro-fuzzy system and its major parts can be seen.

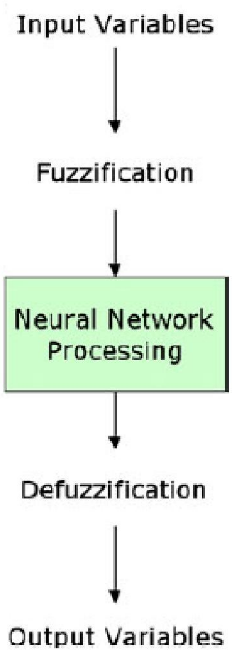

Fig. 1. Neuro-fuzzy Network (Hussein Dia and Sakda Panwai, 2010)

As the driver drives, the neural network sets its parameters so that the prediction becomes continually precise over the time. For example there is an exit on the highway; based on the drivers habits at turns (e.g. When one reduces speed, does one use flashers, its current lane, …) the algorithm can predict how likely it is that the driver changes the lane or takes the exit.

In Figure 2 There is a sample neuro-fuzzy network prediction sudden lane changes. The whole system consists of a number of networks each providing different predictions.

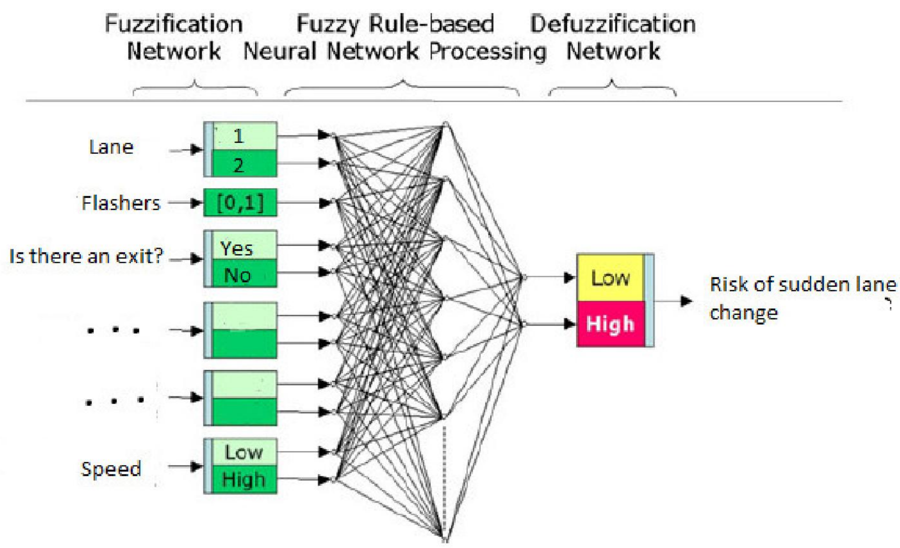

Fig. 2. Neuro-fuzzy interface—compliance model

3.1 FUZZIFICATION

This step describes the conversion of the collected data (crisp data collected by sensors while driving) into the fuzzified inputs shown at the interface to the neural network processing. Fuzzy logic uses a "membership function" to transform input variables into the set [0, 1]. A "possibility" function is defined to have values between 0 and 1 indicating the degree of belief that a certain element belongs to a set. This is a mathematical representation of linguistic information used in fuzzy set theory [15].

3.2 NEURAL NETWORK PROCESSING

The simple feed-forward neural network with three layers is used to learn the relationships between the fuzzified input and output patterns as presented in Figure 2. Input variables are fed into the network and the fuzzification sub-network transforms these real inputs into fuzzified inputs in term of "high" and "low" or '0' and '1' or numerical values. Therefore, the input layer will consists of the sum of possible answers. For instance if we have 5 inputs and each contain two possible values as "high" or "low", we will have 10 neurons.

In this case the output layer has only two neurons predicting whether the driver takes the turn or not. Every neuron in the input layer is connected to every neuron in the hidden layer with a weighted arc. Similarly, every neuron in the hidden layer is connected to every neuron in the output layer with a weighted arc. The weights of these connections will be determined and updated as the training of the neural network continues. The determination of the neural network parameters mainly involves establishing the weights of these connections. This is similar to other statistical modeling approaches such as regression analysis where the modeler determines the parameters of a regression equation [4].

The neural network, let's simplify it as N, may be regarded as a machine which is capable of taking on a number of states, each of which represents a function computable by the machine. These functions map from the input space A (the set of all possible patterns) to an output space *B*. The inputs are encoded as vectors of real numbers indicating parameters such as speed, lane, distance to the next exit and etc. ($A \in R$), and these real numbers lie in a bounded range, such as 1 to 3 for lanes or 0 to 200 km/h for the speed [21]. In this study we are interested in binary outputs such as: will the driver take the exit? Yes (1) or No (0); how much is the risk of sudden lane change? High (1) or Low (0) and etc., so, there, we have $B = \{0,1\}$.

Formalizing mathematically, we may regard N as being characterized by a set Δ of states, a set *A* of inputs, a set *B* of outputs, and a parameterized function $F : \Delta * A \rightarrow B$. For any $\alpha \in \Delta$, the function represented by state α is $h_\alpha : A \rightarrow B$ given by:

$$h_\alpha(x)=F(\alpha,x)$$

Where the function *F* describes the functionality of the network: when the network is in state α it computes the function h_α. The set of functions computable by N is $\{h_\alpha : \alpha \in \Delta\}$, and this is denoted by H_N. For instance, if we have a state $\alpha = (\alpha_1, \alpha_2, \bullet\bullet\bullet, \alpha_n, \theta)$, and the function it represents is:

$$\begin{aligned} h_\alpha(x) &= F(\alpha,x) \\ &= F((\alpha_1, \alpha_2, \bullet\bullet\bullet, \alpha_n, \beta),(x_1, x_2, \bullet\bullet\bullet, x_n)) \\ &= sgn\left(\textstyle\sum^{n}_{j=1} \alpha_j x_j - \beta\right) \end{aligned}$$

Where:

$$sgn(F(x)) = \begin{cases} -1 \ \ when\ f(x) < 0 \\ 0 \ \ when\ f(x) = 0 \\ 1 \ \ when\ f(x) > 0 \end{cases}$$

3.3 DEFUZZIFICATION

This step is the most important in the construction of the neuro-fuzzy network as it give the final results which are the predictions. It aims to compute the crisp result by using a threshold. The main consideration of this method is to represent membership functions of a fuzzified output and to perform defuzzification. The defuzzification consists of two layers: the first layer is the membership functions of the fuzzified output while the second layer is the defuzzification layer (crisp values) [15].

3.4 PERFORMANCE MEASURES

One of the most important indicators for evaluating the performance of a neural network classifier is the Classification Rate (CR) [4] which provides a measure of the correctly predicted outputs and is best depicted using the classification rate matrix as shown in Figure 3. The columns of the classification rate matrix represent the actual results whereas the rows represent the neural network predictions. In the body of the matrix consists of values of 1 and 0 for any given cell where value of 1 means that all desired outputs for that category were correctly predicted and value of 0 in a cell means that none of the desired outputs were predicted. Classification rates obtained during the training stage provide a measure of the calibration results which can help the model to improve and recalibrate itself [22].

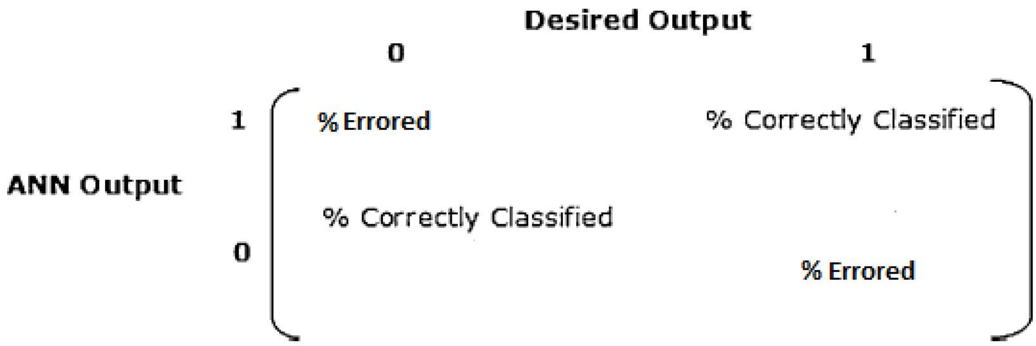

Fig. 3. Classification rate matrix – a measure of ANN prediction accuracy

The whole process discussed in previous sections can be summarized as in Figure 4 where neural and fuzzy aspects of the process have been specified. However, in practice the two aspects are hardly distinguishable.

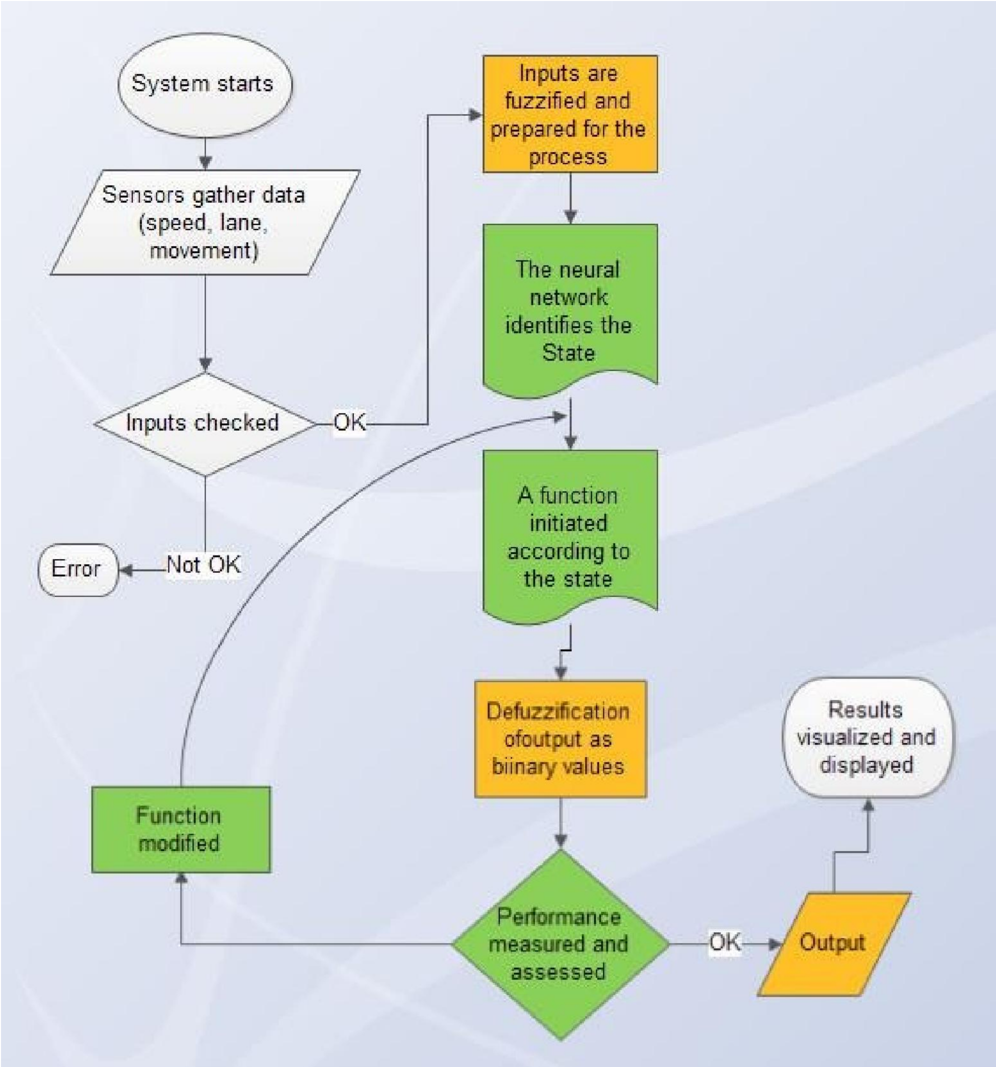

Fig. 4. The whole process flowchart (Green objects form the Neuro part of the process and the orange objects the Fuzzy aspect of the process)

4 IMPLEMENTATION OF METHOD

As mentioned earlier in this paper, an individual Advanced Traveler Information Systems (ATIS) is proposed in this research which is a device that can be implemented in cars.

4.1 HOW DOES THE DEVICE WORK?

The device must consist of following major parts:

1. The device needs to be equipped with a navigation device, such as GPS, to provide a spatial basis for the prediction. Each action on the road is caused by road condition. Therefore, we need to know where we are and what we have ahead of us (a connection with the traffic servers).
2. A screen displaying the road, adjacent cars and notifications.
3. A Gyroscopic sensor to sense car movements on the road [23].
4. A processor capable of learning and modeling processes.
5. A small data storage device for recording calculated (or learned) parameters.
6. An inter-vehicle communication system for receiving and sending parameters to and from other cars.

4.2 WHAT CAN IT DO?

The device learns more as the driver drives the car, accordingly the parameters get continually more precise over time and can answer following questions which are considered as potential characteristics of dangerous driving. In other words each car will be represented as an intelligent agent that imitates that car's behavior on the map.

- Does one usually drive aggressively? (Going too fast or racing)
- Does one ignore traffic lights, road signs or other warnings?
- Does one overtake dangerously or on insight?
- Does the car have dangerous faults?
- Does one turn into the path of another vehicle?
- How far before an exit does one take aside or slow down? Does he or she use flashers beforehand?
- How often does one make sudden brakes?

These and many other questions can be answered using such a modeling technique. Although it may not be one hundred percent accurate but it definitely can reduce the risk of accidents caused by sudden and unpredictable actions in following ways:

- It flags the dangerous driver and it notifies other drivers in case of adjacency to a dangerous driver.
- It warns if there is a high possibility that a nearby car may turn or change the lane suddenly or without flashers.
- It informs the driver to keep a certain distance if the front car has the habit of making sudden brakes.
- It can predict a driver's reaction, given the road conditions.
- It can predict a driver's reaction based on his habits in driving.

5 PUBLIC DEMAND AND EFFICIENCY ANALYSIS

In order to assess the public demand for such a device two surveys were done in two countries where traffic behavior and conditions are completely distinct. The first survey was done among 150 people in Tehran, Iran and the second one was done in Helsinki, Finland.

5.1 A SURVEY IN IRAN

A survey was done in June 2013 in Tehran, the capital city of Iran. Tehran is a big city with a population of more than 12 million. There are a lot of traffic jams and long rush hours. People tend to drive aggressively and many rules are not taken seriously.

In this survey people were asked:

- Question 1: If they have had any accidents caused by another drivers unpredicted action?
- Question 2: How helpful to them can this technology be?

The questioner was distributed among 150 people who had driving experience and the results can be seen in Table 1.

Table 1. Result from survey 1 (Tehran, Iran)

	Number of people with positive answer	Percentage of Positive answers
Q1	127	84.6
Q2	98	65.3

The results show that unpredicted driving actions are considered as a major cause of accident among people and about sixty five percent of people have a positive idea on such a technology.

5.2 A SURVEY IN FINLAND

A survey was done in August 2013 in Helsinki metropolitan area, Finland. Helsinki is a rather big city with a population of slightly more than 1 million. There are few traffic jams and short rush hours. Most people respect traffic rules.

Similar to the first survey in this survey people were asked:

- Question 1: If they have had any accidents caused by another drivers unpredicted action?
- Question 2: How helpful to them can this technology be?

The questioner was distributed among 150 people who had driving experience and the results can be seen in Table 2.

Table 2. Result from survey 2 (Helsinki, Finland)

	Number of people with positive answer	Percentage of Positive answers
Q1	53	35.3
Q2	87	58

Although Finnish people drive more regularly and lawfully, many people complained about people (mostly drunk) break laws and drive aggressively at nights which causes accidents.

Similar to the first survey, people find such a technology useful in increasing roads safety.

5.3 Privacy issues

One of the main concerns which were mentioned by a large number of test subjects was the privacy. People are concerned that their information might be misused by authorities, and most specifically police, which can cause them problems. One of the most important steps which must be taken into account prior to any national development of such technologies is to define a Privacy Act which prohibits authorities from accessing this information for certain purposes. The information must be only conveyed between cars and it will not be stored on any server. Such and other similar approaches can help people to trust this technology without being afraid of their privacy being violated or receiving any tickets.

5.4 Survey conclusion

The results show that demand and need for this technology are higher in developing countries and more populated cities because:

- The traffic rules are less respected, therefore unpredictable and offensive actions are more common.
- Higher population results in more crowded roads, so the driver needs to be more careful about adjacent cars.
- Developed countries have been more successful in improving driving culture among their people which helps to decrease aggressive behavior by drivers.

6 Conclusion

In this paper a device was proposed that can learn the driver behavior and create a model which can be used as a basis for sudden actions prediction. There are three major phases in this process which are: Learning, Modeling and Prediction. Most common approaches in this field are a kind of classification problem which result in discreet values after receiving appropriate inputs. Due to fuzzy nature of our case these approaches cause limitations therefore we offered a new approach; a neuro-fuzzy approach where a neural network is responsible for the learning phase and a fuzzy model is created which keeps on getting updated as the neural networks learns. The final result will contain a number of neuro-fuzzy networks, each responsible for predicting a certain action of driver.

Finally results of two surveys were discussed in this paper, which were done in two completely different situations; a developing country with rather large population and a developed country with small populations. More surveys and analyses need to be done in order to come into a concrete result; however the results from these surveys state that the need for such an ‘Advanced Traveler Information Systems’ (ATIS) is more outstandingly observed in developing countries.

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