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A Driver Assistant System Using Behavior Patterns and Fuzzy Logic to Enhance Safety

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Abstract

In this article, the purpose of using learning algorithms is to create an advanced system of the driver's assistant in order to provide the driver with the driving safety by considering general and personal driving features.We used the decision tree algorithm to represent such a system. At as the first step, appropriate data are collected. The aim is to select the factors influencing the design of the warning system. In the next step, we prepared the data. Then outlier data is differentiated using categorical algorithms. In the next step, input data is prepared using a fuzzy device. The system is a Mamdani fuzzy system. In the last step, we determined the root, branch, and leaves of the decision tree model using the entropy method. In this paper, the rules are extracted from 5 attributes along with a target variable which has four modes. The rules of the fuzzy system are implemented on a local database and the results are provided. Finally, the results of the designed model are compared with the results of the previous.

Keywords: Decision tree, Fuzzy logic, Driving learning algorithms, Mamdani fuzzy system, Entropy method

1. Introduction

Nowadays, with the ever-increasing development of traffic engineering science in the world, many methods and tools have been developed for traffic management. Intelligent Transportation Systems (ITS) (El Faouzi, Leung, & Kurian, 2011; Zhang et al., 2011) are one of these tools. Intelligent transportation systems are a new concept in the field of traffic engineering, which plays a very important role in the security and dynamism of transportation. These systems have increased the efficiency of the transportation and traffic network, which its expansion can solve many transportation problems. In fact, in the intelligent transportation system, the assessment and monitoring of driving behavior, especially for public transportation drivers, including speed, driving experience and atmospheric conditions, have a significant impact on identifying and employing safe drivers in passenger fleet management. On the other hand, monitoring and assessing through encouragement and punishment can reduce risky behaviors, and increase the inclination to drive safely (Rahbari D., 2014; Placzek B., 2014).

2. Procedure

2.1 The selected features

The selected features for developing the methods are as follows:
Age: which has three categorizations, young, middle-aged, and old.

Experience: a driver experience that has two modes: low (less than 10 years old), and high (more than 20 years of experience).
Weather: atmospheric conditions that are divided into two bad and good moods.
Speed: there are three modes of traveling: low (less than 50 km/h), moderate (50 to 70 km/h), and high (over 70 km/h).
Traffic: the road traffic situation, which has two modes, low and high.
Safety: driver safety, which has four modes as the target variable: very dangerous, dangerous, moderate, and safe.

The above data is divided into two groups of training and test data, and by using training data that includes 70% of the data, the models are constructed, and then evaluated for the prediction accuracy using the test set.

2.2. Data analysis

The data analysis process is performed using the Matlab software. The main part of the data analysis in this research is the design of a fuzzy decision tree modeland the results are compared with the Adaptive Neuro-Fuzzy Inference System (ANFIS) which is widely used in the design of prediction systems (Nilashi et al., 2018a; Nilashi et al., 2019b; Kheirandish et al., 2019; Nilashi et al., 2019b; Nilashi et al., 2017; Yadegaridehkordi et al., 2018; Nilashi et al., 2018b). The fuzzy Mamdani method is used to construct the fuzzy system through Triangular membership functions.

2.3. Rule extraction

The decision tree consists of nodes and vectors connecting the nodes. The decision is made from the root node, and the person begins to ask questions to determine which branch tree extension continues until it reaches the leaf node and makes the decision. This structure is presented in Fig. 1. In this figure, non-leaf nodes show benchmarks (tests) and leaf nodes are decision values. The simplest tree may have only one leaf node.

The decision tree is created by selecting the attribute that obtains the maximum value of the two-way information. In order to construct a decision tree, it should be started from the root node. In this regard, among the all attributes, the one attribute should be selected that has the lowest entropy value, or the one that the most information can be obtained from it. Then, it should be placed in the root node (Chen et al., 2014; Manley et al., 2014).

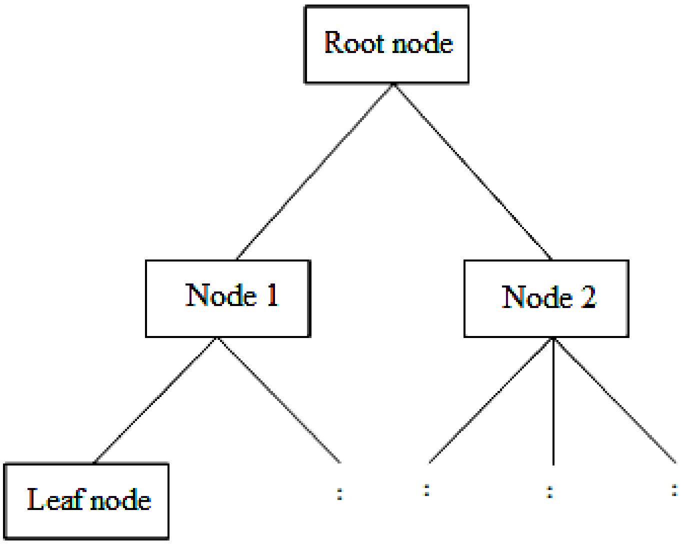

Fig. 1. Root, node, and leaf in the decision tree

2.4 Entropy

In information theory, entropy is an uncertainty about the source of the message. The entropy was first introduced by Shannon in 1948, and the following shows the relation formula:

$$H\big(P(x)|x(X)\big) = \sum_{x \in X} P(x) \log P(x) \tag{1}$$

where $P(x)|x(X)$ is the probability distribution of X limited set. Accordingly, the Shannon entropy is a function in the following form.

$$\mathrm{H}: \mathrm{R} \rightarrow [0, \infty) \tag{2}$$

where P represents the set of all probability distributions on finite sets.

$$P = UP^n, n \in N \tag{3}$$

$$P^n = \left\{(P_1, P_2, \ldots, P_n)|P_i \geq 0, i \in N, \sum_{i=1}^{n} P_i = 1\right\}$$

Therefore, the H function indicates the size of the uncertainty based on the distribution of the probability. By using the above method, the entropy is used to calculate roots which is presented in Table 1. The nodes based on the target attribute are driving risk.

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Table 1
attribute entropy

Rank from the root	Entropy value	Attribute
2	0.309	Atmospheric conditions
0	0.095	Speed
3	0.644	Age
4	0.816	Experience
1	0.175	Traffic

As it can be seen, the velocity or speed attribute is placed in the root with three values, after which the traffic attribute is placed in the next node and from each node of this attribute, the attribute of atmospheric condition is emanated. Finally, the following attributes including of age and driving experience comprise next nodes.

2.5 Design of decision tree

The entropy of each of the attributes is calculated according to Eq. (1) to determine the root node, so the attribute with the least entropy is placed at the root node. This process continues until it reaches the leaf node in each of the verbal variables such as (low, medium, and high) for each attribute. During this process, by selecting any of the attributes as a node, and by removing that node in its corresponding branch, the remaining entropy of the remaining traces is calculated based on the new database (which is formed by removing the previous node), and the smallest value is placed in the new node. This flow continues until it reaches the zero entropy, or the end of the attributes.

2.6 Implementation of Fuzzy Inference System

This section consists of three steps that are as follows.

2.6.1 Fuzzy inputs (attributes) and outputs

In this stage, the attributes are determined based on the linguistic variables, and by using the Trapezoidal and Triangular membership functions the fuzzing process is performed. At this stage, the outputs or the degree of driving safety as the classes in the decision tree is also fuzzy. The reason for the use of Triangular and Trapezoidal membership functions is the use of the fuzzy Mamdani method, in which this form of membership functions has more compatibility with the fuzzy Mamdani (Panchev et al., 2014; Cheng et al., 2014).

The membership function criterion is also given in two general terms which are left and right trapezoidal membership functions.

$$\mathrm{LTrap-MF(x)} = \begin{cases} 0 & if\ x < a \\ \dfrac{b-x}{b-a} & if\ \ a \le x \le b \\ 1 & if\ x > a \end{cases} \tag{4}$$

$$\mathrm{RTrap-MF(x)} = \begin{cases} 0 & if\ x < a \\ \dfrac{b-x}{b-a} & if\ \ a \le x \le b \\ 1 & if\ x > b \end{cases} \tag{5}$$

$$\mathrm{Tring-MF(x)} = \begin{cases} 0 & if\ x < a \\ \dfrac{x-a}{b-a} & if\ \ a \le x \le \dfrac{b+a}{2} \\ \dfrac{b-x}{b-a} & if\ \ \dfrac{b+a}{2} \le x \le b \\ 0 & if\ x > b \end{cases} \tag{6}$$

2.6.2 Placing attributes and classes in the software

This step involves placing each specific attribute as inputs, and security levels as outputs, and the rule base is based on MATLAB software.

2.6.3 Implementation of the fuzzy inference system

After constructing the fuzzy system and incorporating the attributes, and classes in the fuzzy module of Matlab software, for each of the attributes in the fuzzy inference system, driving safety levels are given according to their priority. The fuzzy inference engine calculates the outputs or the strategies, using the rules in the database. It should be noted that, outputs are fuzzy numbers, which are becoming non-fuzzy according to the center of gravity or other methods. Finally, the degrees of membership are expressed in quantitative terms, and are ranked by the obtained score.

2.6.4 Designed system and rules

With the implementation of the above-mentioned algorithm and the design of the fuzzy system, the decision tree is presented in Fig. 2.

By considering the diagram in Fig. 2, a degree of safety can be assigned to all the attributes as well as all the situations that can occur according to the driving attributes, and the system is also designed using decision tree rules and provides safety warnings for driving. Some of the extracted rules are presented in Table 2.

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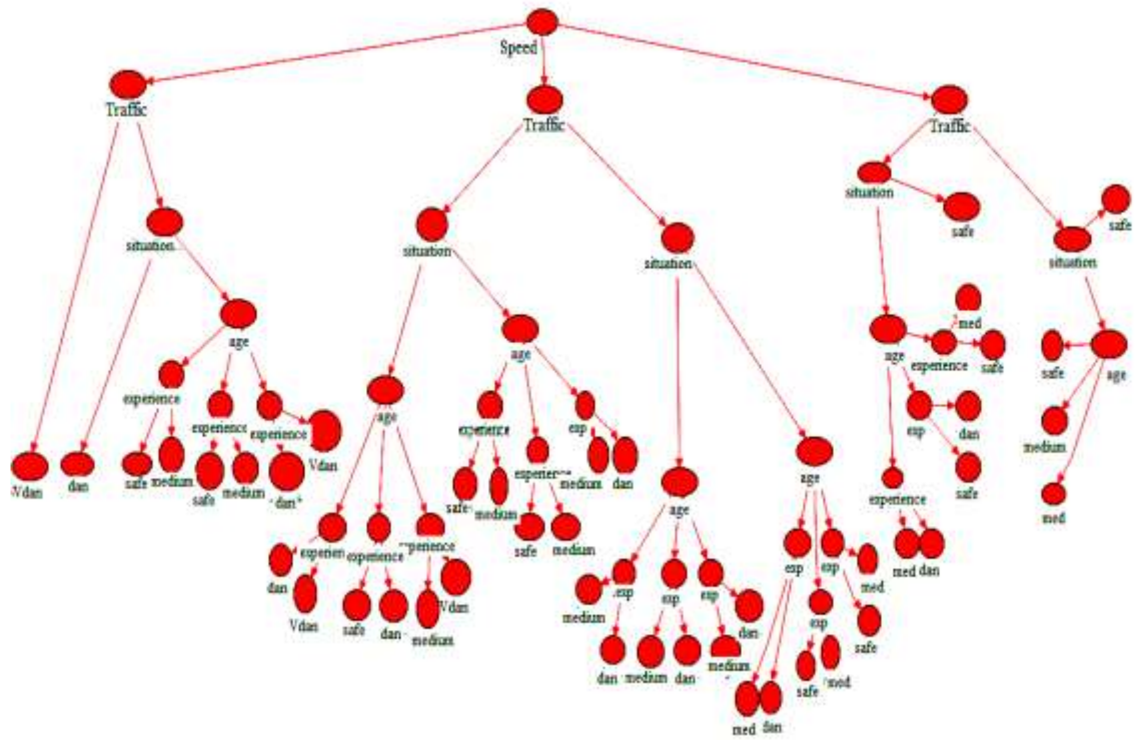

Fig. 2. Designed decision tree diagram.

Table 2
Extracted rules with high coverage

Coverage percentage	Rules	Safety Level
%99	High speed - high traffic	Very dangerous
%95	High speed- high traffic -Bad weather conditions	Dangerous
%88	High speed -high traffic -good weather conditions -old-Experienced	Safe
%81	High speed -high traffic -good weather conditions -old -naive	Medium
%84	High speed -high traffic -good weather conditions -young -naive	Very dangerous
%91	High speed -high traffic -good weather conditions -old -experienced	Dangerous
%88	Average speed – high traffic -Bad weather conditions - young -experienced	Medium
%87	Average speed – high traffic -Bad weather conditions - old -naive	Very dangerous
%90	Average speed – high traffic -good weather conditions - old -naive	Medium
%96	Average speed -low traffic -bad weather conditions -middle-aged -experienced	Medium
%92	Average speed -low traffic -bad weather conditions -middle-aged -naive	Dangerous
%89	Average speed -low traffic -good weather conditions -middle-aged -experienced	Safe
%93	Low speed -high traffic -good weather condition	Safe
%93	Low speed -high traffic -experienced-young -bad weather	Safe
%95	Low speed -low traffic -bad weather conditions -young	Medium
%97	Low speed -low traffic -good weather conditions	Safe

It is clear from the diagrams and rules that the speed attribute is located at the root, and at other levels, there are variables with less entropy. For example, if the speed of the driver is high and traffic is high, then with 99% coverage, driving will be very dangerous in terms of the situation in the class. In order to show the effectiveness of the proposed method, we use several evaluation metrics to evaluate the methods. Specifically, we use MAE, RMSE, MSE and R^2 and compare the results with the ANFIS technique. The results are presented in Table 3.

Table 3
Error criteria for the designed Decision Trees and Fuzzy Neural Network techniques

Model	MAE	RMSE	MSE	R^2
Decision tree	8.419	19.628	385.258	91.084
Fuzzy Neural Network	9.362	21.22	401.648	88.188

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3. Conclusion

The driver assistant system was proposed using data mining techniques. The collected data were analyzed using two different fuzzy decision tree. To determine the variables of the branch, we used the entropy method. Accordingly, the attribute with less entropy was placed in the root, and the attributes with high entropy were placed in the nodes near the leaves. In other words, in the estimation of entropies, speed attribute was placed at the root of the tree and then other attributes including traffic, atmospheric conditions, age, and experience were located in the next nodes. We compared our method with ANFIS technique. The results showed that the Decion Trees (R^2=91.084; MAE=8.419; RMSE=19.628; MSE=385.258) technique outperforms ANFIS (R^2=0.88; MAE=9.362; RMSE=21.22; MSE=401.648). Therefore, by reviewing the results of the three examined models, it can be concluded that using the decision tree in the design of the driver assistant system will be more efficient.

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