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*Research article*

# Smart car system: automobile driver's stress recognition with artificial neural networks

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## Abstract

Nowadays, the world needs safe and smart machines that can prevent human errors in different situations. Stress is an important factor in accidents which causes the human error. Many accidents can be prevented by identifying the stress of the driver and warning them. Due to its complexity, identifying stress in drivers is only possible by intelligent algorithms. In this paper, the Electrocardiogram (ECG) signal from *drivedb* dataset is used to detect stress in drivers, which has useful information that can be recorded more easily while driving. Afterwards, with a set of statistical, entropy, morphology, and chaos features, useful information is extracted from the signal. Then, in order to optimize the features, the Relief feature selector is used. Optimal features information is evaluated using Artificial Neural Networks (ANNs). Using the proposed method, the stress in drivers is detected with an accuracy of 92.6%, which has increased classification accuracy compared to recent researches.

*Keywords:* Smart machine, Stress recognition, ECG, Relief feature selection, Chaotic features, Optimization, Neural networks

## 1- Introduction

Today, computers and artificial intelligence are used in automotive industry to help the driver to avoid some risks. Smart cars have the ability to warn drivers when they are inefficient, such as distraction or fatigue, to remove them from the driving cycle and thus prevent possible accidents [1]. Stress is an important and main factor in most road accidents that lead to great financial and human losses and intelligent car systems can play a role. If a person experiences internal discomfort from external requests, is so-called stressed [2]. Stress while driving creates an inappropriate state in the driver, which can increase the risk of an accident 10 times [3]. Also, official research in Australia shows that the driver's emotions play an important role in accidents because an emotion like stress can weaken the driver's cognitive ability, and in this case, the driver cannot perform well in the event of danger [4]. According to various data, stress is one of the important factors of urban and road accidents, and considering that nowadays drivers are constantly commuting in stressful environments such as the highway, the need for intelligent systems to check the driver's mental state is one of the most important needs of today's society [5].

The implementation of intelligent electronic systems inside the car is one of the necessities of car manufacturing so that by checking the driver's condition, the best decision can be made at the right time and possible risks can be avoided [6]. many intelligent systems have been presented in recent years to detect and identify the state of stress in drivers, These systems are used in different states of the driver's physiology, such as eye movements [7], pupil diameter [8], face movement [9], road criteria [10], etc. Yokoyama *et al.* [11] have presented a method to detect stress by measuring changes in the diameter of the pupil of the driver's eye using 5 small cameras. Schießl *et al.* [12] presented a method, in which using different laser sensors Environmental factors, driver's intention and driver's maneuvers are examined and in a final summary, the driver's mental state is estimated. These methods are very costly and time consuming.

In relation to checking the status of drivers, we need systems that can be implemented in the small space of the car easily and at the lowest cost. Among the different methods to identify stress, the use of vital signals such as electroencephalogram (EEG) [13], electrocardiogram (ECG) [14], Skin Potential Response (SPR) [15], and electromyogram (EMG) have received much attention. By using these signals, stress can be identified with high accuracy and low cost. Dorota *et al.* [16] used EMG and SPR signals to identify the stress of drivers, and KNN and SVM classifiers used the machine to identify stress from normal drivers. Chui *et al.* identified and classified drivers' stress by using a multi-objective optimizer of genetic algorithm and ECG signal. Hadi *et al.* [17] used a method based on EEG signals and used several different classes including random forest to identify stress. Among these signals, the ECG signal has more convenient recording and reliable accuracy to detect stress in drivers [18]. Research has shown that using the ECG signal is a convenient and accurate way to monitor the autonomic nervous system (ANS) [19]. Although the EEG signal is highly accurate for monitoring the nervous system and detecting stress, it has not been noticed because it is difficult to record and it is practically impossible to record EEG [20].

In this paper, in order to identify stress automobile drivers while driving, the ECG signal has been used. Considering that ECG signal has less information than EEG, we used a set of statistical, entropy, frequency, morphology, and chaos features for feature extraction and stress identification. In the next step, the features are optimized by Relief. Using the Relief feature selector makes ineffective features to be removed and useful information from the signal become available. Selecting the optimal feature increases the speed and accuracy of calculations and is essential in the application of drivers' stress detection because quick identification and action must be done. Artificial Neural Networks (ANN) have high ability in pattern recognition applications, and therefore, in the proposed method, the optimal features are classified using ANN. In addition, other classifications such as support vector machine, nearest neighbor, decision tree will also be used for better comparison between the results.

The structure of the article will be such that in the second part, we will examine the database, feature extraction, and select the best features. In the third part, the simulation results of the proposed method will be analyzed, and finally, in the third part, we will discuss and draw conclusions.

**Table 1:** The time (min) of different stages of driving for different people (10 available person) [5].

| | rest | City1 | Hw1 | City2 | Hw2 | City3 | rest | total |
|---|---|---|---|---|---|---|---|---|
| Drive05 | 15.13 | 16.00 | 7.74 | 6.06 | 7.54 | 14.96 | 15.78 | 83.23 |
| Drive06 | 15.05 | 14.49 | 7.32 | 6.53 | 7.64 | 12.29 | 15.05 | 78.38 |
| Drive07 | 15.04 | 16.23 | 10.96 | 9.83 | 7.64 | 10.15 | 15.03 | 84.87 |
| Drive08 | 15.00 | 12.31 | 7.23 | 9.51 | 7.64 | 13.43 | 15.07 | 80.19 |
| Drive09 | 15.66 | 19.21 | 8.47 | 5.20 | 7.06 | 13.21 | NA | 68.82 |
| Drive10 | 15.04 | 15.30 | 8.66 | 5.27 | 7.04 | 12.06 | 14.79 | 78.15 |
| Drive11 | 15.02 | 15.80 | 7.43 | 7.15 | 6.96 | 11.72 | 14.99 | 79.08 |
| Drive12 | 15.01 | 13.41 | 7.56 | 6.50 | 8.06 | 11.68 | 15.01 | 77.23 |
| Drive15 | 15.00 | 12.54 | 7.24 | 5.99 | 6.82 | 12.12 | 15.00 | 74.70 |
| Drive16 | 15.01 | 16.12 | 7.14 | 5.12 | 6.81 | 13.91 | NA | 64.10 |

## 2- Method

In this section, we will review the database and various parts of signal processing, including feature extraction, to identify stress in drivers.

*A. Database*

In the proposed method, the drivedb database available on the Physionet[1] site is used. This database was presented in 2005 by Healy and Pickard and includes recordings of ECG, GSR and EMG signals from 17 healthy volunteers [21]. Each recording lasted between 63 and 90 minutes and recorded signals from people during a daily drive that starts in the parking lot, drives around the city and on the highway, and then returns home. Fig. 1 shows how to connect the electrodes to the driver [21].

City, highway, and rest driving times in this database are different for each person. Table 1 shows the time of different stages of driving for different people (10 available persons) [5]. During the test, drivers went from MIT's East Garage to the River Street Bridge and back via three (city) streets and two freeways. Labeling is done by an expert based on the driver's position in each place of driving.

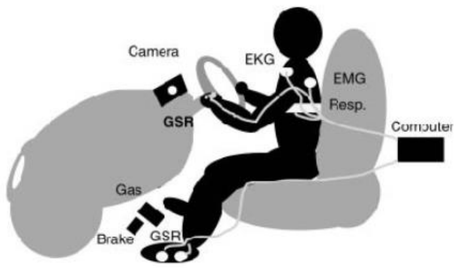


Fig. 1 How to connect the electrodes to the driver [21].

In the following, we will examine feature extraction from the ECG signal available in this database.

[1] https://physionet.org/content/drivedb/1.0.0/

*B. Feature extraction*

In the proposed method, various statistical, morphological, entropy, and chaotic features are used to extract features, which we will examine in order. The first category of features are statistical features which include mean, variance, skewness [22], and kurtosis [23] that calculated according to Equations 1-4.

$$mean\_ECG = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (1)$$

$$\text{var} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - mean(x_i))^2} \quad (2)$$

$$Skewness = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - mean(ECG)}{SD\_ECG}\right)^3 \quad (3)$$

$$Kurtosis = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - mean(ECG)}{SD\_ECG}\right)^4 \quad (4)$$

Other features include special features of ECG, which include Standard Deviation of R-R series (SDRR), and Root Mean Square Distance of Successive R-R interval extract from RR (RMSSD), that calculated according to Equation 5-6 [24].

$$SDNN = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(RR_i - mean(RR_i))^2} \quad (5)$$

$$RMSSD = \sqrt{\frac{1}{N-2}\sum_{i=3}^{N}[RR_i - RR_{i-1}]^2} \quad (6)$$

ECG feature such as mean R-R interval distance, Number of R peaks in ECG that differ more than 50 millisecond, Standard Deviation of R-R series, Power Spectral Entropy, Average Heart Rate Variability are also used in the proposed method.

The third category is entropy features. Entropy of Boltzmann, Shannon, and Kolmogorov-Sinai are calculated according to relations 7-10. Boltzmann entropy calculates thermodynamic entropy [25]. Shannon entropy is responsible for calculating the possible stability in samples [26]. The entropy of the Kolmogorov-Sinai is used for random experiments in the dynamic system [27].

$$Boltzmann\_entropy = k\ \ln(W) \quad (7)$$

$k$ refer to Boltzmann constant equal to $1.38065 \times 10^{-23}$ J/K

$$sh\_entropy = \frac{1}{1-M}\, log(\sum_{i=1}^{N} P_i^m) \quad (8)$$

$P$ is the sequence of signal probability and $M$ is equal to 2 [28].

$$K = \lim_{n\to\infty}\sum_{n}^{N-1}(S_{n+1} - S_n) = \lim_{n\to\infty}\frac{1}{N_\tau}[S_N - S_0] \quad (9)$$

$N$ is sample number and signal entropy is $S$ (in limited time).

The feature of the largest Lyapunov exponent view is one of the chaotic features used in the method. In the dynamic system, the degree of divergence or convergence is determined by the largest Lyapunov [29] that calculated according to Equation 10.

$$LLE = \lim_{t\longrightarrow\alpha}\frac{1}{t}\ln\frac{|\Delta x(x_0,t)|}{|\Delta x_0|} \quad (10)$$

Another feature used in the proposed algorithm is short time Fourier transform (STFT). This feature is in the category of frequency features and checks the complexity of the signal domain and calculated according to equation 11.

$$STFT\,[x_i](m,\omega) \equiv X\,(m,\omega) = \sum_{n=-\infty}^{\infty} x_i\,\omega(n-m)e^{-j\omega n} \quad (11)$$

$\omega$ refer to continuous and $m$ refer to discrete of time series.

*C. Feature selection*

All the features extracted from a signal are not suitable, and in order to increase the accuracy and speed of processing, ineffective features should be removed [30, 31]. In order to select the top features, we use Relief feature selector in the proposed method**.** This selector was introduced in 1992 by kira and

Rendel and used in recent studies [32-34]. This feature selector calculates the proxy statistics of each feature that can estimate the quality of that feature. In this algorithm, this proxy statistic is called weight, which can be a number between 1 and -1. In the first step, by examining the features, it assigns a weight to each one [35, 36]. In this algorithm, the weights are updated according to Equation 12 [37].

$$W[A]=W[A]-diff(A,R_i,H)/m + diff(A,R_i,M)/m \tag{12}$$

In Eq. 12, *H* is a nearest hit, *M* nearest miss (Relief searches is based on two nearest neighbors: *H, M*), *m* is number of random training instances out of n used to update W. After each update, the classification accuracy is obtained by the KNN classifier to measure the quality of the weights. Finally, based on the final weights, the features are ranked and the features with the highest rating are selected [38].

*D. Classifier*

After selecting top features, the data is classified by the classifier. In the proposed method, Artificial Neural Networks (ANN), Support Vector Machine (SVM), K Nearest Neighbor (KNN), and Naïve Bayes (NB) are used for more accurate classification.
Artificial neural networks are designed based on the reactions of human nerve cells and include artificial neurons and connections [39]. The data is first entered into the neurons, and after assigning weight to each, it enters the next hidden neural layers. These weights are updated during several iterations performed by the network, and finally the best weight is obtained for each data [40]. Fig. 2 shows a view of the neural network of the proposed method. In this network, the inputs are the same features and 8 neurons are used in the hidden layer of this network. Finally, the output of the network will define two classes, normal, and stress.

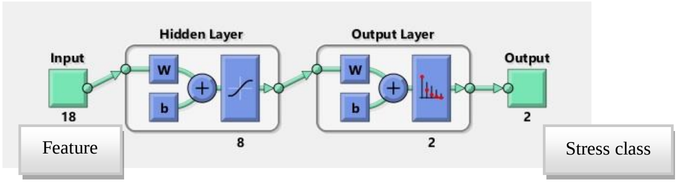


**Fig. 2** View of the neural network of the proposed method.

SVM with Gaussian kernel, KNN with 3 neighbor and RF with 200 tree have been used in our method. In the following, we will examine the results of the simulation.

**3- Results**

1) The simulation of the proposed method has been done in MATLAB 2020b. This version of MATLAB has shown its ability in our previous simulations [41]. For the neural network, 20% of the data is allocated for testing and 10% for evaluation and 70% of the total number of samples were used for training. Also, in order to evaluate other classifications (SVM, KNN, DA), the K-fold method (K=5) has been used.

According to Relief feature selection mean, Shannon entropy, largest lyapunov exponent, STFT, Kolmogorov entropy, avgHRV, sd_RR, nn50, and pse features selected for proposed method and they classified by ANN, DA, SVM, KNN, NB. Table 2 show the accuracy of stress recognition in driver by different classifier. According to Table 2, the best classifier for the proposed method to identify stress in drivers is ANN. In addition to the manual selection method of 70% training data, 20% test and 10% validation, in order to check the neural network more accurately, evaluation leave one out cross-validation has also been used. Leave one out is an evaluation method whose number of folds is equal to the number of features and implements the algorithm separately for each feature and will finally provide the overall answer [42]. Using this evaluation method, the stress classification error using the proposed method is 0.11.

Table 3 shows the values of sensitivity, specificity, and kappa for different classifications in the diagnosis of drivers' stress. As can be seen in Table 3, the highest level of sensitivity and specificity is for the ANN classification.

**Table 2:** Accuracy of stress recognition in driver by different classifier.

| Classifier | Normal accuracy | Stress accuracy | Total accuracy |
|---|---|---|---|
| DA | 0.773 | 0.88 | 0.853 |
| NB | 0.760 | 0.851 | 0.824 |
| SVM | 0.776 | 0.920 | 0.882 |
| KNN | 0.778 | 0.94 | 0.899 |
| ANN | **0.841** | **0.959** | **0.926** |

**Table 3:** Values of sensitivity, specificity, and kappa for different classifications in the diagnosis of drivers' stress.

| classifier | sensitivity | specificity | kappa |
|---|---|---|---|
| DA | 0.82 | 0.86 | 0.76 |
| NB | 0.84 | 0.85 | 0.77 |
| SVM | 0.83 | 0.90 | 0.82 |
| KNN | 0.83 | 0.92 | 0.86 |
| ANN | **0.86** | **0.94** | **0.90** |

Fig. 3 shows ROC diagram of the ANN classifier for normal and stress class. As it is clear in the figure, the neural network has reached the highest possible accuracy with multiple iterations and modification of its weights.

Table 4 shows some recent researches compared to the proposed method. As shown in Table 4, the proposed method has provided the highest accuracy for detecting stress in drivers with ECG signal by using different features and various classifications.

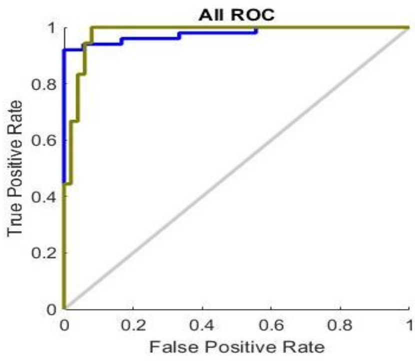


Fig. 3 ROC diagram of the ANN classifier for normal and stress class.

**Table 4:** Some recent researches compared to the proposed method.

| Paper | Signal | Classifier | Year | Accuracy |
|---|---|---|---|---|
| Wang[43] | ECG | KNN | 2013 | 81% |
| Chui [44] | ECG | SVM | 2015 | 76.9% |
| Chui [45] | ECG | MKL-SVM | 2022 | 89.0% |
| Our method | **ECG** | **ANN** | **2022** | **92.6%** |

**4- Conclusion**

In this paper, an intelligent method to detect stress in automobile drivers was presented. The necessity of using smart networks is to be able to give the necessary warning to the driver and prevent possible accidents. The EEG signal is difficult to record and we used ECG because it is easy to record. For this reason, in this method, we used a complete set of features including statistics, entropy, chaos, and morphology in order to obtain more useful information from the signal. Then, using the relief selector, the best features were selected. In this method, several different classifiers were used to check the efficiency of different classifiers, and in the meantime, ANN classifier was more efficient for the proposed method. By using the proposed method, the accuracy of identifying stress in drivers with ECG increased compared to previous researches, and in future researches, by using more features and using meta-heuristic selectors, algorithms can be presented that are more accurate, practical use in Have an automotive industry.

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