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Classification of Stress Recognition using Artificial Neural Network

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Abstract— **This paper presents the results of a study developing expert system to support stress recognition based on Artifical Neural Network (ANN). Developed ANN is trained using data from Physionet database and collected data from other researchers. The implemented system for stress recognition uses drivers ECG signal, Galvanic Skin Response and Respiration Rate as parameters. Developed neural network was validated with 77 samples. Samples are obtained from subjects using Pasco sensors in 7D cinemas.**

Out of 77 samples, in 71% of subjects higher level of stress is recognized, while 29% of subjects are classified as subjects with normal vital functions. An accuracy of 99% and specificity of 98% is obtained.

Keywords - stress, galvanic skin response, heart rate, respiration rate, artificial neural network, classification

I. INTRODUCTION

Stress is human's body way of responding to any kind of demand or threat by releasing a flood of stress hormones including adrenaline and cortisol, which rouse the body for emergency action. The heart pounds faster, muscles tighten, blood pressure rises, breath quickens and senses become sharper [1]. These physical changes increase body's strength and stamina speed reaction time and enhance the focus [1].

Physiological parameters that can be used for stress detection, among others are: galvanic skin response, heart rate and respiration rate [2].

The Galvanic Skin Response (GSR) is one of several electrodermal responses (EDRs). EDRs are changes in the electrical properties of a person's skin caused by an interaction between environmental events and the individual's psychological state [3]. Human skin is a good conductor of electricity and when a weak electrical current is delivered to the skin, changes in the skin's conduction of that signal can be measured. The variable that is measured is either skin resistance or skin conductance [4]. There are several studies which propose different methods of detecting stress levels by measuring skin conductance [7-9].

Heart rate is the speed of the heartbeat measured by the number of contractions of the heart per unit of time, typically beats per minute (bpm) [5]. The heart rate can vary according to the body's physical needs, including the need to absorb oxygen and excrete carbon dioxide. It is usually equal or close to the pulse measured at any peripheral point. Activities that can provoke change include physical exercise, sleep, anxiety, stress, illness, ingesting and drugs [5].

The respiration rate (RR), also known as ventilation rate, ventilation frequency is the rate (frequency) of ventilation, that is the number of breaths (inhalation-exhalation cycles) taken within a set amount of time (typically 60 seconds). A normal respiratory rate is termed eupnea, an increased respiratory rate is termed tachypnea and a lower-than-normal respiratory rate is termed bradypnea [6]. Human respiration rate is measured when a person is at rest and involves counting the number of breaths for one minute by counting how many times the chest rises [6].

As these physiological parameters are great indicators of stress, they have been used as inputs for developing artificial neural networks in several scientific papers.

Sharma and Gedeon [7], in their paper investigated classification of stress in reading for males and females based on an artificial neural network model (ANN). An experiment was conducted with stressful and non-stressful reading material as stimuli. The classification was based on galvanic skin response (GSR) signals and subjects were classified into two output classes [7].

Furthermore, Avci, Akbas and Yuksel [8] in their paper proposed an efficient and easy implementation metrics to determining stress level of drivers. For the evaluation, data from Stress Recognition in Automobile Drivers database in the PhysioNet databank were used. Evaluations have been completed by using the available segment based arrays of electromyography (EMG), foot based galvanic skin response (Foot GSR), hand based galvanic skin response (Hand GSR), heart rate (HR) and instantaneous respiratory rate (IRR) derived from respiration by using peak detection algorithm [8].

Singh and Queyam [9] in their research, presented a method based on a correlation analysis and developed a mathematical function for the estimation of automobile driver stress level. The proposed methodology monitors driver's stress level using features extracted from selected physiological parameters. The results obtained indicate a strong correlation between the stress level of driver and the stress function formed. The stress function acts as a direct indicator of stress level of the automobile diver whose physiological parameters are monitored continuously under variable traffic conditions [9].

This paper presents the result of developing ANN for stress recognition based on equations developed by Singh and Queyam [9].

II. METHODS

Feedforward backpropagation network with two layers has been used, and according to the experts and previous papers [7-10], it is sufficient to properly perform the classification tasks. The input layer consists of 4 network inputs that are followed by a hidden layer which consists of 7 neurons. Each neuron performs a weighted summation of the inputs. Output Layer consists of one neuron and output value parameter is the level of the stress, as it is presented on Figure 1.

The network has been tested with different number of neurons in hidden layer in order to get the best possible results of classification. Thus, it was tested with 1, 5, 7, 10 and 15 neurons. In order to define the ratio between the estimation and validation datasets different kind of test combinations had to be performed.

Guided by the experience of previous researchers [7-10], Levenberg - Marquardt function was used for training, and mean square error function as performance function. Since the connection between physiological parameters and stress recognition is linear [10], linear transfer functions in input and hidden layers were used (Fig. 1).

Input parameters to developed ANN were: heart rate, respiration rate, foot galvanic skin response and hand galvanic skin response. Output data was classified into two output classes: stress and no stress (Fig. 2). In order to distinguish presence or absence of stress, the threshold had to be found. By looking at the results of the function given by Singh and Queyam [9] and by the experimentally performed test it was concluded that threshold is 3.8. The threshold is set to this value because the person with the lowest level of stress shows to have value higher than threshold. If output is lower than 3.8, the stress is not detected in automobile driver. However, every value higher than 3.8 indicates stress [9].

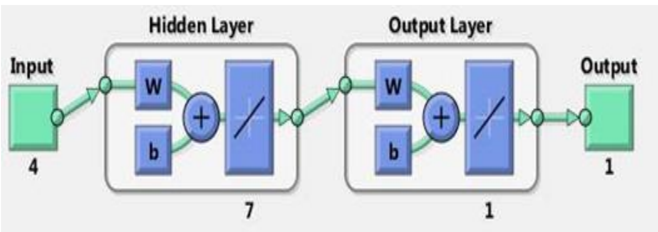

Figure 1. ANN architecture

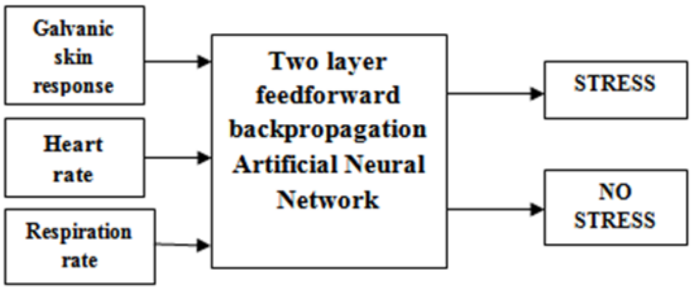

Figure 2. Block diagram of developed system for stress classification

On the Fig. 1 it is illustrated ANN architecture. It shows that with four parameters, 7 neurons in hidden layer and linear transfer functions, ANN was trained to give output that will classify the stress.

For validation purpose, data collected from 77 subjects from the Multiplex 7D Cinema Sarajevo, Bosnia and Herzegovina were used. All subjects wore sensors from Pasco production for HR and GSR, whereby acquisition of recorded values was directly executed.

The block diagram that is represented on the Fig. 2 illustrates the entire process of stress classification including its inputs, functions and output.

III. RESULTS

The ANN was tested with 1, 5, 7, 10 and 15 neurons. The best result has been achieved with 7 neurons in the hidden layer. Even though, the results with 10 and 15 neurons are negligibly better, they were neglected because of the increased computational complexity of the network.

On the Fig. 3 regression analysis of the training process for all tested neurons is shown. It presents disregarding difference between 7, 10 and 15 neurons. If regression is equal to 1 it means that there is an exact linear relationship between outputs and targets.

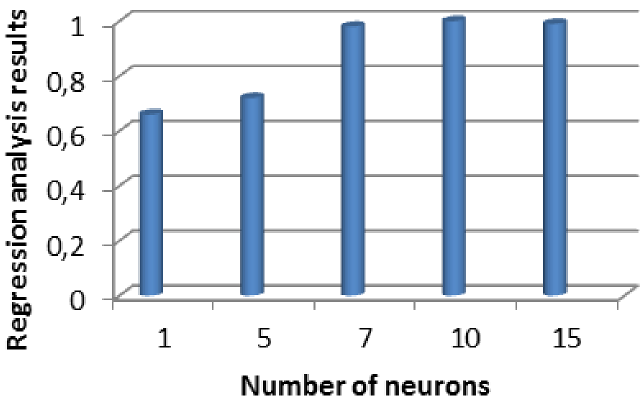

Figure 3. Regression analysis with respect to number of neurons

On performance plot which is shown on the Fig. 4, it can be seen that the validation, training and test curves are almost identical, which indicates that there was no problem with the training.

Validation of ANN was performed with 77 samples aquired from Multiplex 7D Cinema in Sarajevo using Pasco sensors. Results of stress classification are given in Table 1. Accuracy, specificity, sensitivity and error rate of ANN are represented in Table 2.

It is expected that the output of ANN will be numerical value which will show stress level. If F is lower than 3.8, the stress is not detected in automobile driver, however every value higher than 3.8 indicates stress.

The Table 1 shows that among 77 tested samples, it is expected that 54 samples are under stress and 23 correspond to "no stress" class. ANN correctly classified 76 samples, while it incorrectly classified 1 sample.

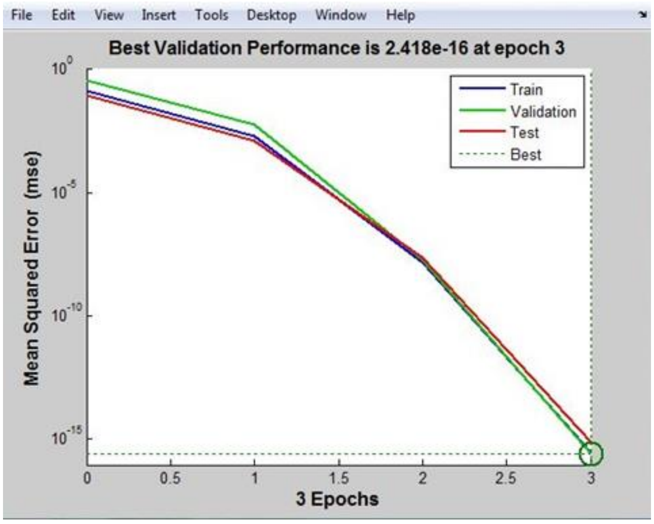

Figure 4. Validation performance plot

TABLE1. CONFUSION MATRIX FOR STRESS CLASSIFICATION

N=77	PREDICTED "NO STRESS"	PREDICTED "STRESS"
CLASS "NO STRESS"	22	0
CLASS "STRESS"	1	54

TABLE2. ACCURACY, SENSITIVITY, SPECIFICITY AND ERROR RATE

ACCURACY	**99%**
SENSITIVITY	**98%**
SPECIFICITY	**100%**
ERROR RATE	**1%**

Using data from Table 1, accuracy, sensitivity, specificity and error rate are calculated and shown in Table 2.

From total sum of 77 samples the ANN correctly classified 76, while it incorrectly classified one sample. This gives ANN accuracy of 99% for stress classification.

IV. CONCLUSION

When a threat is perceived, body responds by releasing a flood of stress hormones, changing heart rate and respiratory rate. In some cases it is necessary to collect feedback in order to control these symptoms because it can become dangerous in certain situations. One of these dangerous situations is while driving. The decision-making power and slower reaction are consequences of accumulated stress, and some thoughtless decisions can easily be made. To prevent this, device which will be used as an alert to every driver to calm down or to be more careful can be made. Before making a device it is necessary to develop the system which can recognize the stress.

In this paper ANN for stress classification is presented. This two layer feedforward backpropagation network proved to be a great tool for classification of patient's disease and state.

Using sufficient number of appropriate parameters for training, ANN is able to give precise and reliable results with accuracy of 99% and sensitivity of 98%.

These results are very promising and further development of this network can be used for making revolutionary device system, that can be built-in the cars and inform the driver about the situation that is happening in his/her body. For the purpose of the use of this developed solution in the hospitals, in the future authors will also develop Graphical User Interface (GUI), similar like in [12-14].

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