Prediction of individual psychophysiological stress level with artificial neural network

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Abstract

Prediction of psychophysiological stress on the basis of biosignals is a challenging task. Each individual's reaction to stress is higly different. In this study, an artificial neural network (ANN) method was applied to predict the stress level of an individual. The method predicts the stress level of an individual, based on heart rate, systolic blood pressure, and diastolic blood pressure. The method was evaluated, based on data collected from 10 subjects (including 10 consecutive measurements per subject). The results were encouraging: the method predicted individual stress level successfully (accuracy of prediction better than 20%) for 7 of 10 subjects.

Keywords: *stress reactions, heart rate, blood pressure*

1. Introduction

Physiological stress response is the body's reaction to a perceived mental, emotional or physiological stress [1,2,3]. Physiological stress reactions are a general problem in society, and there is a lot of active research in this field [4,5,6]. One problem encountered, when trying to determine the stress level of an individual, is that differences in how people react to stress is high [7]. Characteristics of blood pressure and heart rate are part of complex pathofysiological symptoms chain linking psychosocial stress with the metabolic syndrome to an increased risk of coronary diseases [8,9,10,11,12].

In this study we developed an artificial neural network (ANN) method, which predicts the physiological stress level of an individual, on the basis of resting heart rate, systolic blood pressure, and diastolic blood pressure. The method concentrates on each individual and his/her special characteristics between stress, and the stress-related parameters.

In the literature we found ANN methods applied to analysis of stress [13]. None, however, concentrated especially on individual prediction. In another application, ANNs have been used for individual analysis. As an example they have been applied for individual dosage of drugs for kidney transplantation patients [14].

In this study, the quantitative goal in the analyses is to predict the stress level of an individual as accurately as possible. From a methodological point of view, the goal of the study is to evaluate the development of the quality of stress level prediction due to the increasing amount of data per individual. Also, the following interesting point is studied here: what is the reason why, in some individuals, there is a clear relationship between selected stress-related parameters and physiological stress, but in others not.

The remainder of the paper is organized as follows: Section (2) describes the material and methods used in the study, Section (3) presents the results and Sections (4) and (5) contain the discussion and state the conclusion.

2. Material and methods

Subjects and data

The data analyzed in this study included 10 subjects (7 men and 3 women). Each subject's stress level, systolic blood pressure, diastolic blood pressure and resting heart rate was measured 10 times, on different days, during a period of 4 months. The measurements were performed in an undisturbed laboratory condition. A calming down period of 3-5 minutes preceded each measurement. In the first step of the measurement, the subject made a subjective estimate of his/her own psychophysiological stress level. This was carried out with a 100 mm long Visual Analysis Scale (VAS), where the range of stress was no stress at all, to the highest imaginable level of stress [15]. Next, the subject measured his/her diastolic and systolic blood pressures, and resting heart rate, from the right upper arm, with a fully-automatic Omron M4-I sphygmomanometer [16]. The measurement results were recorded on a computer. Table 1 shows the characteristics of the subjects, and the collected data.

Table 1. Characteristics of the data.

Variable	***Mean***	***Std***
Age (years)	42	13
Weight (kg)	83	11
Height (cm)	175	8
Stress level (VAS, mm)	28	18
Diastole BP (mmHg)	83	10
Systole BP (mmHg)	133	13
Resting HR (bpm)	67	9

Neural network method

An artificial neural network (ANN) is a parallel distributed processor, built of simple processing units, which naturally store experiential knowledge, and make it available for use [17]. In many technical analysis problems, where there is a need for nonlinear input-output mapping, an ANN is a good analysis tool of choice [18, 19, 20]. Also, ANN's are suitable for time series prediction [21]. In various cases, ANN's have advantages over statistical methods [22]. AAN's can also be designed to tolerate noisy inputs [23].

In this study, a special kind of ANN, a generalized regression network (GRNN) [24], was applied to predict the stress level of an individual. The GRNN is specially suited for function approximation. The GRNN used in this study has two layers: the radial basis layer and the linear layer, as depicted in Fig. 1. The first layer categorizes the input, while the second layer weights the categorized inputs, and produces the output. The purpose of training the network is to obtain good function approximation properties.

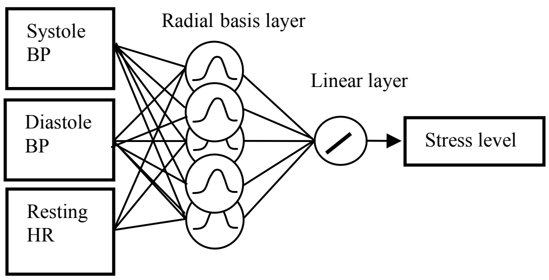


Fig. 1. ANN used in this study.

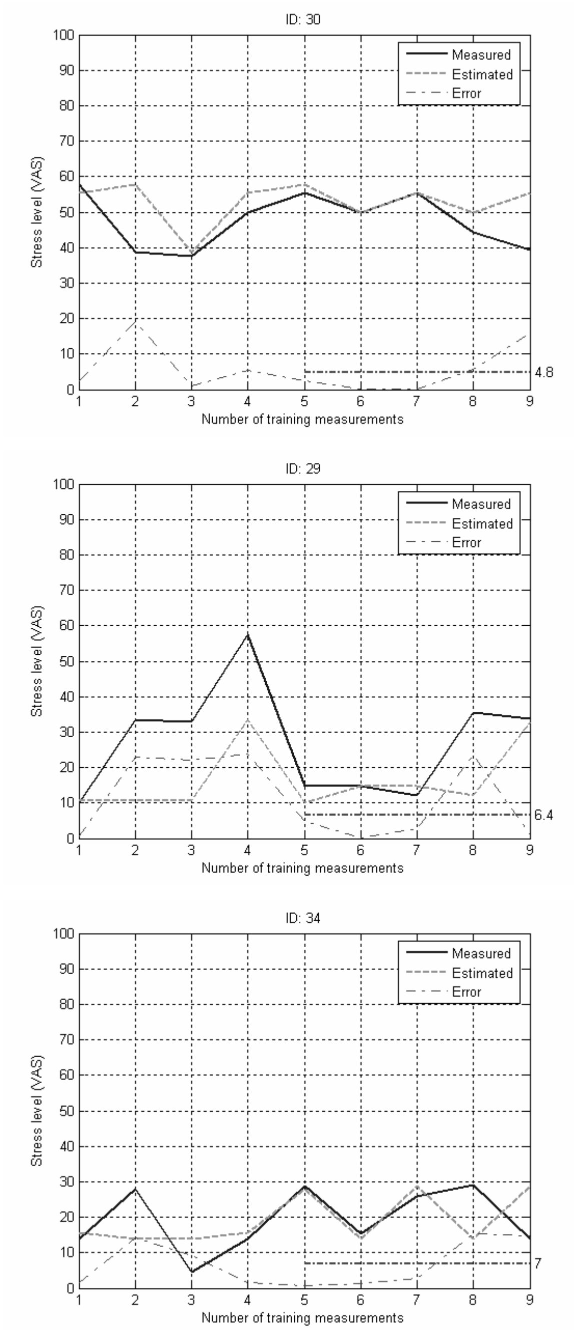
The ANN in Fig. 1 takes in the stress-related parameters, processes the data with the appropriate weights and activation functions in the network, and produces the estimate of stress level as an output. Before use of the ANN for stress level prediction, it is trained with previously measured data.

In this study, the function of the ANN was clearly stated: predict stress level as accurately as possible. Methodologically, however, the interesting point in our study is the development of the quality of prediction. For this purpose, we trained the ANN iteratively, as follows:

To begin, the AAN is trained with the first set of measurements (one set of stress-related parameters and one stress parameter). Next, the second set of stress-related parameters is fed into the ANN. The predicted output is then compared to the measured, and the absolute error is calculated. Next, the AAN is trained with data from the first and second measurement times. The prediction of third measurement is compared to the measured data, and again the absolute error calculated. This procedure is repeated until last measurement is computed. This result is nine pairs of measured, predicted and absolute error values for the stress level of each individual. By investigating the development of the absolute error of an individual, we get interesting information about the predictability of subject's stress level. During the training process, the ANN learns more and more about the connection between an individual's stress-related parameters and the stress itself. If the relationship between the parameters of an individual is clearly predictable, the error in the prediction should decrease during the training process.

3. Results

The ANN, shown in Fig. 1, was implemented in Matlab® [25], and trained as described above. Figure 2 shows the measured stress level (solid line), predicted stress level (dashed line), absolute error between measured and predicted stress level (thin dash-dot line), and the mean absolute error of the last 5 predictions (bold dash-dot line). The number of input-output pairs, used in the training before each prediction, is shown on the x-axis. The individual's ID-number is show on top of each picture.



(Fig. 2, continues on next page)

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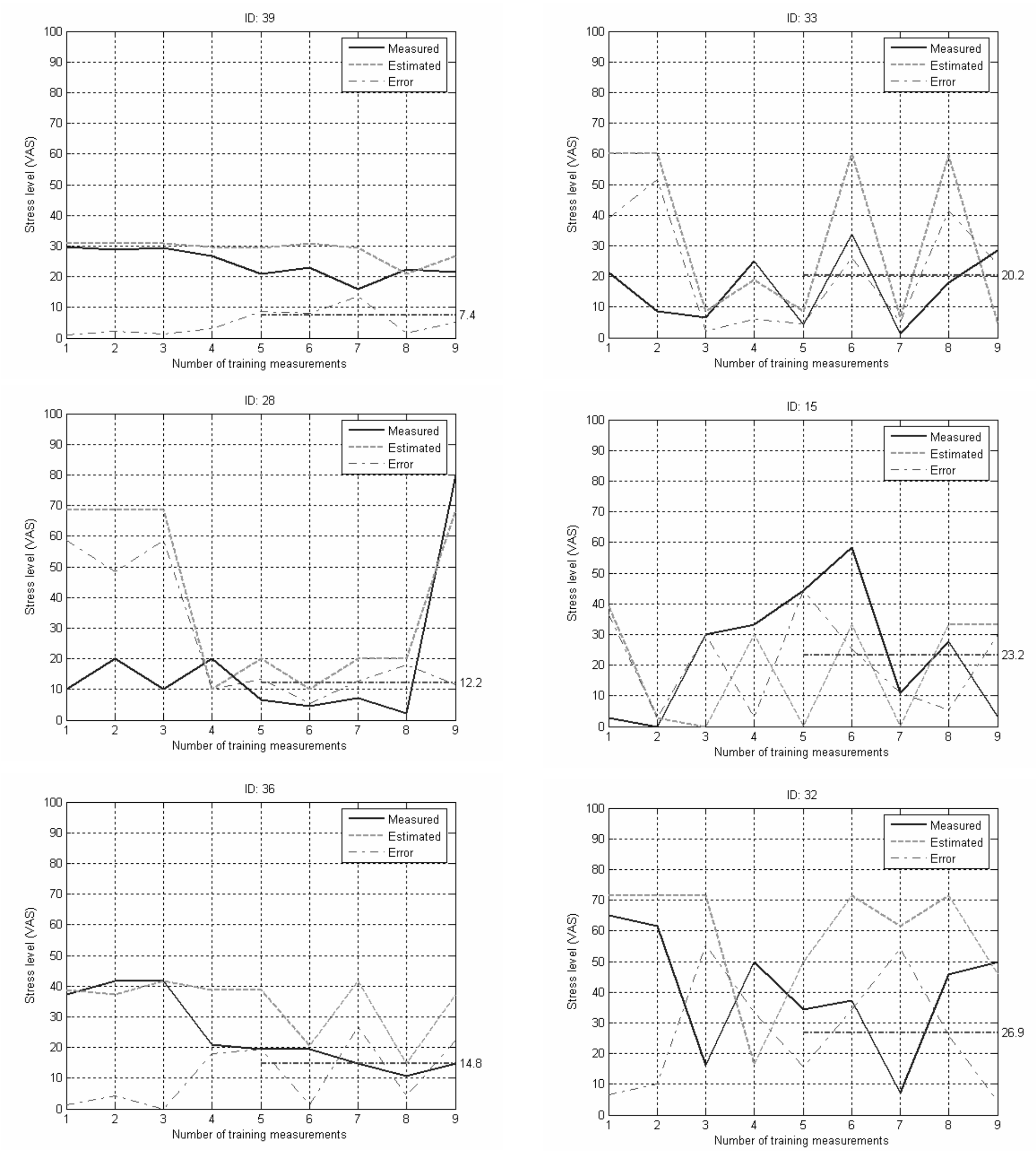

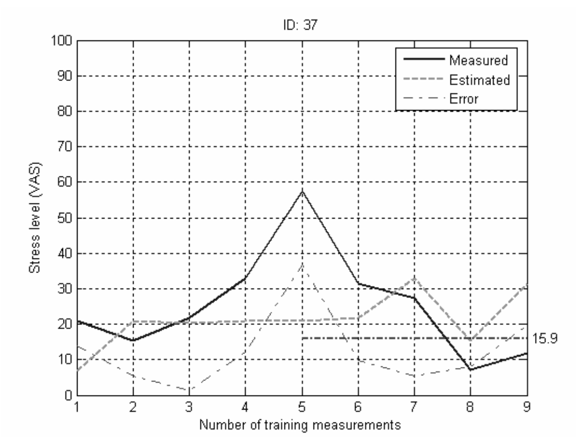

Fig. 2. Results of training.

After each iterative training round, the result is an ANN for stress prediction of the individual. As can be seen in Fig. 2 for individuals 30, 29, 34 and 39, ANN stress prediction is accurate; the mean error of the last 5 predictions is less than 10 units (10%). The prediction error for individuals 28, 36 and 37 was rather accurate; less than 20 units (20%). Among the last three i.e. individuals 33, 15 and 32, the error is larger than 20 units (20%).

4. Discussion

In this study, an ANN method was proposed, which, from a set of 10 subject total, functions accurately for four

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individuals, and rather accurately for three. The ANN method, however, did not learn how to predict stress level on the basis of the input variables of the remaining three cases.

Hence, for some individuals, the developed method learns clear dependencies between input and output, even though the number of training measurements per individual is small. Moreover, the absolute error curves in the results show that the method clearly does not work for three individuals in the data. It seems that, for those individuals, there are no clear dependencies between input and output variables. What is reason for this? Are those individual's actually stress-resistive, whose physiological reactions to stress are minimal? Or, is the prediction inaccurate because those individuals understand "stress" so much differently? It should be noted further, that one reason for good prediction results, in some cases, is the small variation of an individual's stress level.

Also, when interpreting the results, the restricted amount of data used in the study should be noted (maximum 9 training data sets for each individual). Statistical analyses, with large amount of data (tens of training data sets per individual), should be used to evaluate the method more accurately. Further, in this study, the quality of the ANN at each time instance was evaluated based on the absolute error between the predicted and measured stress value. Some other prediction quality estimate could also be used; one that combines ANN quality with both present training, and current validation data, in some appropriate way.

In the presented ANN iterative training process for an individual, the inaccuracy in the beginning is due to small amount of training data. As the amount of training data increases, the ANN tries to adapt to the individual's personal features. Thus, the probability of receiving more and more accurate results should increase. This procedure lays a general basis for the prediction of individual features without the danger of inaccurate presumptions.

The ANN method presented in this paper can also be used to predict psychophysiological stress, by using different input parameters. This study shows that the core analysis seems to function reasonably well, even with very small data sets. Therefore, it should be possible to apply the same analysis using different parameters, which are likely to be stress dependent with at least some individuals. Such parameters include heart rate variability parameters, blood count variables, respiratory rate and other biosignals.

Our future plan is to first collect a substantial amount of measurement data, from a large number of subjects. Next, we plan to develop a comprehensive stress level prediction method, which collects stress level and stress-related parameter data, and analyses it using the procedure presented in this study. The comprehensive method could automatically self-evaluate its performance, and communicate with its user. In this way, the user could receive information about his/her individual psychophysiological stress-level.

5. Conclusion

Prediction of phsychophysiological stress, with the developed ANN, was somewhat accurate (error less than 20%) for 7 of studied 10 individuals. The prediction method is simple, its performance is self-evaluating, and it can be easily applied to stress-related parameters other than the ones used in this study.

Perceiving appropriate individuality in quantative prediction of stress levels gives fertile insight to the quantitative analysis of pshychophysiological stress.

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