Classification of Physiological Sensor Signals Using Artificial Neural Networks

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Abstract. Physiological signals have certain prominent characteristics that distinguish them from other types of physiological signals which are familiar to experts and assessed by inspection. The aim of this paper is to develop a computational model that can distinguish electrocardiogram, galvanic skin response and blood pressure signals acquired from sensors as well as detect corrupted signals which can arise due to hardware problems including sensor malfunction. Our work also investigates the impact of the signal modeling for various time lengths and determines an optimal signal time length for classification. This provides a method for automatic detection of corrupted signals during signal data collection which can be incorporated as a support tool during real-time sensor data acquisition.

Keywords: signal classification, artificial neural networks, physiological signals, time series data, signal modeling.

1 Introduction

Physiological signals are generated by the human body and have been analyzed to classify different states of a person including health condition detection [1-3] and affective state classification [4, 5] however little attention has been given to develop models for model free recognition of physiological signals and detection of corrupted signals. Filtering techniques have been utilized for artifact classification in physiological signals such as EEG signals [6]. Our work is focused on computationally capturing the underlying properties that distinguish the nature of the different types of signals and separate the different types of signals.

Artificial neural networks (ANNs), inspired by biological neural networks, have characteristics for learning patterns to classify input tuples into classes. It is made up of interconnected processors, known as *artificial neurons*, which are connected by weighted links that pass signals between neurons to learn relationships between tuples and output classes. In this work, we used feed-forward ANNs trained using backpropagation to generate signal classification models.

This paper presents the signal data that will be modeled using ANNs for classification. The ANN models to model and classify physiological signals and corrupted signals using individual-independent models and models for a particular individual are proposed. We provide results of the ANNs on the data and analyses of the results.

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We also investigated how the length of the signal affects the performances of the ANNs for signal classification. The paper concludes by summarizing the work and suggests future work.

2 Physiological Signal Sensor Data

The physiological sensor signal data used for our models were obtained from the data set collected in [7]. Three different types of physiological signals are used in this work and they are electrocardiogram (ECG), blood pressure (BP) and galvanic skin response (GSR). Examples of the signals in the data set are shown in Fig. 1.

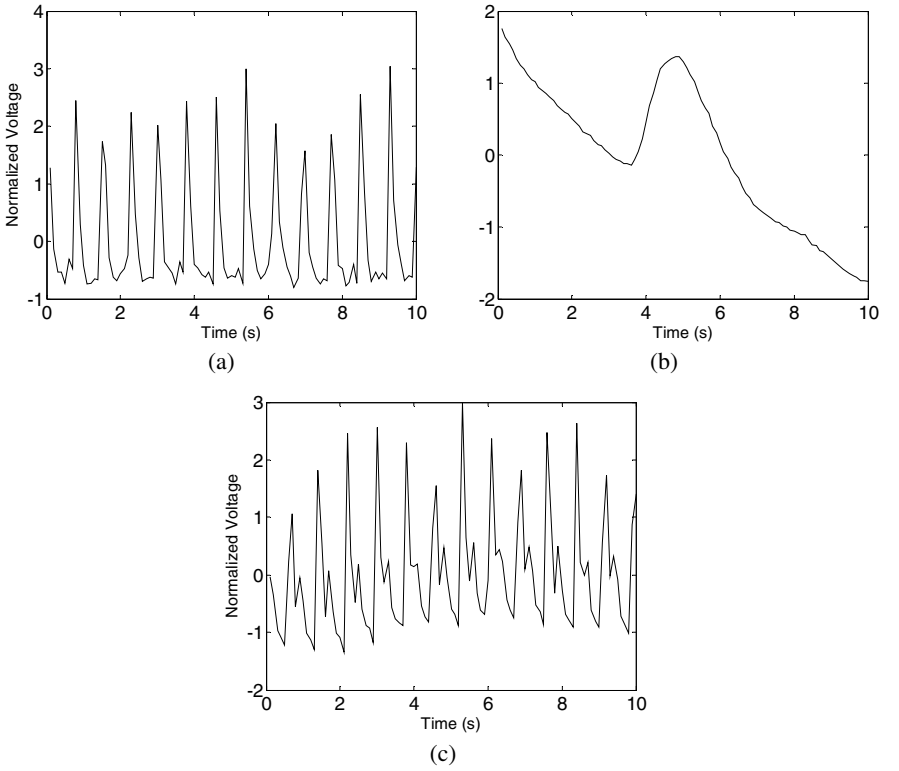


Fig. 1. Sample physiological signals (a) ECG signal (b) GSR signal (c) BP signal

The physiological signals modeled in this work are produced by different activities in the Autonomic Nervous System of the human body. An ECG signal captures electrical activity produced by the impulse of ions flowing through cardiac muscles, which dissipates into the region around the heart with diminished amounts spreading around the surface of the body. The ECG waveform is characterized by the dominant QRS wave where the R is the peak of the wave. ECG signals can be used to determine cardiovascular fitness, and dynamic and cumulative load of a person [8].

A GSR signal provides a measurement of the flow of electricity through the skin of an individual. Variations in GSR have been found to reflect stress levels in

individuals while they played a competitive racing game [9]. In addition, cognitive load [10] and work performance [11], which can be seen as stressors [12, 13], have strong correlations with GSR. GSR waveforms may have consistent shapes in reaction to stressors but are not usually periodic.

A BP signal shows the amount of pressure exerted on the walls of blood vessels due to blood circulation. The signal shows variations of the pressure between a systolic (maximum) and a diastolic (minimum) pressure.

The physiological sensor signal data set was used to model the three types of signals spanning 15 minutes for 22 subjects. For the purpose of this work, the signals were sampled at 10 Hz and this captured the main properties of the physiological signals such as the QRS waveforms in the ECG signals and the systolic and diastolic pressures in the BP signals as shown in Fig. 1. There were 10 other subjects who had their signals recorded but at least one of their signals were corrupted by manual inspection. This data was used to develop modeling systems that recognized corrupted signals as well as the physiological signals. Further, the signals were normalized to minimize the impact of individual bias, offset and noise in the signals for modeling and to better capture the underlying properties of the signals such as the QRS waveform for ECG signals.

3 Artificial Neural Network Signal Classifiers

ANN models were developed to recognize the different physiological signals and corrupted signals. The ANNs differed in terms of the data modeled and the topology. They are described as follows:

1. **ANN-10s:** the ANN modeled signals segmented in 10 seconds time segments and used data from all subjects for training and testing the model
2. **ANN-Ind-10s:** the ANN modeled signals segmented in 10 seconds time segments and used data from a particular individual (i.e. one subject) for training and testing the model
3. **ANN-10s-Corrupt:** the ANN modeled signals segmented in 10 seconds time segments and used data from all subjects and subjects who had corrupted signals for training and testing the model

Similarly, **ANN-5s**, **ANN-Ind-5s**, **ANN-5s-Corrupt, ANN-1s**, **ANN-Ind-1s**, **ANN-1s-Corrupt, ANN-0.5s**, **ANN-Ind-0.5s** and **ANN-0.5s-Corrupt** were developed for signals segmented in 5 seconds, 1 second and 0.5 seconds time segments. The ANNs that modeled corrupted signals in addition to the physiological signals had four output neurons, which was one more neuron than the ANNs that did not model the corrupted signals.

Each type of ANN defined above had three different topologies for the hidden layers:

1. One hidden layer with 7 neurons
2. Two hidden layers with 7 neurons in the first hidden layer and 5 neurons in the second hidden layer
3. Three hidden layers with 7 neurons in the first hidden layer, 5 neurons in the second hidden layer and 3 neurons in the third hidden layer

Additionally, ANN models were developed that took two types of physiological signals as input:

1. ANN-ECG-GSR: the ANN was modeled to recognize ECG and GSR signals
2. ANN-ECG-BP: the ANN was modeled to recognize ECG and BP signals
3. ANN-GSR-BP: the ANN was modeled to recognize GSR and BP signals

All the ANNs were implemented and tested using MATLAB. The MATLAB *adapt* function was used for training the ANN on an incremental basis. Each ANN was trained using the Levenberg-Marquardt algorithm for 1000 epochs or until the magnitude of the gradient for the mean squared error (MSE) was less than 10^{-5} during the validation phase.

4 Results and Discussion

The ANNs for signal recognition were trained and tested on the sensor signal data sets collected in [7] using 10-fold cross-validation process. The process was executed 20 times to obtain the mean and standard deviation of the recognition rates for the different types of signals.

Results of the individual-independent ANNs for physiological signal classification are shown in Fig. 2. ANN-1s produced the best recognition rates for all the signals and the results were statistically significant according to the Student's T-test ($p < 0.001$).

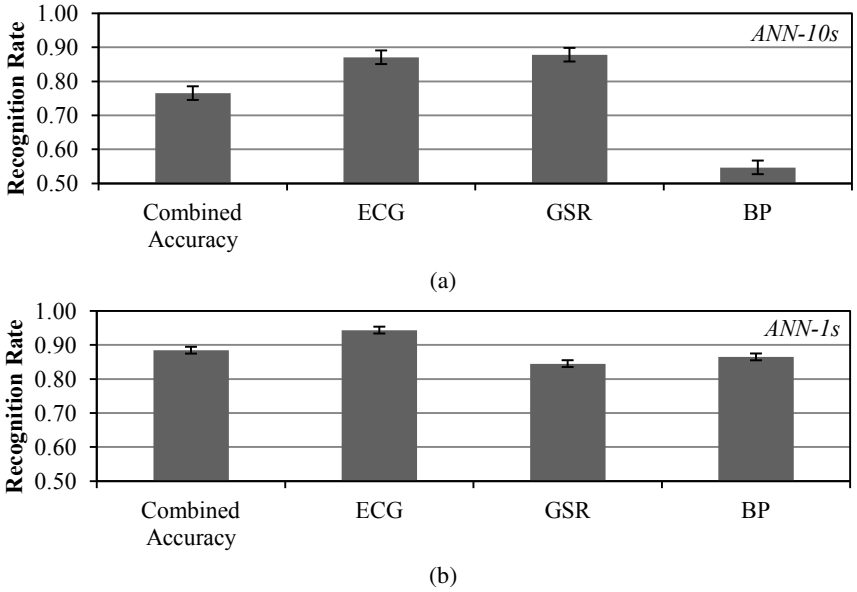
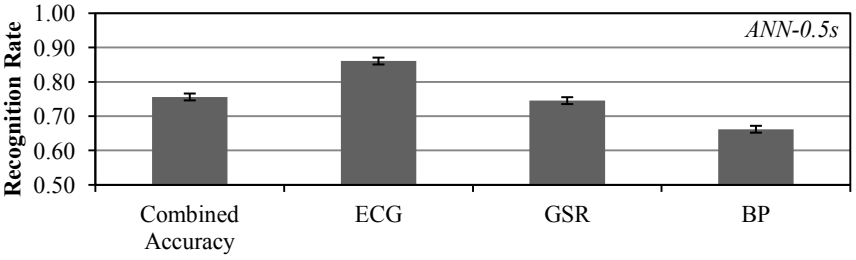


Fig. 2. Recognition rates for the physiological signals from individual-independent ANN classifiers based on 10-fold cross-validation (a) ANN-10s – its recognition rates were similar to ANN-5s (b) ANN-1s – it produced optimal results (c) ANN-0.5s



(c)

Fig. 2. (*Continued*)

The trend in the signal recognition rates for ANN-Ind-10s on each individual signal data set was statistically similar ($p < 0.05$) to the trend in the signal recognition rates for ANN-10s in that the GSR, ECG and BP signals had the highest, second highest and the lowest recognition rates respectively. The recognition rates for ANN-Ind-10s are provided in Fig. 3. Trends in the recognition rates for ANN-Ind-5s, ANN-Ind-1s and ANN-Ind-0.5s were similar to ANN-5s, ANN-1s and ANN-0.5s in the same way as well.

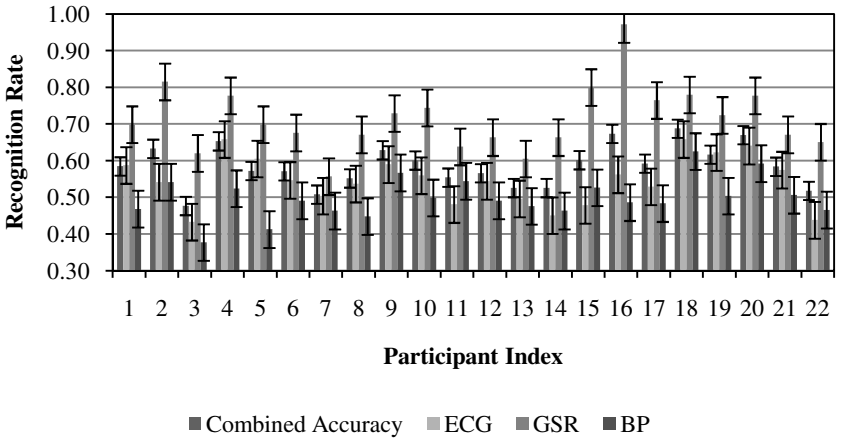


Fig. 3. Recognition rates for the physiological signals for individuals from ANN classifiers based on 10-fold cross-validation for ANN-Ind-10s

The recognition rates of the ANNs modeled on only two types of signals using the data provided to ANN-10s are provided in Table 1. The results show that ANN-ECG-BP produced the lowest classification rates compared to ANN-ECG-GSR and ANN-GSR-BP. The accuracy for ANN-ECG-BP was at least 0.27 lower than the other two ANNs. The ANN could not distinguish the ECG and BP signals as strongly as GSR

and the other types of signals. From the results, GSR signals were less similar to the other two types of signal so this explains why the GSR recognition rates were the highest for ANN-10s and with similar reasoning, it explains the trend in the recognition rates for the other types of signals. Further, the data provided to ANN-5s, ANN-1s and ANN-0.5s were provided to ANNs that modeled two types of signals to explain their trends in a similar fashion.

Table 1. Signal recognition rates produced from ANN models classifying two types of signals

ANN	Accuracy	ECG	GSR	BP
ANN-ECG-GSR	0.99	1.00	0.99	-
ANN-ECG-BP	0.68	0.73	-	0.62
ANN-GSR-BP	0.95	-	0.96	0.95

The recognition rates for ANN-10s-Corrupt, ANN-5s-Corrupt, ANN-1s-Corrupt and ANN-0.5s-Corrupt are shown in Fig. 4. Results show that the recognition rate for corrupted signals was the highest for ANN-10s-Corrupt compared to the other ANNs that recognized corrupted signals. Nevertheless, the ANN-1s-Corrupt produced the highest combined classification accuracy and the highest recognition rates for the other signals i.e. physiological signals just as ANN-1s did.

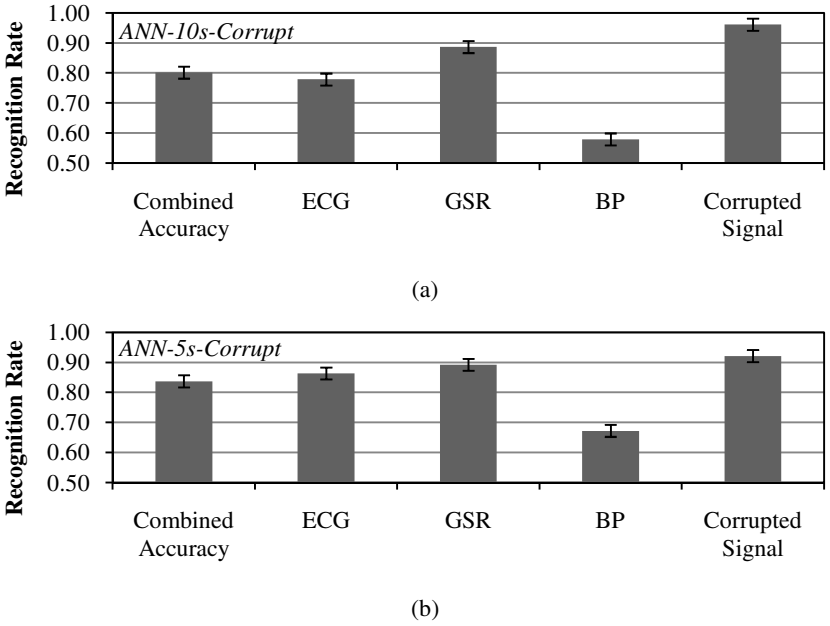
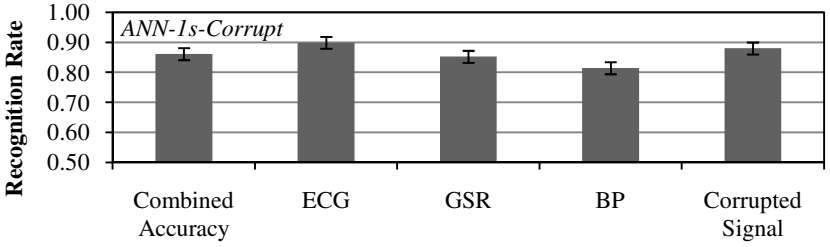
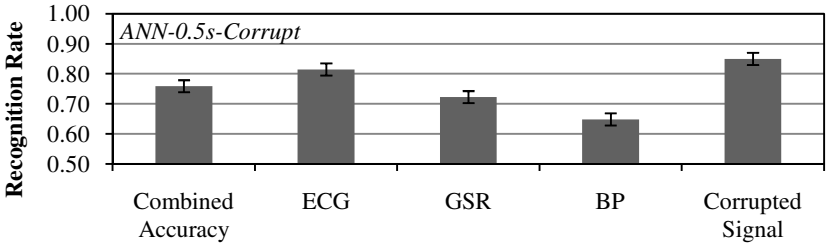


Fig. 4. Recognition rates for the physiological signals and corrupted signals from individual-independent ANN classifiers based on 10-fold cross-validation (a) ANN-10s-Corrupt (b) ANN-5s-Corrupt (c) ANN-1s-Corrupt (d) ANN-0.5s-Corrupt



(c)



(d)

Fig. 4. (*Continued*)

The results in Fig. 2 and Fig. 4 show that the best signal classification rates are achieved when signals segmented into one second time lengths are modeled. Signals that spanned 0.5 seconds did not have sufficient data in input tuples for ANNs to recognize patterns that distinguished one type of signal from the others as well as signals that spanned one second. ANNs that modeled signals which spanned more than one second learnt less general and poorer relationships between data in the signals for the time lengths and the signal class type.

Further, the different topologies of the hidden layers of the ANNs did not show a statistical difference between the classification results according to the Student's T-test ($p > 0.1$). Future work could investigate optimizing the topology of the ANNs including investigating recurrent ANNs and time-delay ANNs for signal classification.

5 Conclusion and Future Work

Different physiological signals were modeled and classified by individual-independent ANNs and ANNs for a particular individual. Signals spanning various time lengths were modeled. Results showed that the highest accuracy values for physiological signals without corrupted signal recognition were produced by the ANNs that modeled signals with a span of one second. However, corrupted signal recognition rates were the highest for ANNs that modeled signals spanning 10 seconds.

Future work can investigate developing an ANN that classifies signals using signals of different time lengths and produce classification rates that are highest for both physiological signals and corrupted signals. Alternatively, it may be beneficial to develop a system that uses a sampling frequency recognizing corruption which is different to the best frequency for recognizing physiological signals. The latter would be better for cutting through the noise which is in some ways the converse of recognizing corrupted signals. Further, the proposed classification system can be extended to model and recognize other types of physiological signals and applied to automatic online signal classification.

References

[1] Jacobson, M.: Analysis and classification of physiological signals using wavelet transforms. In: International Conf. on Electronics, Circuits and Systems, pp. 906–909 (2003)
[2] Killgore, W.D., et al.: Insomnia-related complaints correlate with functional connectivity between sensory–motor regions. NeuroReport 24, 233–240 (2013)
[3] Sharma, N., Gedeon, T.: Objective measures, sensors and computational techniques for stress recognition and classification: A survey. Computer Methods and Programs in Biomedicine 108, 1287–1301 (2012)
[4] Wagner, J., Kim, J., André, E.: From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification. In: Int. Conf. on Multimedia and Expo, pp. 940–943 (2005)
[5] Gouizi, K., Bereksi Reguig, F., Maaoui, C.: Emotion recognition from physiological signals. Journal of Medical Engineering & Technology 35, 300–307 (2011)
[6] Sweeney, K.T., et al.: Intelligent artifact classification for ambulatory physiological signals. In: Int. Conf. of the IEEE Engineering in Medicine and Biology Society, pp. 6349–6352 (2010)
[7] Sharma, N., Gedeon, T.: Modeling Stress Recognition in Typical Virtual Environments. In: Int. Conf. on Pervasive Computing Technologies for Healthcare (2013)
[8] Healey, J.A., Picard, R.W.: Detecting stress during real-world driving tasks using physiological sensors. IEEE Transactions on Intelligent Transportation Systems 6, 156–166 (2005)
[9] Bersak, D., et al.: Intelligent biofeedback using an immersive competitive environment. In: Designing Ubiquitous Computing Games Workshop, USA (2001)
[10] Shi, Y., et al.: Galvanic skin response (GSR) as an index of cognitive load. In: CHI 2007 Extended Abstracts on Human Factors in Computing Systems, USA, pp. 2651–2656 (2007)
[11] Lin, T., et al.: Do physiological data relate to traditional usability indexes? In: Australia Conference on Computer-Human Interaction, pp. 1–10 (2005)
[12] Miller, L.H., Shmavonian, B.M.: Replicability of two GSR indices as a function of stress and cognitive activity. Journal of Personality and Social Psychology, 753–756 (1965)
[13] McEwen, B.S., Sapolsky, R.M.: Stress and cognitive function. Journal of Current Opinion in Neurobiology 5, 205–216 (1995)