Iranian Journal of Medical Physics
Vol. 13, No. 3, September 2016, 163-173
Received: May 08, 2016; Accepted: June 16, 2016

IJMP

Original Article

Fusion Framework for Emotional Electrocardiogram and Galvanic Skin Response Recognition: Applying Wavelet Transform

Atefeh Goshvarpour[1], Ataollah Abbasi[1*], Ateke Goshvarpour[1], Sabalan Daneshvar[2]

Abstract

Introduction
To extract and combine information from different modalities, fusion techniques are commonly applied to promote system performance. In this study, we aimed to examine the effectiveness of fusion techniques in emotion recognition.
Materials and Methods
Electrocardiogram (ECG) and galvanic skin responses (GSR) of 11 healthy female students (mean age: 22.73±1.68 years) were collected while the subjects were listening to emotional music clips. For multi-resolution analysis of signals, wavelet transform (Coiflets 5 at level 14) was used. Moreover, a novel feature-level fusion method was employed, in which low-frequency sub-band coefficients of GSR signals and high-frequency sub-band coefficients of ECG signals were fused to reconstruct a new feature. To reduce the dimensionality of the feature vector, the absolute value of some statistical indices was calculated and considered as input of PNN classifier. To describe emotions, two-dimensional models (four quadrants of valence and arousal dimensions), valence-based emotional states, and emotional arousal were applied.
Results
The highest recognition rates were obtained from sigma=0.01. Mean classification rate of 100% was achieved through applying the proposed fusion methodology. However, the accuracy rates of 97.90% and 97.20% were attained for GSR and ECG signals, respectively.
Conclusion
Compared to the previously published articles in the field of emotion recognition using musical stimuli, promising results were obtained through application of the proposed methodology.

Keywords: Electrocardiogram, Emotion, Galvanic Skin Responses, Neural Networks, Wavelet Analyses

1. *Computational Neuroscience Laboratory, Department of Biomedical Engineering, Faculty of Electrical Engineering, Sahand University of Technology, Tabriz, Iran.*
2. *Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran.*

*Corresponding author: Tel: +98 4133459356; Fax: +98 4133444322; E-mail: ata.abbasi@sut.ac.ir

1. Introduction

Emotions play an important role in people's lives in terms of social communication, clinical application, and human-computer interaction. Therefore, evaluation of the physiological responses during emotional experiences is of major importance. Music stimuli have a surprising ability to evoke emotions. Music is proposed to lead to arousal and mood regulation, anxiety and stress reduction, and attention enhancement.

According to previous findings, the effects of emotions elicited from music resulted in physiological signals, which are reliable, simple, and non-invasive. Although, in some studies, electroencephalogram (EEG) is the proposed emotion recognition system is proposed, but there is not a general consensus regarding which EEG channels have the highest activity during emotion processing [1-4]. Kim and Andre proposed galvanic skin response (GSR) as a reliable physiological signal for evaluation of human arousal [5]. Several studies confirmed alteration in cardiac functioning while listening to music with different emotional contents [6-7]. Thus, GSR and electrocardiogram (ECG) signals were selected in this study.

There are plenty of methodologies for signal analysis. In emotion-recognition problems, various feature extraction approaches are reported, which are mainly focused on spectral and frequency procedures. Due to the non-stationary nature of the signals, which cannot be established in the conventional methods, time-frequency-based methods have been proposed. The robustness of the wavelet transform technique in the extraction of time-frequency resolution from non-stationary signals is proved compared to Fourier transform or short-time Fourier transform (STFT). Regardless of its efficiency for non-stationary signals, there has not been much effort in applying wavelet analysis of ECG and GSR signals for emotion recognition, and limited studies have performed wavelet analysis of EEG signals [8- 10].

Considering music as an emotional inspiration method, there are few investigations on emotion recognition using intelligent algorithms and classifiers. Kim and Andre explored the capability of the four-channel physiological signals including electromyogram (EMG), ECG, respiration changes (RSP), and skin conductivity (SC) for emotion recognition while participants were listening to music. Entropy, time, frequency and spectral measures, and geometric analysis were calculated to find the most appropriate features [5]. In their study, subject-dependent and subject-independent classifications were carried out.

Duan et al. assessed the performance of the nearest neighbors methods for support vector machine (SVM) and the least squares in the emotion recognition task through EEG signal. In their study, the capability of EEG power spectrum features was examined [11]. After smoothing the features, the dimension of features was reduced by means of minimal redundancy maximal relevance (MRMR) and principal component analysis (PCA). To optimize the classification of EEG signals while listening to music, Lin et al. exerted machine learning algorithms [12]. They demonstrated that some power spectrum features can be considered as sensitive measures for characterizing emotional brain dynamics.

To study the effects of music, numerous scholars have examined biological signals separately. Since emotional stimulation produces physiological arousal in different parts of the body, taking into account the interaction among these signals or their features can provide beneficial information for emotion recognition. Despite the importance of this effect, in very few investigations the fusion techniques have been applied. To distinguish emotions in four categories, Naji et al. examined forehead biosignals (FBS) [2]. After extracting low-frequency band features of data and utilizing a feature reduction method, the performance of three different classifiers was evaluated.

In another investigation, the researchers used the advantages of including another physiological signal (i.e., ECG) in their proposed methodology [13]. Therefore, fusion of ECG and FBS signals was employed in the emotion classification methodology.

Previously, to integrate the most desirable characteristics of different images, some researchers applied wavelet-based fusion methodologies [14]. Arivazhagan et al. proposed a modified wavelet-based multi-focus and multi-spectral image fusion technique. Their results indicated that the visual quality of images was enhanced compared with the conventional methods [15]. In another study, a fusion technique based on wavelet analysis and local binary patterns resulted in optimum face recognition in different databases [16]. Although in image fusion studies remarkable achievements were obtained by wavelet-based algorithms, there are few attempts to combine the information of different biosignals. In the current study, the benefit of GSR and ECG signal modality fusion is proposed by introducing novel wavelet analysis for the first time.

2. Materials and Methods

The emotion recognition methodology applied in the current study is exhibited in Figure 1. ECG and GSR signals of 11 healthy female students were recorded simultaneously while the subjects were listening to music clips with different emotional contexts (the process of data acquisition is discussed in details in the following subsection). Then, the normalized GSR and ECG signals were decomposed at level 14 applying Coiflets wavelet (coif5). Afterwards, the feature level fusion was performed on the extracted coefficients and the signal was reconstructed. Finally, the absolute values of the statistical features were fed to probabilistic neural network (PNN).

2.1. Data acquisition

To study the effects of different emotional responses elicited by music, GSR and ECG signals of 11 female university students (age range: 22.73±1.68 years) were collected. Informed consent was obtained from all the subjects before participating in the study.

To describe emotions, one of the most commonly used approaches is dimensional model in which few independent dimensions are considered on discrete or continues scales. In this approach, two main dimensions of arousal and valence are usually chosen. In the current protocol, the emotional states in all the four quadrants of valence and arousal dimensions were selected.

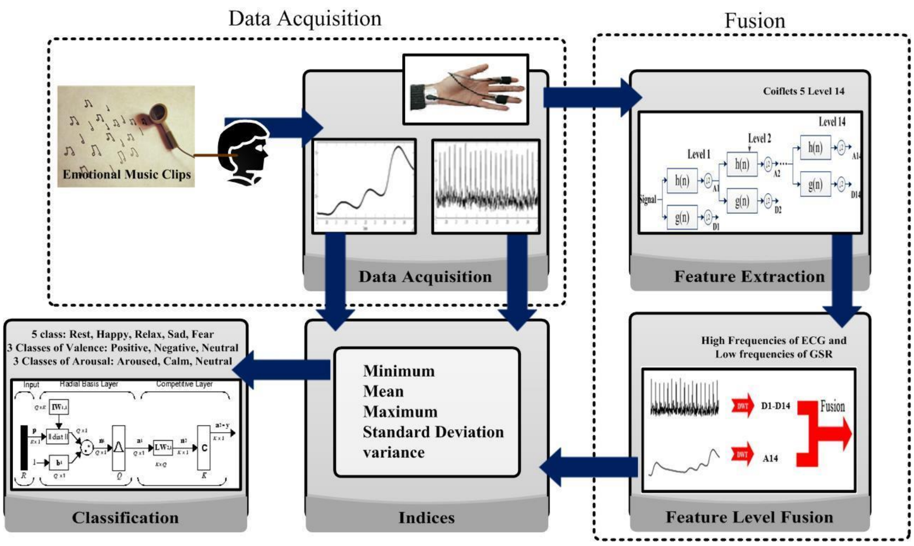

Figure 1. Proposed methodology. Normalization is performed on the fusion level

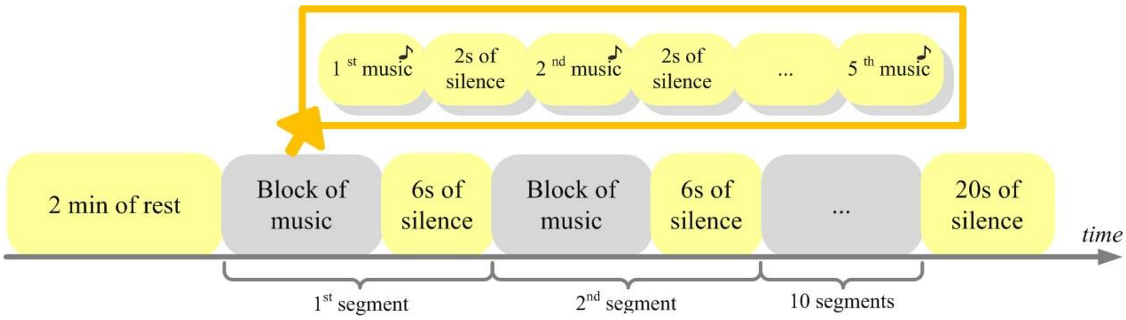

Figure 2. Experimental procedure

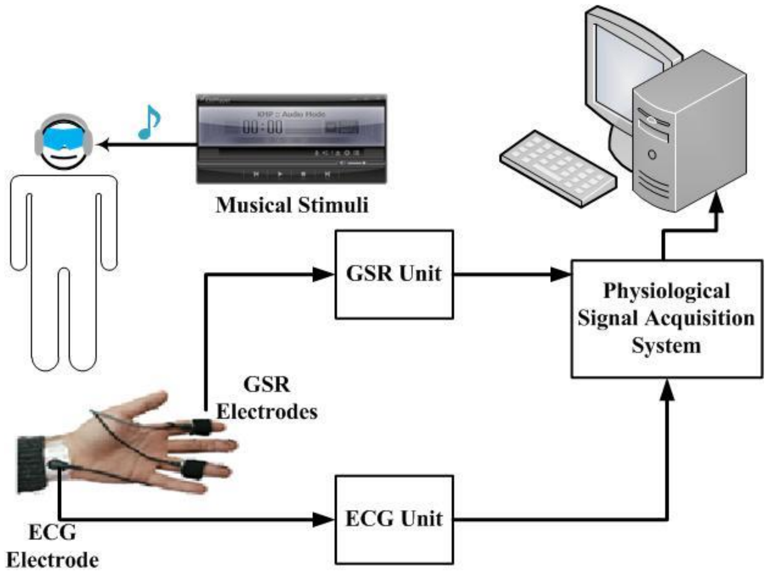

Figure 3. Data acquisition procedure

Therefore, peacefulness (low arousal and positive valence), happiness (high arousal and positive valence), sadness (low arousal and negative valence), and threat (high arousal and negative valence) were chosen for a space of valence and arousal for musical study. Finally, 56 short musical excerpts with fourteen stimuli per each emotional set were selected, which were validated by Vieillard et al. [17]. They consisted of a melody with accompaniment composed in piano timbre, and followed the rules of the Western tonal system [17].

The subjects listened to 12 blocks of music; each block consists of musical excerpts with the same emotional category. Music excerpts from the same emotional class (including 14 excerpts of each quadrant) were assigned randomly into three different blocks. The same protocol was used for all the participants. Figure 2 illustrates the inducement structure schematically. The participants were instructed to put on headphones, lie down in supine position, and try to remain still during data acquisition. The initial baseline measurement was carried out for two minutes with eyes closed followed by about 15 minutes of emotional music. All the tests were performed in controlled temperature and light and in the specific times of the day (9 am to 13 pm). The mean temperature of the room was about 23^{o}C. Musical pieces were presented via headphones at a comfortable volume using KM player software. Figure 3 exhibits the data acquisition procedure. Afterwards, the subjects were asked to fill out the questionnaire for evaluation of induced emotions.

The GSR and ECG signals of all the participants were collected in Computational Neuroscience Laboratory using a 16-channel PowerLab (manufactured by AD Instruments). To remove any artifacts of alternating current line noise, a digital notch filter was applied at 50 Hz; the sampling rate was 400 Hz. Figure 4 presents sample signals while listening to music clips arousing positive emotions.

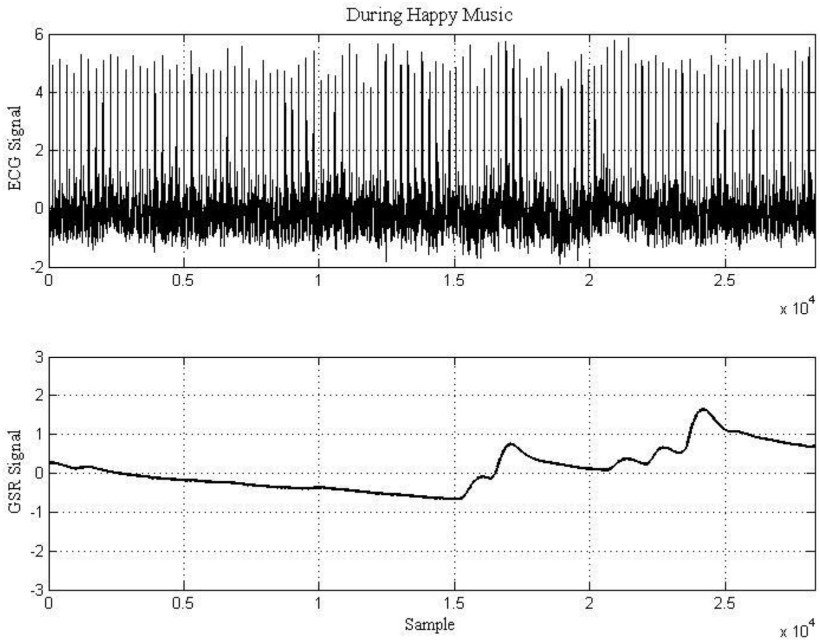

Figure 4. Example of GSR and ECG signals from one subject during happy music

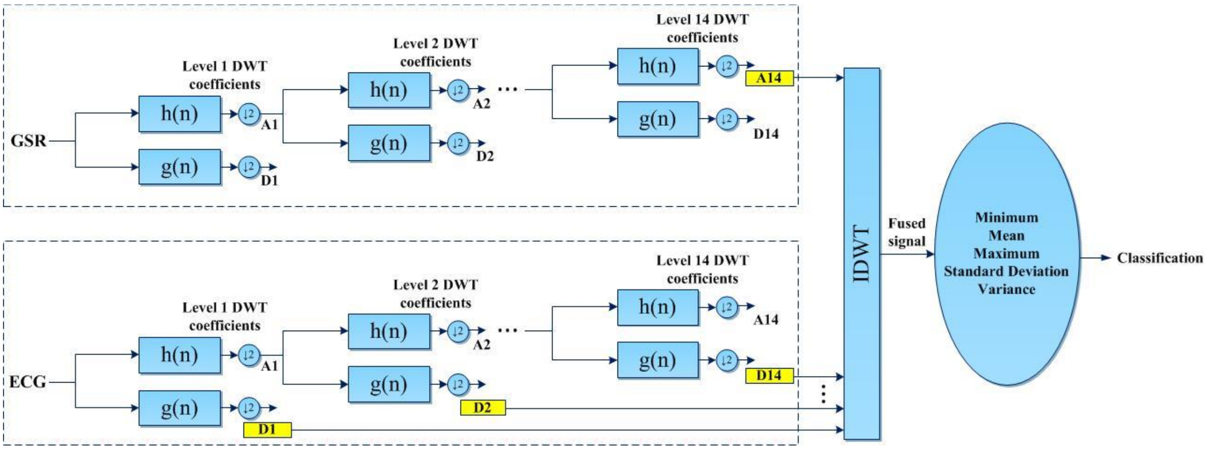

Figure 5. Novel feature level fusion framework

2.2. Feature Extraction Using Wavelet Transform

Wavelet transform deals with resolution in both frequency and time domain, which cannot be attained by Fourier transform. Discrete wavelet transform (DWT) is obtained from continuous wavelet transform (CWT) by sampling on the dyadic grid. Applying DWT, a signal can be decomposed into some scales, each demonstrating a particular roughness of the signal [18]. Each step comprises of digital filters followed by a factor of two down-sampler. The high-pass filter (HPF) is derived from the low-pass one (LPF) as:

$$g(L-1-n)=(-1)^n h(n) \tag{1}$$

where the length of the filter (in number of points) is reflected in *L*; g(n) is an HPF and h(n) is an LPF.

In detail, D1 and the approximation, A1 coefficients, and the outputs of g(n) and h(n) are down-sampled by a factor of two, respectively. The two filters, h(n) and g(n), are known as quadratic mirror filters. The first approximation, A1, further breaks down as in the previous stage. The DWT filtering processes along with sub-sampling are given by:

$$y_{low}(k)=\sum_n x(n)h(-n+2k) \tag{2}$$

$$y_{high}(k)=\sum_n x(n)g(-n+2k) \tag{3}$$

GSR and ECG signals consist of diverse structures on different time scales; applying wavelet analysis, one can distinguish these structures. Daubechies, Coiflet, Haar, Symlet, and Meyer are some of the standard wavelets. It is crucial to select the suitable wavelet and the number of decomposition levels. In the current study, various types of wavelets were examined and the one with maximum efficiency was selected. Finally, wavelet decomposition was carried out at level 14 applying Coiflets wavelet (coif5). The key advantage of coif5 wavelet is the complete convergence of ECG signals.

2.3. Feature-Level Fusion

Signal fusion algorithm, proposed in the current study, was as follows: the input biosignals (ECG and GSR) were first subjected to 14 levels of DWT decomposition. To examine different frequency components of the signals, in the next stage, D1-D14 coefficients (high-frequency sub-bands) of ECG signals and A14 coefficients (low-frequency sub-bands) of GSR signals were chosen and the wavelet reconstruction process (consisting of up-sampling and filtering) was performed according to these values and a new feature was formed. In other words, the fused signal was achieved using inverse DWT on the fused wavelet coefficients. The selection of these coefficients was based on the nature of GSR and ECG signals.

Naturally, the GSR signal is less than 1 mV in amplitude with a frequency band of DC to 5 Hz (low frequencies). In contrast, ECG contains high-frequency changes (especially for QRS waves). Therefore, low-frequency sub-band of GSR (A14 coefficients) and high-frequency sub-bands of ECG (D1-D14 coefficients) signals were selected to include more information of both signals. Next, statistical indices (maximum, mean, minimum, standard deviation, and variance) of the fused signal were calculated and the absolute value of these indices was chosen as input of the classifiers. Figure 5 depicts the proposed feature-level fusion methodology.

Consequently, we aimed to identify whether a fusion of different wavelet coefficients extracted from different biosignals (ECG and GSR) is successful in emotion recognition. Precisely, the goal was to find out if the combination of GSR and ECG features performs more efficiently than a single signal.

2.4. Classification Using Probabilistic Neural Network

Applying an input into the probabilistic neural network, in the first layer, the distance between the input vector and the training input vectors is calculated, which results in a vector whose elements determine the closeness between the points of inputs and the training vector [19]. In the second layer, for each class of inputs, some measures are added to produce output vector. Finally, the maximum of the probabilities on the second layer is chosen by a transfer function called compete layer, and it results in one for that class and zero for the other classes [19]. The architecture for this system is demonstrated in Figure 6.

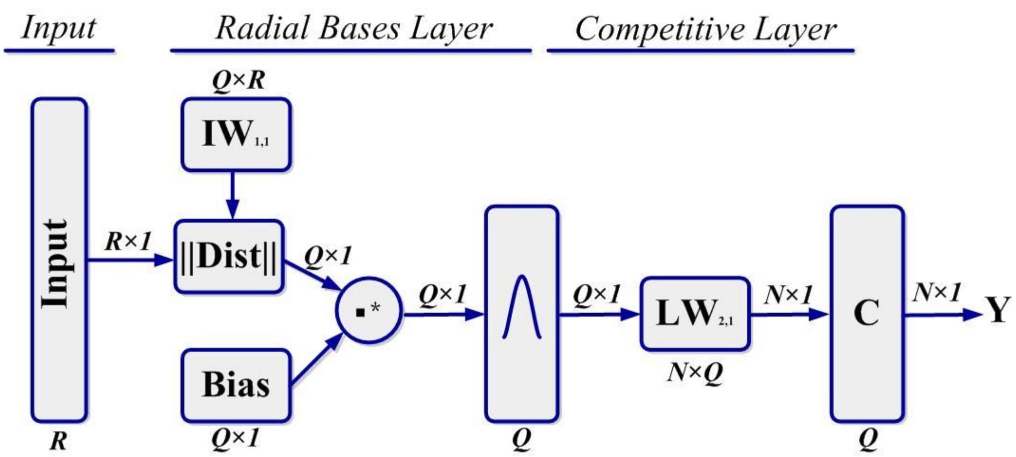

Figure 6. Architecture of the probabilistic neural network

In this network (Figure 6), there are Q input/target pairs (the number of neurons in the first layer) and each target vector contains N elements (the number of neurons in the second layer), one of which is one and the others are zero. The input weights of the first layer, $IW_{1,1}$, are adjusted to the transpose of the matrix fashioned from the Q training pairs [20]. Offering an input, ||Dist|| function produces a vector in which the closeness of the input vector to the training set vector is shown. The outputs of ||Dist|| box are multiplied by the bias and sent to transfer function. Output vector (O^1) adopts a value close to 1 when an input element is close to a training vector.
The weights of the second layer, $LW_{1,2}$, are adjusted to the target vector (T). In this case, each vector includes 1 only in the row related to that certain class of input, and 0's elsewhere. The multiplication TO^1 sums the elements of O^1 due to each of the N input classes. Finally, the compete layer, the second-layer transfer function, devoted a 1 corresponding to the largest component of C box inputs and 0's elsewhere. Therefore, PNN has classified the input into a particular one of N classes because that class is highly probable to be correct.
In the training process of PNN, a crucial step is the determination of the sigma value (the smoothing parameter), which can be concluded by trial and error. Similar to other networks, PNN has some advantages and disadvantages. These networks can be employed for classification problems, they have a straightforward design and do not depend on the training process. Providing enough training data, PNN is guaranteed to converge to a Bayesian classifier [21]. In addition, the generalization of this network is good. Since PNN uses more computation, its operation for classification or function approximation is slower in comparison with other kinds of networks.

3. Results

In the current study, GSR and ECG signals were collected from 11 healthy young university students. Wavelet coefficients were extracted from normalized GSR and ECG signals at level 14 applying coif5. The raw data was normalized based on standard scores (means and standard deviations). At the next stage, a novel fusion technique was applied on the extracted coefficients. Considering the nature of ECG and GSR, A14 coefficients of GSR signals and D1 to D14 coefficients of ECG signals were fused to reconstruct new features. Subsequently, for the purpose of emotion recognition, the absolute values of the extracted statistical features were fed to the PNN. Therefore, based on dimensional structure of the emotional space, accuracy of the classifiers is examined considering:

Table 1. Overall classification accuracies, output error, and elapsed time for probabilistic neural network with the proposed methodology.

		Sigma=0.2			Sigma=0.1			Sigma=0.05			Sigma=0.01		
	Signal	Accuracy (%)	Error	Elapsed time (s)	Accuracy (%)	Error	Elapsed time (s)	Accuracy (%)	Error	Elapsed time (s)	Accuracy (%)	Error	Elapsed time (s)
5C	*ECG*	31.47	0.13	0.84	38.46	0.10	0.84	53.15	0.04	0.84	97.20	0.01	0.83
	GSR	56.64	0.33	0.86	69.93	0.24	0.82	79.02	0.22	0.88	95.10	0.06	0.81
	Fusion	69.23	0.25	0.84	85.31	0.25	0.87	94.41	0.08	0.83	100	0	0.83
3V	*ECG*	48.95	0.10	0.85	58.74	0.01	0.88	67.83	0.04	0.86	97.20	0.01	0.84
	GSR	69.93	0.17	0.85	81.82	0.10	0.83	87.41	0.06	0.83	97.90	0.01	0.84
	Fusion	81.12	0.05	0.83	92.31	0.02	0.82	95.80	0.03	0.85	100	0	0.82
3A	*ECG*	51.05	0.01	0.85	58.04	0.11	0.85	68.53	0.15	0.85	96.50	0.02	0.82
	GSR	69.23	0.20	0.84	79.02	0.11	0.85	82.52	0.10	0.85	95.80	0.01	0.86
	Fusion	78.32	0.13	0.84	90.91	0.04	0.84	94.41	0.01	0.86	100	0	0.84

Note- 5C: 5 Classes of Emotions, 3V: 3 Classes of Valence, 3A: 3 Classes of Arousal.

1- Four categories of emotions (happy, sad, scary, and peaceful) and the rest as a different class; i.e., five classes are considered (5C).
2- Positive emotional arousal (happy and scary) is considered as one category and negative emotional arousal (peacefulness and sadness) is assumed to be a unique class. As a result, the number of classes is reduced to three, including positive arousal (stimulating), negative arousal (relaxing), and silence (3A).
3- Similarly, three classes for valence, including pleasant (peacefulness and happy), unpleasant (scary and sadness), and the rest, are chosen (3V).

In the present study, the smoothing parameter (sigma) was selected by trial and error. Considering the introduced dimensions, Table 1 shows the classification accuracies, error, and elapsed time for each category with different sigma values (0.2, 0.1, 0.05, and 0.01). To compare the results, each physiological signal (ECG and GSR) was used as an input of the PNN separately.

According to the results, optimum classification rates were achieved with sigma=0.01 in all the three classes (5C, 3V, and 3A). Considering different values for sigma parameter, the best recognition rates were achieved in valence dimension. The maximum accuracies of 97.90% and 97.20% were reached for GSR and ECG signals (sigma=0.01), respectively. However, applying the proposed fusion technique, these values were increased to 100% in all the conditions.

4. Discussion

Examination of the physiological signals, which can address the emotional-related variations, poses a great challenge. Among physiological measurements, the GSR is a non-invasive, simple, reproducible, and useful method for capturing autonomic response as a parameter of the sweat glands function [22]. On the other hand, ECG signals make information available for evaluation of the autonomous nervous system. Its efficiency, cost-effectiveness, and non-invasive nature encourage researchers to study and analyze this signal. Previously, the efficacy of GSR and ECG analyses in recognizing emotions was approved [5-7, 22,23]. Therefore, the current study aimed to offer a new methodology based on the information obtained from these signals in emotion recognition. Generally, we merged the information of both signals, by examining the advantages of the fusion methods. To this end, we investigated the possible effects of the fusion of the extracted indices from ECG and GSR signals in the emotion recognition scheme.

After collecting GSR and ECG signals, wavelet coefficients (coif5 at level 14) were extracted. Considering the nature of the signals, D1 to D14 coefficients of ECG and A14 coefficients of GSR signals were selected. Thereafter, wavelet reconstruction process (consisting of up-sampling and filtering) was applied. The new extracted features were fed into the neural network to discriminate between different emotional categories. Herein, three classifiers were designed: valence classifier, arousal classifier, and two-dimensional model (four quadrants of valence and arousal dimensions). Our results revealed that the highest recognition rates were accomplished with sigma=0.01 in all the three classes (5C, 3V, and 3A). Applying the proposed fusion methodology and PNN, mean classification rate of 100% was reached. Accordingly, the new feature vector is not only able to distinguish between the three emotional classes accurately, but also can successfully differentiate the five emotional categories.

Studying physiological signals to assess musical-induced emotions is still in its primary stages compared to other methods. On the other hand, evaluation of influences of different emotional categories (considering each quarter of emotional space or arousal and valence as a separate variable dimension) applying automatic classification approaches can be problematic. In a study examining ECG, EMG, SC, and RSP in three male subjects [5], the average accuracy rate of 70% was obtained in discriminating four musical emotions (in the two-dimensional emotional model).

Duan et al. proposed an algorithm to differentiate between different emotional states using EEG signals in five students, where the mean accuracy rate of 81.03% was attained [11]. To recognize four emotional states (joy, pleasure, sadness, and anger) across 26 subjects, Lin et al. [12] assessed the frequency band powers in 32-channel EEG signals. Applying SVM, the maximum classification rate of 82.29%±3.06% was obtained. More recently, the emotional responses to musical stimuli (engaging, soothing, boring, and annoying) in 3-channel FBS was examined in 25 healthy individuals [2]. After calculating the proposed features, based on the fuzzy rough model and sequential forward floating selection, the informative features were selected. The highest classification accuracy rate of 87.05% was obtained, which corresponds to the highest arousal classification rate of 93.66% and the best valence classification rate of 93.29%.

In another investigation, Naji et al. included ECG features in the FBS data, which yielded improvements in valence (93.63%), arousal (94.91%), and total classification rates (88.78%) [13]. Although some success has been achieved in former studies, but each suffers from some limitations, as well. In some studies, use of large amounts of information from multiple signals resulted in high dimensional features, and consequently, augmented computational complexity and reduced computing speed [5, 12]. In some of the previous studies, the proposed algorithms were used to separate a limited number of emotional categories or considered only one emotional dimension [8, 11]. In the present study, the advantages of fusion techniques for two easily collected signals were applied. Using wavelet-based technique, the proposed algorithm does not suffer from high computational complexity. Moreover, it successfully overcame the problem of emotion discrimination with different numbers of emotion categories.

In general, the results of the current study confirmed the effectiveness of wavelet analysis for extracting different information from physiological signals while listening to affective music. Compared with previously published articles on emotion recognition using music inducement, promising results were achieved. In addition, in the present investigation, simple signals and more straightforward feature extraction techniques were applied.

The main limitation of the current study is associated with the sample size. We evaluated the physiological signals of 11 college students while experiencing emotions. Since it has been established that women show stronger emotional responses than men [24], female subjects were included in the study. Future studies are recommended to apply the suggested emotion recognition scheme on larger sample sizes and both genders.

5. Conclusion

This study presents a wavelet-based fusion methodology involving GSR and ECG data for emotion recognition. With respect to the frequency components of the signals, high-frequency sub-bands of ECG signal (D1-D14 coefficients) and low-frequency sub-bands (A14 coefficients) of GSR signals were chosen to form a new feature. Combination of GSR and ECG features performed better than one signal separately. In this case, the recognition rates were improved and output error was diminished. Compared with the previous studies on this subject, promising results were obtained through employing the proposed fusion methodology.

Acknowledgements

We gratefully acknowledge Computational Neuroscience Laboratory, where the data were collected and all the subjects volunteered for the study.

References

1. Hoseingholizade S, Hashemi Golpaygani MR, Saburruh Monfared A. Studying emotion through nonlinear processing of EEG. In: Rahbar-Shamskar AR. The 4th International Conference of Cognitive Science. Tehran, Iran: Elsevier; 2012. 163–69. Doi: 10.1016/j.sbspro.2012.01.026.
2. Naji M, Firoozabadi P, Azadfallah P. Emotion classification during music listening from forehead biosignals. Signal, Image and Video Processing. 2015; 9:1365-75. Doi: 10.1007/s11760-013-0591-6.
3. Goshvarpour A, Abbasi A, Goshvarpour A. Dynamical Analysis of Emotional States from Electroencephalogram Signals. Biomed. Eng-App. B. C. 2016; 28: pp. 12. Doi: 10.4015/S1016237216500150.
4. Goshvarpour A, Abbasi A, Goshvarpour A. Combination of sLORETA and Nonlinear Coupling for Emotional EEG Source Localization. Nonlinear. Dynamics. Psychol. Life. Sci. 2016; 20: 353-68.
5. Kim J, Andre E. Emotion recognition based on physiological changes in music listening. IEEE. Trans. Pattern. Anal. Mach. Intell. 2008; 30: 2067–83. Doi: 10.1109/TPAMI.2008.26.
6. Vaish A, Kumari P. A Comparative Study on Machine Learning Algorithms in emotion State recognition using ECG. In: B. V. Babu, et al. Proceedings of the Second International Conference on Soft Computing for Problem Solving, Advances in Intelligent Systems and Computing. Jaipur, India: Springer; 2012. 1467-76. Doi: 10.1007/978-81-322-1602-5_147.
7. Chang-wei MA, Guang-yuan G. Feature extraction, feature selection and classification from electrocardiography to emotions. In: Qi L, Tian X. International Conference on Computational Intelligence and Natural Computing. Wuhan, China: IEEE; 2009. 190–93. Doi: 10.1109/CINC.2009.126.
8. Murugappan M, Rizon M, Nagarajan R, Yaacob S, Zunaidi I, Hazry D. EEG feature extraction for classifying emotions using FCM and FKM. Int. J. Comput. Commun. 2007; 1: 21-5.
9. Murugappan M, Nagarajan R, Yaacob S. Classification of human emotion from EEG using discrete wavelet transform. JBiSE. 2010; 3: 390-6. Doi: 10.4236/jbise.2010.34054.
10. Murugappan M, Nagarajan R, Yaacob S. Combining Spatial Filtering and Wavelet Transform for Classifying Human Emotions Using EEG Signals. J. Med. Biol. Eng. 2010; 31: 45-51. Doi: 10.5405/jmbe.710.
11. Duan R-N, Wang X-W, Lu B-L. EEG-Based Emotion Recognition in Listening Music by Using Support Vector Machine and Linear Dynamic System. In: Huang T, et al. 19th International Conference on Neural Information Processing. Doha, Qatar: Springer Berlin Heidelberg; 2012. 468–75. Doi: 10.1007/978-3-642-34478-7_57.
12. Lin Y-P, Wang C-H, Jung T-P, Wu T-L, Jeng S-K, Duann J-R, et al. EEG-based emotion recognition in music listening. IEEE. Trans. Biomed. Eng. 2010; 57: 1798-806. Doi: 10.1109/TBME.2010.2048568.
13. Naji M, Firoozabadi P, Azadfallah P. Classification of music-induced emotions based on information fusion of forehead biosignals and electrocardiogram. Cogn. Comput. 2013; 6: 241-52. Doi: 10.1007/s12559-013-9239-7.
14. Amolins K, Zhang Y, Dare P. Wavelet based image fusion techniques — An introduction, review and comparison. ISPRS. J. Photog. Rem. Sens. 2007; 62: 249-63. Doi: 10.1016/j.isprsjprs.2007.05.009.
15. Arivazhagan S, Ganesan L, Subash Kumar TG. A modified statistical approach for image fusion using wavelet transform. Signal. Image. Video. P. 2009; 3: 137-44. Doi: 10.1007/s11760-008-0065-4.
16. Zheng Goh Y, Beng Jin Teoh A, Kah Ong Goh M. Wavelet local binary patterns fusion as illuminated facial image preprocessing for face verification. Expert. Syst. Appl. 2011; 38: 3959–72. Doi: 10.1016/j.eswa.2010.09.057.
17. Vieillard S, Peretz I, Gosselin N, Khalfa S, Gagnon L, Bouchard B. Happy, sad, scary and peaceful musical excerpts for research on emotions. Cognitioin and Emotion, 2008; 22: 720-52. Doi: 10.1080/02699930701503567.
18. Daubechies I. The wavelet transform, time frequency localization and signal analysis. IEEE Trans. Inform. Theory 1990;36: 961-1005. Doi: 10.1109/18.57199.
19. Zhang X. Neural Network-Based classification of single phase distribution transformer fault data. A Senior Honors Thesis, Dept Elect Eng, Texas A&M Univ. 2006.
20. Demuth H, Beale M. Neural network toolbox for use with MATLAB: User's Guide (version 4). The MathWorks Inc; 2000.
21. Specht DF. Probabilistic neural networks. Neural Networks. 1990 Jan 1; 3(1):109-18.

22. Shahani B, Halperin J, Boulu P, Cohen J. Sympathetic skin response - A method of assessing unmyelinated axon dysfunction in peripheral neuropathies. J. Neurol. Neurosurg. Psychiatr. 1984; 47: 536–42. Doi: 10.1136/jnnp.47.5.536.
23. Salimpoor V, Benovoy M, Longo G, Cooperstock JR, Zatorre R. The rewarding aspects of music listening are related to degree of emotional arousal. Plos. One. 2009; 4: 1-14. Doi: 10.1371/journal.pone.0007487.
24. Baumgartner T, Esslen M, Jancke L. From emotion perception to emotion experience: Emotions evoked by pictures and classical music. Int. J. Psychophysiol. 2006; 60: 34-43. Doi:10.1016/j.ijpsycho.2005.04.007.