



Original Article

The effect of traditional Persian music on the cardiac functioning of young Iranian women



Behzad Abedi^b, Ataollah Abbasi^{a,*}, Atefeh Goshvarpour^c, Hamid Tayebi Khosroshai^d, Elnaz Javanshir^e

^a Computational Neuroscience Laboratory, Department of Biomedical Engineering, Faculty of Electrical Engineering, Sahand University of Technology, Tabriz, Iran

^b School of Advanced Medical Sciences, Tabriz University of Medical Sciences, Tabriz, Iran

^c Computational Neuroscience Laboratory, Department of Biomedical Engineering, Faculty of Electrical Engineering, Sahand University of Technology, Tabriz, Iran

^d Division of Internal Medicine, Imam Reza Hospital, Tabriz University of Medical Sciences, Tabriz, Iran

^e Department of Cardiology, Cardiovascular Research Center, Tabriz University of Medical Sciences, Tabriz, Iran

ARTICLE INFO

Article history:

Received 14 July 2016

Accepted 21 December 2016

Available online 10 January 2017

Keywords:

Electrocardiogram (ECG)

Discrete Wavelet Transform (DWT)

Music

SVM

ABSTRACT

In the past few decades, several studies have reported the physiological effects of listening to music. The physiological effects of different music types on different people are not similar. Therefore, in the present study, we have sought to examine the effects of traditional Persian music on the cardiac function in young women. Twenty-two healthy females participated in this study. ECG signals were recorded in two conditions: rest and music. For each of the 21 ECG signals (15 morphological and six wavelet based feature) features were extracted. SVM classifier was used for the classification of ECG signals during and before the music. The results showed that the mean of heart rate, the mean amplitude of R-wave, T-wave, and P-wave decreased in response to music. Time-frequency analysis revealed that the mean of the absolute values of the detail coefficients at higher scales increased during rest. The overall accuracy of 91.6% was achieved using polynomial kernel and RBF kernel. Using linear kernel, the best result (with the accuracy rate of 100%) was attained.

© 2016 Published by Elsevier B.V. on behalf of Cardiological Society of India. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

The ECG is a biometric signal, which reflects the electrical activity of the heart muscle. An analysis of the ECG signal provides useful information about the heart's performance. The heart's electrical activity during normal heartbeat is characterized by five basic waves P, Q, R, S, and T waves and sometimes U wave. The P wave and T wave represent atrial depolarization and ventricle repolarization, respectively. In addition, the QRS wave represents ventricular depolarization.¹ The intervals and amplitudes defined by ECG features provide useful clinical information.

It has been previously established that ECG signals can be affected by different factors such as age, cardiovascular diseases, and mental stress.² In addition, in the past few decades, several

studies in music, psychology, and medicine have reported the physiological effect of listening to music.^{3,4} Loomba et al. claimed that music could decrease systolic blood pressure, diastolic blood pressure, and heart rate, significantly.⁵ This may be attributed to brain and autonomic nervous system (ANS) activity, but the relationship between music features and ANS activity is not completely understood.^{6,7}

These effects have been examined in response to different kinds of music, such as sedative music and excitative music.² Since the 1918s, studies were started in which the quantitative differences of cardiac autonomic function during music and rest were extracted.⁸ However, the effect of music on cardiac function have varied from research to research. Rickard et al.⁹ studied the physiological responses of sedative music. They showed that heart rate was reduced by sedative music. In other studies by Davis et al.¹⁰ and Vanderark et al.¹¹ it has been shown that music made no changes to the heart rate. Therefore, it can be concluded that the physiological effect of different music types on different people

* Corresponding author.

E-mail address: ata.abbasi@gmail.com (A. Abbasi).

are not similar. These different effects can be related to method, findings, music types, and gender.¹²

Dousty et al.² investigated the relationship between music types and cardiovascular function. They focused on two types of music, namely, sedative and arousal music. They claimed that the heart responded differently when different kinds of music were played. Khazaei et al. represented that music can be used as a powerful method for reducing stress and anxiety in generalized anxiety disorder patients.¹³ Other physiological effects of music have been summarized in Table 1.

Most of the previous studies focused on statistical measures, such as mean and variances and tried to assess the physiological effects of music. It has been previously established that frequency domain measures of ECG signals can be significantly affected by music. One appropriate tool for studying of these differences is Discrete Fourier Transform (DFT) and extraction of features from ECG signal power spectrum. An important drawback in the Fourier analysis is that the technique does not provide any information regarding the exact location of frequency components in time.²⁰ Short Time Fourier (STF) analysis has been proposed for overcoming this limitation by windowing the area of interest. However, the main weakness of this technique is that its time frequency precision is not optimal.²¹ Among the different time-frequency transformations, Discrete Wavelet Transform (DWT) is used in the current study in order to investigate the physiological effect of listening to music. DWT is an effective tool for analysis of non-stationary signals like ECG.²¹ Furthermore, it has been established that applying DWT to ECG signals can be helpful in detecting clinically significant features that may be missed by other analysis techniques.^{22–24} In our previous study,¹² we studied the effect of gender differences on electrical function of the heart in response to traditional Persian music. It has been shown that the mean heart rate signals in men increased during music; however, it decreased in the same protocol in the women's group. We also reported that the heart rate signals of women's group represented maximum power spectrum, twice more than that of the men's group. In addition, it seemed the physiological effect of Persian music was higher in the women's group than the men's group. Therefore, the present study focused on other techniques for studying the ECGs of the female group during music and rest. The present work is organized as follows: In the second part, the ECG dataset, which was collected from a group of young female students before and during listening music, are briefly described. In the third part, the wavelet co-efficient based features and morphological features were developed. Next, the results and

comparison between participants' heart rate during music and rest is presented. Finally, discussion and conclusion are presented. A block diagram of the proposed method is shown in Fig. 1.

2. Methods

2.1. Data collection

Twenty two healthy females participated in this study. The age range of the subjects was 20–24 years. All the participants were students of Sahand University of Technology and had no previous history of neurological diseases. ECG signals were recorded under two different conditions from each subject. Initially, the participants were asked to lie in a supine position comfortably and close their eyes for five minutes. Then, five minutes of traditional Persian music was played for participants at a comfortable volume. The ECGs – lead II – were recorded by 16-channel PowerLab (ADInstruments, UK) at a sampling rate of 400 Hz. A digital notch filter was used to remove the 50 Hz Power-Line Interference from the ECG signal. The signals were recorded in MAT, which is a common MATLAB file type.

2.2. Discrete Wavelet Transform

DWT^{25,26} is a powerful technique, which can be used to analyse different kinds of biomedical signals like ECG. DWT uses a low pass filter (LPF) and a high pass filter (HPF) to decompose the signal into a number of scales related to frequency components and analyses each scale with a certain resolution. The output coefficients of the LPF and HPF are called approximations and details, respectively. Amplitude of the wavelet coefficients represents the energy density of the signal at particular frequencies and moments. The original signal can be reconstructed by using complementary filters. DWT can be defined as follows:

$$\phi_{m,n} = \frac{1}{\sqrt{a^m}} \phi\left(\frac{t - nba^m}{a^m}\right) dt \quad (1)$$

where ϕ represents the mother wavelet, which is dilated by integers m and translated by integers n . DWT can be used to provide salient information about the local features of the ECG signals because it has good localization abilities in both time and frequency domain. Choosing a wavelet family, which closely matches the signal to be processed, plays an important role in wavelet applications.²⁷ As shown in Fig. 2, the Daubechies wavelet family is similar in shape to the QRS complex.²⁸

Table 1
Physiologic effects of music.

Study	Number of participants	Music type	Result(s)
Salimpoor et al. ¹⁴	26	1.Self-selected intensely pleasurable music 2.Neutral music	There is a strong positive correlation between ratings of pleasure and emotional arousal.
Orini et al. ⁶	75	1.Pleasant music 2.Sequences of Shepard tones 3.Unpleasant sounds	Pleasant music increased the heart and respiratory rates.
Nakahara et al. ¹⁵	13	1.Performance of Music 2.Perception of Music	Musical performance would lead to a greater effect of emotion-related modulation in cardiac autonomic nerve activity than musical perception.
Kemper et al. ¹⁶	81	Designed music	The HRV parasympathetic parameter was significantly lower with music than rest.
Ugglä et al. ¹⁷	24		Music significantly lowered the HRV and stress levels of children undergoing haematopoietic stem cell transplants.
Archana and Mukilan ¹⁸	30	Preferential music	Listening to pleasant music could be an effective method of relaxation, and it can shift the autonomic balance towards the parasympathetic activity.
Oh et al. ¹⁹	60		Listening to pleasant music could be an effective nursing intervention for alleviating anxiety during non-stress test.

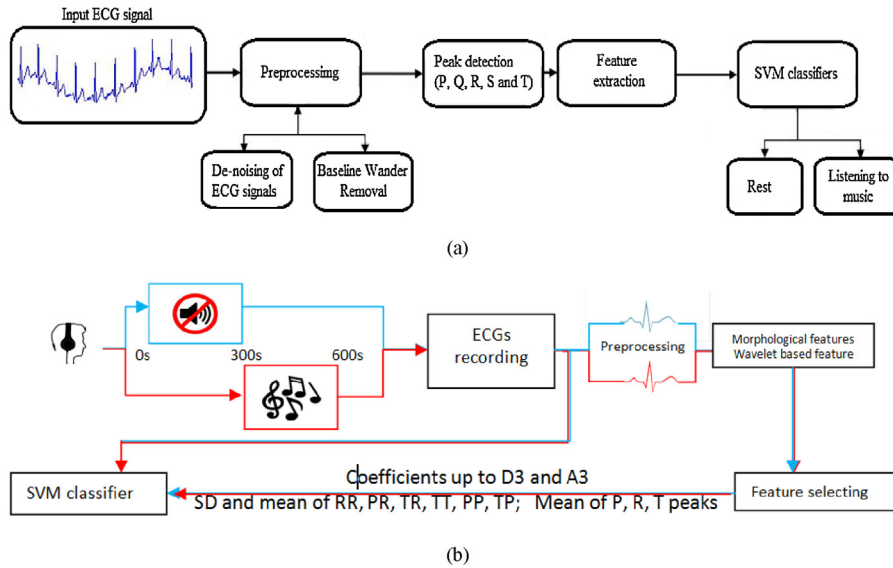


Fig. 1. Block diagram of the proposed method.

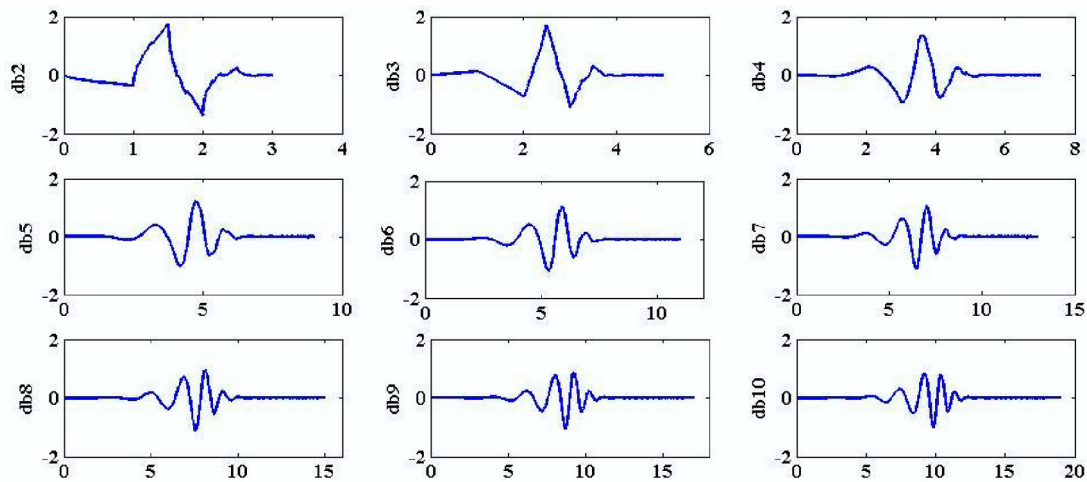


Fig. 2. Daubechies wavelet family.

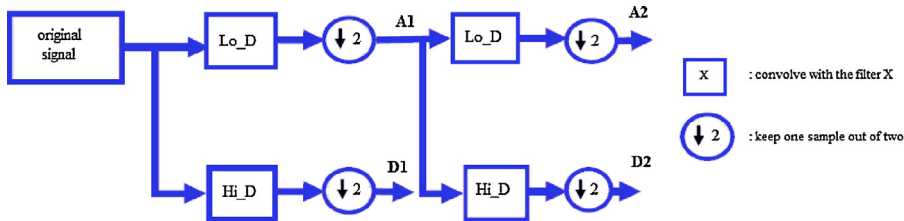


Fig. 3. The algorithm of the DWT.

In the present study, Daubechies wavelet of order six (db6) with eight levels of wavelet decomposition was used to filter and analyse noisy ECG signals. Fig. 3 represents the basic multi-resolution decomposition steps for signal 'Original signal'.

2.3. Preprocessing

2.3.1. De-noising

The ECG is often contaminated by noises of different kinds. These noises are usually generated by recording instruments or

movements of subjects. In the current study, db6 is employed for removing various kinds of noises from ECG signals.²⁹ The proposed de-noising algorithm can be summarized as follows:

- The ECG signals decomposed at level eight using db6.
- Soft thresholding technique employed for quantization of detail wavelet coefficients on each level.
- ECG signal reconstructed by using approximation wavelet coefficients of last level N and the de-noised detail wavelet coefficients of all levels.

2.3.2. Baseline shifting removing

Baseline wandering is one of the noise artefacts that strongly affect ECG signal analysis.³⁰ Electrode and respiration impedance changes due to perspiration play an important role in generating baseline wander. By removing baseline wander, we can minimize the changes in beat morphology. Normally, the frequency content of the baseline wander is concentrated in very low frequencies. In the present study, median filters were applied to minimize the influence of baseline drift. The proposed process consists of two steps. In the first step, the original ECG signal is smoothed with a moving average filter of length 150. In the second step, the filtered signal subtracted from the 'Signal+ Baseline drift noise' signal and a signal with baseline drift elimination is obtained.

2.4. Peak detection

Accurate detection of ECG peaks plays an important role in ECG signal analysis. This is because a lot of clinical information can be derived from the amplitudes and intervals defined by P, Q, R, S, T peaks.³¹ In the present study, the DWT method was used to detect the position of the occurrence of the P-QRS-T waves. The proposed algorithm consists of four important steps. In the first step, the ECG signals decomposed at level 8 using db6. In the second step, details between levels 3 and 5 were kept and all the rest removed. The attained signal samples were then squared to stress the signal. Then, R wave was detected using automatic thresholding techniques. In the second step, all the details down to level 5 were removed. Then the ECG signal was reconstructed. The reconstructed ECG signal and minimum signal strength about each R peak within 0.1 s registered as Q and S waves.²⁵ In the third step, details between levels 1 and 5 were kept and all the rest removed and two zero crossing points of the signal were determined. Finally, for the detection of the P and T waves, only details between levels 4 and 8 were kept and all the rest were removed, Fig. 4.

2.5. Feature extraction

For classifying ECG signals during rest and music, it was necessary to extract appropriate features. There are several ways to

extract the feature of ECG signal.³² The present study focused on two types of features namely 'Wavelet co-efficient based features' and 'Morphological features of ECG signal'.³² Applying approximation and detail coefficients to the classifier directly has negative effects on SVM operation. Therefore, statistics of wavelet coefficients are used instead of high dimensional wavelet coefficients. The following statistical features were selected to exhibit the general behaviour of time-frequency energy distribution of the ECG waveforms:

- An average of the absolute values of approximation wavelet coefficients at any sub-band.
- Standard Deviation (SD) of approximation wavelet coefficients at each level.
- Average of the absolute values of detail wavelet coefficients at any sub-band.
- SD of detail wavelet coefficients at each level.

Besides the wavelet co-efficient based features, morphological features were also extracted from ECG signals. The selected morphological features were mean and SD values of RR interval, TT interval, PP interval, PR interval, TR interval, PT interval, and maximum and mean values of P, Q, R, S, T peaks.

2.6. Support vector machine

SVMs are supervised machine learning methods suggested by Cortes and Vapnik in 1995.³³ SVM aims to find the best hyperplane that separates all data points of one class from those of the other classes. This is equivalent to maximizing the margin between the two classes. Consider a linearly separable sample set:

$$T = \{(x_1, y_1), \dots, (x_i, y_i)\} \quad (2)$$

$$i = 1, 2, 3, \dots, i; x_i \in R^n, y_i \in \{\pm 1\}$$

where x_i is called an input and y_i represents the class labels. The equation of a separating line can be written as follows:

$$\langle w, x \rangle + b = 0 \quad (3)$$

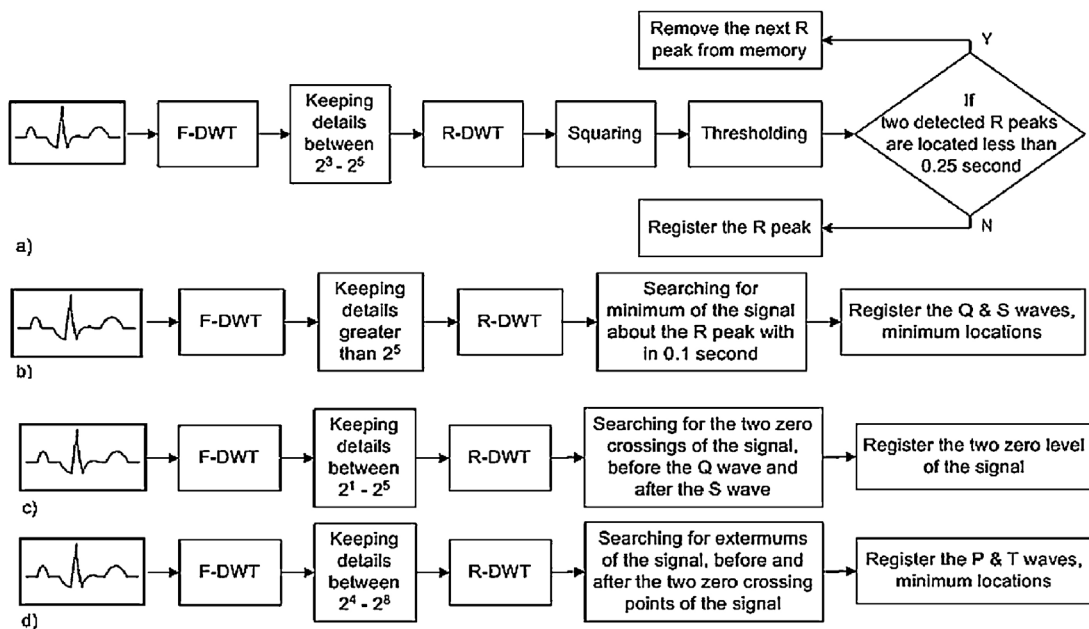


Fig. 4. Detection procedure. a) R wave detection b) Q & S Waves detection. c) Zero level detection. d) P & T detection.²⁹

where $w \in R^d$, $\langle w, x \rangle$ represents the inner product of w and x , and b is bias. Therefore, the problem of best separating line is given as follows:

$$(\langle w, x \rangle + b) \geq 1 \tag{4}$$

Then the distance from closet sample to separating line is $\frac{w^t x_i + b}{\|w\|} = \frac{1}{\|w\|}$. Thus the margin is $\frac{2}{\|w\|}$. Maximizing the margin is equivalent to minimizing $\langle w, w \rangle / 2$, and then the problem of finding the best separating line is converted into the following optimization problem:

$$\begin{aligned} \min_{w,b} & \frac{1}{2} \|w\|^2 \\ \text{s.t.} & z_i(w^t x_i + w_0) \geq 1 \quad \forall i \end{aligned} \tag{5}$$

The sample set can be divided into two classes by solving the above equation. While data is most likely to be not entirely separable, the slack variable and penalty parameter introduced in the formula weaken the constraint to a certain degree. Thus, the basic problem of SVM is transformed into:

$$\min \psi(w, \xi) = \frac{1}{2} \|w\|^2 + C \left(\sum_{i=1}^n \xi_i \right) \tag{6}$$

subject to $[y_i(w \cdot x_i) + b] - 1 + \xi_i \geq 0, i = 1, \dots, n$

where $(x_i, y_i), i = 1, \dots, n, x_i \in R^d, y_i \in \{-1, +1\}$

C is a constant minimizing the errors by maximizing the margin. Using the Lagrangian method to solve the above equation, it is transformed to its dual problem:

$$\min_{y,b} \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m y_i y_j \alpha_i \alpha_j (x_i \cdot x_j) - \sum_{i=1}^m \alpha_i \tag{7}$$

constrained to $\sum_{i=1}^m y_i \alpha_i = 0, 0 \leq \alpha_i \leq C, i = 1, \dots, m$

Then the classifier is,

$$f(x) = \text{sgn} \left(\sum_{i=1}^m \alpha_i y_i (x_i \cdot x) + b^* \right) \tag{8}$$

where $b^* = y_i - \sum_{i=1}^m y_i \alpha_i (x_i \cdot x_j)$

α_i represents Lagrange multipliers. In the case of nonlinear classification, by replacing the inner product term $(x_i \cdot x)$ in (8) with a proper kernel $K(x_i, x_j)$; the input data is projected onto a higher

dimensional space.³³ Then a separating hyperplane is constructed to separate the data points of one class from those of the other classes.

3. Results

ECG signals recorded from 22 young female participants were analysed utilising the methodology described in Section 2. Following the pre-processing stage, ECG signals were decomposed into wavelet coefficients. Fig. 5 shows the mean of the absolute values of the detail and approximation wavelet coefficients of the ECG signal during rest and music.

Apart from wavelet co-efficient based features, the morphological feature of ECG signal is also extracted. Fig. 6 summarizes the SD and mean values of morphological features.

Good understanding of amplitudes defined by ECG peaks can provide useful clinical information. Fig. 7 shows the maximum, minimum, and mean values of R-wave amplitude, T-wave amplitude, and P-wave amplitude respectively.

Using all of the extracted features is not suitable for classification of ECG signals during rest and music. In the present work, the paired t -test was used for analysing the significance in extracted features during rest and music using SPSS software. P-value less than 0.05 was considered significant. The selected features are given in Table 2.

The extracted features were stored in a single feature vector. These feature vectors were used as input for the SVM classifiers. The linear kernel, polynomial kernel, and RBF kernel are used in SVMs. Seventy percent of feature vectors were selected randomly as training data set and the remaining vectors were used for validation of the classifiers. This process is repeated 10 times. The performance of the proposed algorithm is measured in terms of accuracy. We have achieved an overall accuracy of 91.6% using polynomial kernel and RBF kernel whereas 100% accuracy was achieved using linear kernel. These results confirm the physiological effects of music on cardiovascular function. The performances of different α kernels have been shown in Table 3.

4. Discussion

The ECG is a graphical representation of the heart electrical activity which is widely used for diagnosing cardiovascular diseases. ECG signal can be affected by physiological state changes and emotional factors such as listening to music. The present study aimed to examine the effects of music on cardiac function in young women. Therefore, 10 min of ECG is recorded from each of the normal participants during rest and music.

Direct visual monitoring of ECGs by human personnel is a time consuming process and usually involves a loss of information. To handle this problem, computer-based systems have been developed for detecting ECG characteristic points. Due to time-varying morphology of the QRS wave, and the presence of severe baseline drift and other high frequency noises in the ECG signal, an accurate

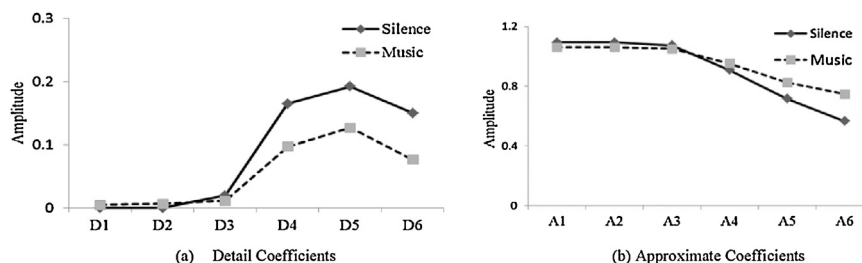


Fig. 5. Mean of the absolute values of the detail and approximation wavelet coefficients.

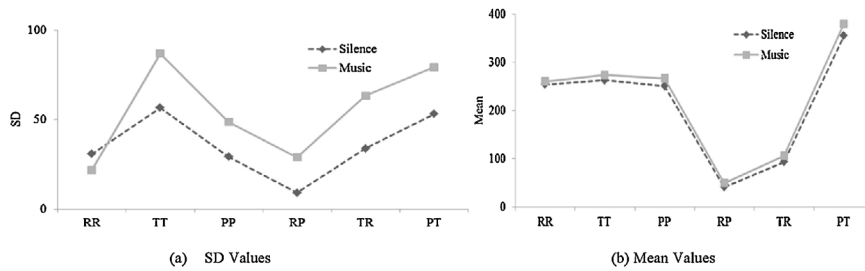


Fig. 6. SD and mean values of morphological features.

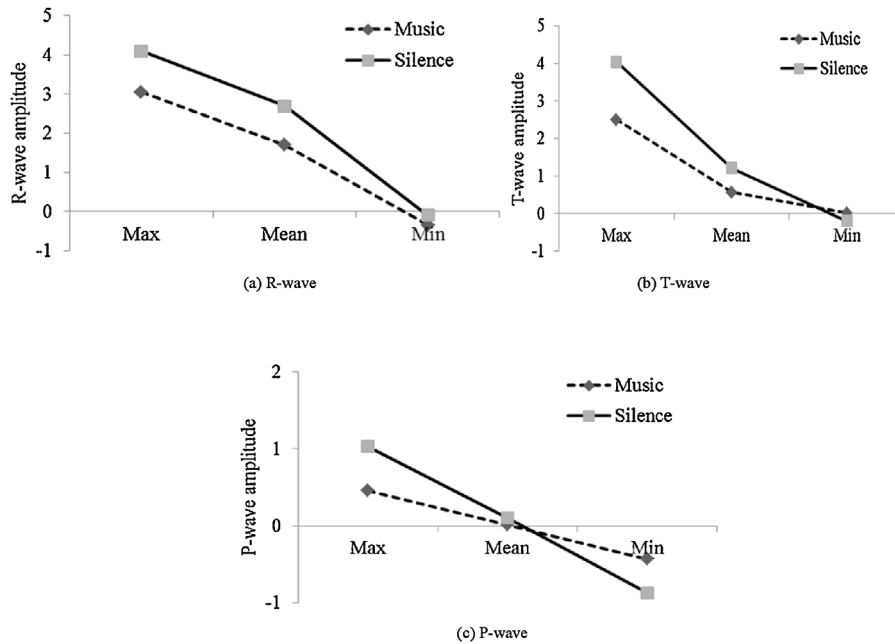


Fig. 7. The maximum, minimum and mean values of P, R, T peaks.

detection of P wave, QRS complex, and R wave, in an ECG signal is a challenging issue.³⁴ As ECG signal has semi-periodic patterns, an appropriate tool for detecting P-Q-R-S-T waves is DWT and extraction of wavelet co-efficient based features.³¹ As described in Section 2, in the present study the Daubechies wavelet of order 6 were used to distinguish ECG waves from noises and baseline drift.

Feature extraction is the most important step in pattern recognition. There are several ways to extract the feature of ECG signal.³² In this work, there are two types of extracted features of ECG waveforms. The present study focused on two types of features named ‘Wavelet co-efficient based features’ and ‘Morphological features of ECG signal’.³² Morphological characteristics of ECGs are well-known features that are widely used in making clinical decisions and in medical research. Therefore, these features are used in the present study. In addition, the ability to represent data in compressed parameters form (features) is one of the main application of DWT.³²

In order to overcome SVM over fitting, two important steps need to be taken: (1) K-fold cross validation; and (2) parameter optimization. Variations on cross-validation include leave-k-out cross-validation and k-fold cross-validation. Data sample is small in our study; therefore, leave-k-out cross-validation cannot be used in the present study. Instead, we used k-fold cross-validation. Seventy percent of feature vectors were selected randomly as training data set and the remaining vectors were used for validation of the classifiers. This process was repeated 10 times and an average of the resulting measurements were taken.^{35–37} In addition, it has been suggested that, to avoid the risk of SVM over fitting due to the small training sets, parameter optimization can be omitted.³⁸ Therefore, we omitted parameter optimization. In addition, similar to previous studies,³⁸ we used C = 1000; $\gamma = 0.1$ for all experiments and before the classification step, the features are linearly normalized to [0,1].

Table 2 Selected features for classification ECG signals during rest and music.

Feature type	Selected attributes
Wavelet based features	Details coefficients up to D3. (3 features) (p < 0.05, confidence interval: 95%) Approximates coefficients up to A3. (3 features) (p < 0.05, confidence interval: 95%)
Morphological features	SD values of the RR, TT, PP, RP, TR AND PT intervals. (6 features) (p < 0.05, confidence interval: 95%) Mean values of the RR, TT, PP, RP, TR AND PT intervals. (6 features) (p < 0.05, confidence interval: 95%) Mean values of P, R, T peaks. (3 features) (p < 0.05, confidence interval: 95%)

Table 3
Performance of different kernels.

Kernel	TP	FN	TN	FP	Accuracy(%)	Sensitivity(%)	Specificity(%)	AUC
RBF	20	2	21	1	93.18	90.90	95.45	0.9318
Linear	21	1	22	0	97.72	95.45	100	0.9773
MLP	12	10	12	10	54.54	54.54	54.54	0.5455
Polynomial	21	1	21	1	95.45	95.45	95.45	0.9545

As shown in Fig. 7, mean R-wave amplitude, mean T-wave amplitude, and mean P-wave amplitude decreased in response to music. These results are in the line with Dousty et al.² who found mean R-wave amplitude and T-wave amplitude reduced by sedative music.

The mean heart rate signals before listening to music is about 78.53, whereas this value is about 77.28 during the music. These results are in the line with Goshvarpour et al.¹² who found mean heart rate signals in the women's group decreased during music.

Apart from the morphological features, the wavelet coefficient based features are also extracted from ECG signals. The approximations are the low-frequency components of the signal. The results suggested that in both conditions (before and during the music) the energy spectrums are concentrated in low frequencies. In addition, the behaviours of detail and approximate coefficients at low scales are almost similar during rest and music. In contrast, the general appearance of detail and approximate coefficients at high scales are significantly different during rest and music ($p < 0.001$). As shown in Fig. 5, during rest the mean of the absolute values of the detail coefficients at higher scales show amplitude even more than two times that of music period.

After studying the wavelet co-efficient based features and morphological features, we tried to quantify the difference between women's ECG signals during and before music on the basis of obtained results. In the present study, both wavelet co-efficient based features and morphological features were utilized because some studies established their capacity in the classification of ECG signals. Therefore, for each of the ECG signals, 21 morphological and wavelet co-efficient based features have been selected accordingly to provide best result. These features have provided significant distinction between participants' ECG signals during and before music. It seems, this is the main reason for better results of linear kernel in comparison with kernel and RBF kernel. In addition, because of the SVM power in ECG Pattern classification, it is applied for classification of ECG signals during and before the music. The performance of the proposed algorithm is determined in terms of accuracy. We achieved an overall accuracy of 91.6% using polynomial kernel and RBF kernel whereas 100% accuracy is achieved using linear kernel. The results of the present assay confirm the effects of music on cardiac function in young women.

5. Conclusion

There is a need for more detailed studies to enrich the understanding of the physiological effects of music. However, the results of the present work confirm the effects of music on cardiac function in young women. In the other words, it seems that the heart can synchronize with traditional Persian music in young women.

Conflicts of interest

The authors have none to declare.

Acknowledgment

The authors would like to give their special thanks to the Dr. Keyvan Saket for the composition of the music, Neda Karamloo and Fatemeh Ghorbani for their assistance in data collection process and the students who participated in this study. The authors sincerely acknowledge Computational Neuroscience Laboratory of Sahand University of Technology.

References

- Jones SA. *ECG Notes: Interpretation and Management Guide*. FA Davis; 2009.
- Dousty M, Daneshvar S, Haghjoo M. The effects of sedative music, arousal music, and silence on electrocardiography signals. *J Electrocardiol*. 2011;44:e391–e396.
- Iwanaga M, Kobayashi A, Kawasaki C. Heart rate variability with repetitive exposure to music. *Biol Psychol*. 2005;70:61–66.
- Longhi E, Pickett N, Hargreaves DJ. Wellbeing and hospitalized children: can music help? *Psychol Music*. 2015;43:188–196.
- Loomba RS, Arora R, Shah PH, Chandrasekar S, Molnar J. Effects of music on systolic blood pressure, diastolic blood pressure, and heart rate: a meta-analysis. *Indian Heart J*. 2012;64:309–313.
- Orini M, Bailón R, Enk R, Koelsch S, Mainardi L, Laguna P. A method for continuously assessing the autonomic response to music-induced emotions through HRV analysis. *Med Biol Eng Comput*. 2010;48:423–433.
- Koelsch S, Jäncke L. Music and the heart. *Eur Heart J*. 2015;ehv430.
- Hyde IH, Scalapino W. The influence of music upon electrocardiograms and blood pressure. *Am J Physiol Legacy Content*. 1918;46:35–38.
- Knight WE, Rickard NS. Relaxing music prevents stress-induced increases in subjective anxiety, systolic blood pressure, and heart rate in healthy males and females. *J Music Ther*. 2001;38:254–272.
- Thaut MH, Davis WB. The influence of subject-selected versus experimenter-chosen music on affect, anxiety, and relaxation. *J Music Ther*. 1993;30:210–223.
- Vanderark SD, Ely D. University biology and music majors' emotional ratings of musical stimuli and their physiological correlates of heart, rate, finger, temperature, and blood pressure. *Percept Mot Skills*. 1994;79:1391–1397.
- Goshvarpour A, Abbasi A, Goshvarpour A, Karamloo N, Ghorbani F. Effects of music on cardiac functioning in young women and men. *Appl Med Inf*. 2013;33:40.
- Khazaei D, Setarehdan SK, Mehran YZ. The effectiveness of music on human biological signals. *Bio Eng Appl Basis Commun*. 2016;28:1650002.
- Salimpoor VN, Benovoy M, Longo G, Cooperstock JR, Zatorre RJ. The rewarding aspects of music listening are related to degree of emotional arousal. *PLoS One*. 2009;4:e7487.
- Nakahara H, Furuya S, Obata S, Masuko T, Kinoshita H. Emotion-related changes in heart rate and its variability during performance and perception of music. *Ann NY Acad Sci*. 2009;1169:359–362.
- Kemper KJ, Hamilton CA, McLean TW, Lovato J. Impact of music on pediatric oncology outpatients. *Pediatr Res*. 2008;64:105–109.
- Uggla L, Bonde L, Svahn B, Remberger M, Wrangsjö B, Gustafsson B. Music therapy can lower the heart rates of severely sick children. *Acta Paediatr*. 2016;.
- Archana R, Mukilan R. Beneficial effect of preferential music on exercise induced changes in heart rate variability. *J Clin Diagn Res*. 2016;10:.
- Oh MO, Kim YJ, Baek CH, et al. Effect of music intervention on maternal anxiety and fetal heart rate pattern during non-Stress test. *J Korean Acad Nurs*. 2016;46:315–326.
- Vaessen M. *An Approach to ECG Delineation Using Wavelet Analysis and Hidden Markov Models*. Universiteit Maastricht, Department of Mathematics; 2006.
- Saritha C, Sukanya V, Murthy YN. ECG signal analysis using wavelet transforms. *Bulg. J. Phys*. 2008;35:68–77.
- Ji S-Y, Belle A, Ward KR, et al. Heart rate variability analysis during central hypovolemia using wavelet transformation. *J Clin Monit Comput*. 2013;27:289–302.
- Martínez JP, Almeida R, Olmos S, Rocha AP, Laguna P. A wavelet-based ECG delineator: evaluation on standard databases. *IEEE Trans Biomed Eng*. 2004;51:570–581.
- Banerjee S, Mitra M. Application of cross wavelet transform for ECG pattern analysis and classification. *IEEE Trans Instrum Meas*. 2014;63:326–333.
- Ara I, Hossain MN, Rahim MA. ECG signal analysis using wavelet transform. *Int J Sci Eng Res*. 2014;5.

26. John AA, Subramanian AP, Jaganathan SK, Sethuraman B. Evaluation of cardiac signals using discrete wavelet transform with MATLAB graphical user interface. *Indian Heart J.* 2015;67:549–551.
27. Patil G, Subba Rao K, Niranjan U, Satyanarayan K. Evaluation of QRS complex based on DWT coefficients analysis using daubechies wavelets for detection of myocardial ischaemia. *J Mech Med Biol.* 2010;10:273–290.
28. Javadi M, Arani SAAA, Sajedin A, Ebrahimpour R. Classification of ECG arrhythmia by a modular neural network based on mixture of experts and negatively correlated learning. *Biomed Signal Process Control.* 2013;8:289–296.
29. Mahmoodabadi S, Ahmadian A, Abolhasani M. ECG feature extraction using Daubechies wavelets. *Proceedings of the Fifth IASTED International Conference on Visualization, Imaging and Image Processing.* 2005;343–348.
30. Lele V, Holkar K. Removal of baseline wander from ECG signal. *Int J Electron Commun Soft Comput Sci Eng.* 2013;60.
31. Li C, Zheng C, Tai C. Detection of ECG characteristic points using wavelet transforms *Biomedical Engineering. IEEE Trans Biomed Eng.* 1995;42:21–28.
32. Rai HM, Trivedi A, Shukla S. ECG signal processing for abnormalities detection using multi-resolution wavelet transform and Artificial Neural Network classifier. *Measurement.* 2013;46:3238–3246.
33. Cortes C, Vapnik V. Support-vector networks. *Mach Learn.* 1995;20:273–297.
34. Saxena S, Kumar V, Hamde S. Feature extraction from ECG signals using wavelet transforms for disease diagnostics. *Int J Syst Sci.* 2002;33:1073–1085.
35. Osadchy M., Keren D. Incorporating the boltzmann prior in object detection using svm. 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06). Vol 2: IEEE; 2006: 2095–2101.
36. Li J, Allinson N, Tao D, Li X. Multitraining support vector machine for image retrieval. *IEEE Trans Image Process.* 2006;15:3597–3601.
37. Byvatov E, Fechner U, Sadowski J, Schneider G. Comparison of support vector machine and artificial neural network systems for drug/nondrug classification. *J Chem Inf Comput Sci.* 2003;43:1882–1889.
38. Nanni L, Costa YM, Lumini A, Kim MY, Baek SR. Combining visual and acoustic features for music genre classification. *Expert Syst Appl.* 2016;45:108–117.