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Empirical Mode Decomposition-Based Analysis of Heart Rate Signal Affected by Iranian Music

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Abstract
Purpose: Several studies have been done measuring the effects of music on various vital signs more frequently on the electrocardiogram (ECG) and consequently the heart rate (HR). This study has been conducted to address the effects of Iranian music on cardiac functioning by thoroughly examining the extracted HR from ECG signals. A strong mathematical method is needed to extract signal features. One of the adaptive mathematical analyses is empirical mode decomposition (EMD), which is implemented to analyze the nonlinear and non-stationary data. This method can decompose any complicated signal into a group of intrinsic mode functions (IMFs) through a sifting process. *Basic methods:* In this paper the EMD-based feature extraction algorithm of HR signal which does not require a priori functional basis will be described. Fast Fourier transforms (FFT) are used to identify the peaks in the signal. Then maximum amplitude (MaxFFT) and maximum frequency (MaxFreq) using FFT and sample entropy (SampEn) for each extracted IMF and their combinations are calculated. SampEn algorithm is applied to calculate the complexity of each IMF and their combinations. Paired sample t-test was also conducted to assess if there were any significant differences between MaxFFT, SampEn and MaxFreq values of the IMFs. *Main results:* Considering the high frequency IMFs, results indicate that the MaxFFT values are decreased, but the SampEn and MaxFreq values are increased during listening to Iranian music. *Conclusion:* Experimental results from 62 subjects showed that the proposed methodology can be useful to show the differences between pre-music and during-music stages.

Keywords: Empirical mode decomposition; Fast Fourier Transform; Heart Rate (HR); Iranian music; Sample entropy

Introduction

The ability of music to improve the quality of life or concentration has been documented for many years ago [1,2]. The electrocardiogram (ECG) signal is a recording of the cardiac activity and is extensively used for the analysis of heart behavior without involving any invasive medical procedures [3]. It is challenging to detect and interpret the variations of the ECG signal features due to the presence of noises [4]. Also, the variables in ECG signal are considered to be non-stationary stochastic [5]. The composite nature of ECG signal also ensures the need of robust and efficient signal processing techniques to develop a reliable and trust worthy signal processing system [6]. Hence, analyzing the heart rate (HR) signal may be also useful. Mathematical techniques are applied to automatically extract HR from noisy ECG signal. A nonlinear and non-stationary HR signal indicates the subtle variations of the underlying ECG signal [7]. Various cardiac and non-cardiac diseases have been diagnosed using HR signals [7,8]. Applying linear and nonlinear techniques, studies of HR time series, have proved significant changes in heart behavior while listening to music. This change, leads to additional insight into the underlying dynamics of HR and provides additional information of cardiac autonomic function during music in two genders (males and females) [2,9]. However, probing the effects is a complex phenomenon, involving cardiovascular changes [10]. Nonlinear decomposition method for time series is usually a good approach to identify intrinsic oscillatory modes of the signal by its characteristic time scales [11].

The empirical mode decomposition (EMD) method [12] is a technique for processing nonlinear and non-stationary signals [11]. This algorithm has been widely used in various applications such as artifact reduction [13], ECG enhancement [3], interpreting depth of anesthesia [14], analysis of high frequency fetal heart rate variability [15], ECG based personal identification [16], baseline wander correction [17], R-peak detection [18], emotion recognition [19,20] and feature extraction [21]. EMD, decomposes signals into finite basis functions called the intrinsic mode functions (IMFs) [19]. It is known that the fastest changing component of a composite signal is always sifted out first by the EMD method. Each IMF contains lower frequency oscillations than the previous one [22].

The other method, which will be helpful for probing the music effects, is the analysis of signal in frequency domain [19]. The spectral parameters of signal are used to gain insight into the autonomic nervous system (ANS) response induced by music. Frequency domain methods estimate the power spectral densities applying parametric and nonparametric methods [1]. The nonparametric method of analysis is done by applying Fast Fourier Transforms (FFT). These methods can indicate the changes, in terms of the frequency components [23]. In 1991, approximate entropy (ApEn) was developed for nonlinear physiological signals [24,25]. With respect to computation and accuracy of signal regularity, the sample entropy (SampEn) is an improvement of ApEn [26,27]. Therefore, additional information can be extracted from HR using SampEn compared to ApEn.

The purpose of this research was to separate pre-music and during-music stages using HR signals. Additionally, the effect of Iranian music on the nonlinear behaviors is assessed by examining the EMD method. Therefore, the maximum amplitude (MaxFFT), maximum frequency (MaxFeq) using FFT and SampEn for each extracted IMF and their combinations is extracted. Finally, the results are statistically analyzed.

Material and Method

ECG signal recording

ECG signals were independently collected before and during Iranian music from 62 students, (22 females and 40 males with age range of 19-27) by POWERLAB, built by ADINSTRUMENT with a 400 Hz sampling rate. LABCHART5 was used as POWERLAB software. All subjects included in this study, were healthy and none of them reported any symptoms of neurological disorders. Data acquisition was carried out in two sequential stages. At the first stage (pre-music stage), subjects were asked to lay in the supine position and keep their eyes closed. ECG signals were recorded for about 5 minutes for each subject at this stage. Afterwards, in the second stage, another segment of ECG signals, with the same duration, was recorded while the subjects were listening to a piece of music composed by Iranian musician, Dr. Keyvan Saket (during-music stage). To suppress the power line noise, a digital notch filter at 50 Hz was designed [1,28]. The time interval between two consecutive R peak which is located using Pan and Tompkins algorithm [29,30], is termed as the RR interval (RR). HR is defined as [4]:

$$HR_{bpr} = 60/t_{RR} \quad (1)$$

where bpm = beat per minute

Empirical Mode Decomposition (EMD)

One of the most adaptive models for nonlinear signal analysis is the EMD model which directly depends on signal data and does not rely on any assumptions about the linearity of the signal [12]. EMD, decomposes the signals based on their local time and scale, into a group of intrinsic mode functions (IMFs) which are AM and FM modulated waveforms [4]. Unlike EMD, that does not require any priori known information about the signal, most of commonly used data analysis, like frequency domain analysis and Fourier transforms methods rely on a finite set of predefined basic functions to represent the signal. Hence the EMD is especially well suited for non-stationary signals such as HR signals. EMD applies a sifting process to decompose the signal (x(t)) into sum of IMFs and a residue:

$$x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t) \qquad (2)$$

where $c_n(t)$ and $r_N(t)$ are respectively called the nth order IMF and the residue which is a constant without any useful information about the signal, and commonly is ignored. Residue can be regarded as a monotonic slope, a function with only one extrema, or the last IMF [20]. In Functional behavioral assessments, being regarded as an IMF, each function needs to meet two expectations: a) the number of extrema and zero crossings should be equal or at most differed by ones and b) Its envelopes should be symmetric with respect to zero. So, considering the subjective nature of the signal, factors such as length of data and the number of extrema, the number of IMFs will not be constant [20]. Similar to Fourier analysis, IMF represents the repetitive variations of signals. The order of the IMF, corresponds with the pace of oscillations. This implies that the higher and lower orders of the IMFs, capture the fast and slow oscillations, respectively [17].

Four IMFs of HR signals for two stages (pre-music and during-music) were extracted and analyzed in this study. HR signal and four IMFs obtained from EMD for pre-music and during-music stages of subject one are shown in Figure 1 and Figure 2, respectively.

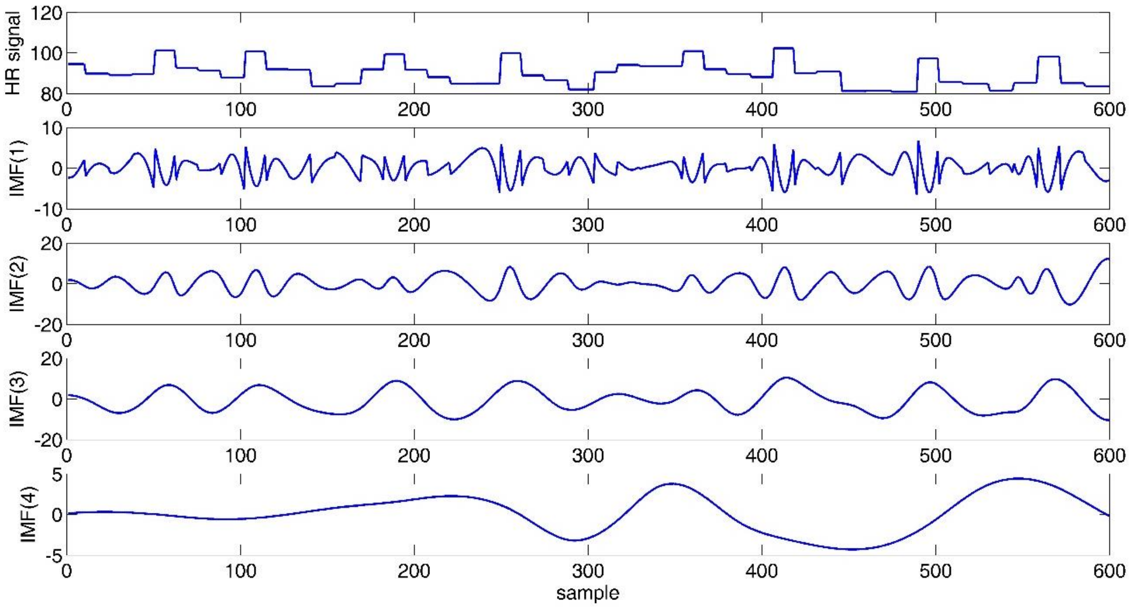


Figure 1. Up to down: HR signal and 4 IMFs for the pre-music stage

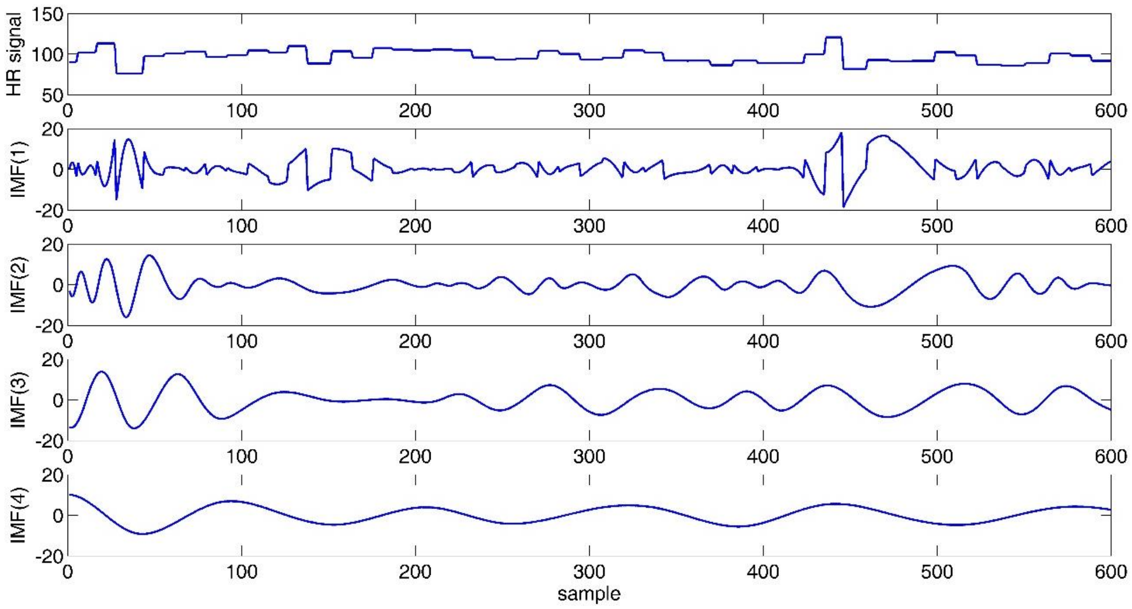


Figure 2. Up to down: HR signal and 4 IMFs for the during-music stage

Figure 1 and Figure 2 indicate the presence of high dense oscillations in lower order IMF's. The density of oscillations reduces as the order of IMF increases. It can be noticed that the instantaneous frequency is higher for IMF (1) and reduces consecutively for IMF (2), (3) and (4). In this study, the experiment is designed such that IMFs combinations which are needed for the analysis are acquired by sample entropy and FFT.

Sample Entropy (SampEn)

SampEn is a measure of complexity in signal [14,31]. Higher values of SampEn describe the lack of symmetry and abnormality in the time series. It is more refined than ApEn. In order to appraise sample entropy, points are continuously matched inside a coefficient of tolerance as radius 'r', and the process will last as long as pairs exist. SampEn is given by (3):

$$SampEn(k,r,N) = -\ln\left[\frac{A(k)}{B(k-1)}\right] \tag{3}$$

where A(k) and B(k)contain the information of matched templates [4]. For k = 0, 1, …, m – 1, (m is the maximum template length), with B(0) = N, (N is the length of the HR signal), r is taken as 0.2 and m is set to 2 [32], and SampEn of each IMF and their combinations are extracted.

Fast Fourier Transform (FFT)

FFT is a nonparametric method of analysis that makes the effects clear in terms of the frequency components [23]. It is also used to identify the peaks in the ECG signal [33]. Initially FFT is applied on each IMF using (4). For a discrete time series *x(n)*, with *N-sized* blocks, the FFT is defined as below:

$$X_k = \sum_{n=0}^{N-1} x(n) e^{-\frac{2\pi i}{N}nk}, \quad k = 0,\ldots,N-1 \tag{4}$$

Statistical Analysis

Statistical analyses were performed on features to determine the effect of music on ECG signals. Mean values of features from both stages were compared in order to probe the significant changes using paired-sample t-test at a significance level of 0.05.

An overview of the whole procedure is shown in the Figure 3.

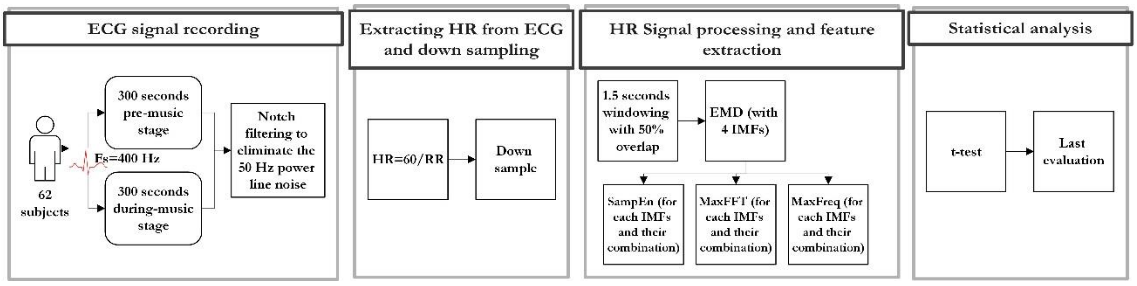


Figure 3. The overall process

Results

Table 1, Table 2 and Table 3 present the mean and STD (standard deviation) values of MaxFFT, MaxFreq and SampEnof the HR signals associated with each IMF and their combinations, respectively. The last columns show the *p*-values, and a marker sign for valid significant levels.

Table 1. Mean values of MaxFFT for 62 subjects

Feature	Pre-music stage		During-music stage		*p*-value
	Mean (μV)	STD (μV)	Mean (μV)	STD (μV)	
MaxFFT (1)	218	206	191	189	<0.001
MaxFFT (2)	460	440	403	394	<0.001
MaxFFT (3)	801	590	677	510	<0.001
MaxFFT (4)	970	3596	910	3380	0.682
MaxFFT (1+2)	398	366	342	322	<0.001
MaxFFT (2+3)	919	653	766	522	<0.001
MaxFFT (3+4)	1272	3582	1141	3382	0.370
MaxFFT (1+3)	715	522	609	478	<0.001
MaxFFT (1+4)	954	3598	892	3381	0.675
MaxFFT (2+4)	1059	3582	972	3373	0.555
MaxFFT (1+2+3)	795	546	661	437	<0.001
MaxFFT (2+3+4)	1339	3570	1180	3366	0.275

MaxFFT: the maximum amplitude of the FFT; STD: standard deviation;
(-): number of the IMF; (-+-): numbers of the combined IMFs

Table 2. Mean values of MaxFreq for 62 subjects

Feature	Pre-music stage		During-music stage		*p*-value
	Mean (Hz)	STD (Hz)	Mean (Hz)	STD (Hz)	
MaxFreq (1)	13.846	8.630	15.989	19.830	0.001
MaxFreq (2)	10.375	5.320	11.345	7.269	<0.001
MaxFreq (3)	5.230	1.830	5.879	3.555	<0.001
MaxFreq (4)	2.440	0.977	2.556	1.667	0.037
MaxFreq (1+2)	10.530	7	12.766	18.445	<0.001
MaxFreq (2+3)	5.940	2.320	6.699	4.845	<0.001
MaxFreq (3+4)	4.040	1.940	4.165	2.859	0.160
MaxFreq (1+3)	5.057	1.820	7.720	18.966	<0.001
MaxFreq (1+4)	2.686	1.965	4.445	17.468	0.001
MaxFreq (2+4)	3.859	3.530	4.47	5.687	0.121
MaxFreq (1+2+3)	5.699	2.045	7.849	16.646	<0.001
MaxFreq (2+3+4)	4.566	2.269	4.969	4.730	0.005

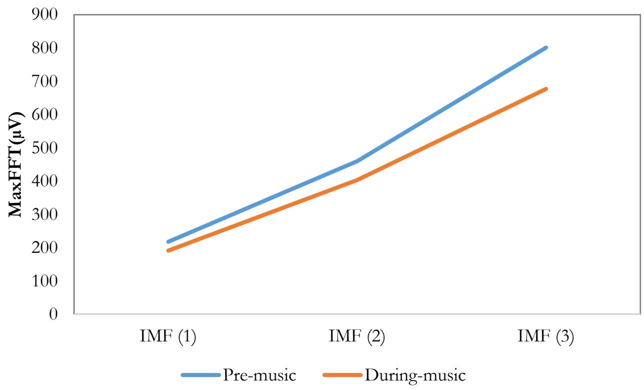
MaxFreq: the maximum frequency of the FFT; STD: standard deviation;
(-): number of the IMF; (-+-): numbers of the combined IMFs

Table 3. Mean values of SampEn for 62 subjects

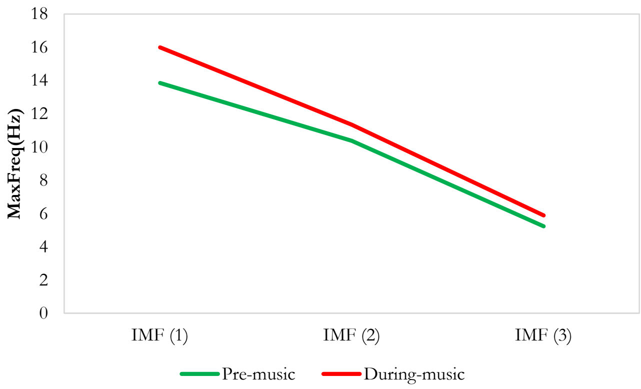
Feature	Pre-music stage		During-music stage		*p*-value
	Mean (Hz)	STD (Hz)	Mean (Hz)	STD (Hz)	
SampEn (1)	0.610	0.095	0.623	0.131	0.003
SampEn (2)	0.454	0.103	0.465	0.128	0.014
SampEn (3)	0.300	0.091	0.311	0.098	0.002
SampEn (4)	0.117	0.055	0.125	0.075	0.002
SampEn (1+2)	0.456	0.128	0.488	0.244	<0.001
SampEn (2+3)	0.358	0.085	0.378	0.136	<0.001
SampEn (3+4)	0.242	0.085	0.247	0.098	0.084
SampEn (1+3)	0.463	0.113	0.497	0.222	<0.001
SampEn (1+4)	0.518	0.115	0.534	0.210	0.013
SampEn (2+4)	0.371	0.105	0.383	0.153	0.014
SampEn (1+2+3)	0.200	0.075	0.237	0.247	<0.001
SampEn (2+3+4)	0.317	0.083	0.336	0.140	<0.001

SampEn: the sample entropy; STD: standard deviation;
(-): number of the IMF; (-+-): numbers of the combined IMFs

Mean values of MaxFFT, MaxFreq and SampEn, associated with IMF (1) to (3) are visualized in part (a), (b) and (c) of Figure 4, respectively. The violet lines describe the pre-music and the green ones describe the during-music stage.

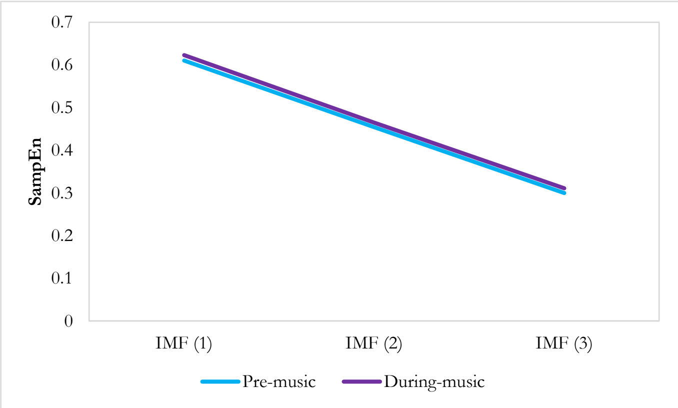


(a)



(b)

Figure 4. Mean values of (a) MaxFFT, (b) MaxFreq associated with IMFs (1), (2) and (3)



(c)

Figure 4. Mean values of (c) SampEn, associated with IMFs (1), (2) and (3)

Discussion

Measuring various effects of music on vital signs, has been frequently done on ECG and consequently on the HR in several studies. This article aimed to propose a method implemented in HR signals to probe the Iranian music effects. The presented approach has been applied directly to the HR signals through two stages, aiming to extract EMD-based nonlinear features.Extended results have presented the efficiency of the suggested method.

The obtained HR signal was down sampled, (one sample per each 20 samples) and every 600 samples of the data points, with 50% overlapping, were assumed as a periodic data window. The two stages were compared based on these windows.

Table 1, Table 2 and Table 3, correspond to the mean values of MaxFFT, MaxFreq, and SampEn of IMFs. In each table, there exist some orders of IMFs that, the corresponding features, are significantly changed during the two stages. In Tables 1-3, there are 7, 10, and 11 valid changes, respectively. Regarding to these tables, if all the three values of MaxFFT, MaxFreq and SampEn, associated with an IMF, are significantly changed, that IMF is chosen as a suitable feature. So the IMFs (1), (2), (3), (1+2), (2+3), (1+3), and (1+2+3) are such features.

From Table 2 it can be noticed that the highest frequency value is related to IMF (1) and this value decreases consecutively from IMF (1) to IMF (2), (3) and (4). Hence, the major effects of listening to music occur at high frequencies (5.230 to 13.846 Hz for pre-music stage and 5.879 to 15.989 Hz for during-music stage). However, for the lower frequencies, the changes are not valid.
From Figure 4 it is obvious that, the MaxFFT values are decreased, but the SampEn and MaxFreq values are increased during the music. Increased values of SampEn describe more irregularities in the HR signals during listening to music. It is also worth noting that, without considering the stage of recorded signals, by increasing the order of IMF, the MaxFFT values are increased, while the MaxFreq and SampEn values are decreased.

Some studies report that Lyapunov exponents' fluctuations are higher in the women's group than that of men's group in both conditions (during rest and music) [1]. In some researches it can be observed that the classification accuracy of low frequency spectral power of the emotional features obtained from the IMF's is higher than the high frequency and total (low and high frequency) spectral power. So comparing the frequency ranges, it can be concluded that the most of the emotional information lies at low frequencies [20]. The results indicate that by using this method, the signal will be analyzed further and is possibly matching better with the varying nature of ECG biosignals[11]. In some researches, it is reported that the characteristic time scales of the signal are represented in IMFs being a complete, orthogonal, local and adaptive decomposition which preserve physical properties [12]. Other researchers have been applied Hilbert transform to the selected slowest intrinsic mode component in order to determine instantaneous frequency, and this feature is considered as a discriminative index to classify ECGs of different individuals [16]. It is shown that after applying the Hilbert transform to a signal, comparisons are made between Fourier spectra of the obtained IMFs and that of the original signal to find out the relationships between IMFs and vibration modes. Then by computing the amplitude weighted average frequencies based on the Hilbert spectra, modal frequencies can be identified [21]. The investigation of SampEn showed that the value of the SampEn falls suddenly during some disease like epileptic seizure and this fact is utilized in the proposed diagnosis system [32]. Others concluded that if the entropy is small, it indicates that the patient status is in anesthesia. If the entropy is large, it indicates that the patient is awake [14].

Conclusion

In conclusion, both qualitative and quantitative measures suggest that the proposed EMD-based method provides promising information. In addition, it can be a useful tool to analyze the effects of the Iranian music on the non-stationary HR signal. Also, it can be used to successfully separate between pre-music and during-music stages.

Conflict of Interest

The authors declare that they have no conflict of interest.

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