ORIGINAL ARTICLE

Music-Induced Emotion Recognition Based on Feature Reduction Using PCA From EEG Signals

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Abstract

Purpose: Listening to music has a great impact on people's emotions and would change brain activity. In other words, music-induced emotions are trackable in electrical brain activities. Therefore, Electroencephalography can be a suitable tool to detect these induced emotions. The present study attempted to use electroencephalography in to recognize four types of emotions (happy, relaxing, stressful, and sad) induced in response to listening to music excerpts, using three classifiers.

Materials and Methods: In this empirical study, electroencephalography signals were collected from 20 participants, as they were listening to pieces of selected music. The collected data were then pre-processed, and 28 linear and nonlinear features for recognizing the aforementioned emotions were extracted. Feature-space components were then reduced through a principal components analysis. Finally, the first ten components of feature-space were used as input for three classifiers based on Neural Network (NN), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) algorithms to identify the induced emotions.

Results: The outputs showed that the suggested method was well capable of emotion recognition. Evaluating the music excerpts, on the self-assessment manikin scale, demonstrated that the labeling of the music tracks was accurate. The highest accuracy found among NN, KNN, and SVM algorithms were %84, %84, and %89 for happy emotions, respectively.

Conclusion: The findings of this study provide useful insights into emotion classification and brain behavior related to induced emotion extraction. Happiness was the most recognizable emotion and the support vector machine had the highest performance among the classifiers. In the end, the outcomes of the proposed method demonstrate that this system is better than the previous research in EEG-based emotion recognition.

Keywords: Emotion Recognition; Electroencephalography; Principal Component Analysis; Classification; Music.

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1. Introduction

Listening to music can influence human emotions. A wide range of emotions can be expressed through rhythms, chords, melodies, and music styles. Due to its emotional weight, music has a deep effect on the human spirit, morale, personality, and emotions [1]. The personal experiences of most people show that the type of music they listen to can cause such emotions as relaxation, pleasure, stress, or sadness. Though the use of music for altering emotions as a therapeutic effect goes back to Plato and Aristotle [2]. There have been many recent developments in this field by neurology researchers [3]. Musical therapy is among the non-invasive and non-chemical methods for treating depression and altering emotions. Measurement and recognition of emotions based on EEG signals were first introduced by Picard [4]. To measure and evaluate emotions, various theories have been provided, among which, studies by Ekman (discrete theory), and Lange (Dimensional theory) are more common in research [5]. The discrete theory defines emotions separately, without overlap. Based on Ekman's theory, emotions include happiness, sadness, anger, fear, hatred, and wonder. However, Lange's dimensional theory classifies emotions with overlap, on two or multiple dimensions, especially based on valence and arousal [6, 7].

Previous studies have focused on EEG signals and activated brain regions, as well as their correlation and application in emotion recognition in response to music. Brain activity in the left and right hemispheres is different during emotion induction. Most findings showed a direct correlation between frontal lobe activity and the emergence of emotions. Studies by Davidson *et al.* identified the left frontal lobe, as the center of emotional responses [8], whereas Daly *et al.* demonstrated activity in both hemispheres in response to various auditory inputs, with different induced emotions [9]. Recording and analyzing electric brain activity via Electroencephalography (EEG) is the only real-time direct method capable of recognizing emotions induced in the brain. However, this is a highly challenging task, as emotions are generated through a complex process. Studies have utilized such various methods as time-frequency feature analysis, wavelet analysis, brain connectivity analysis, and pattern recognition via artificial intelligence to tackle this challenge [10, 11]. For instance, Raja *et al.* [12] classified four emotional responses (happiness, sadness, fear, and relaxation) using Hjorth parameters; while Petrantonakis [13] used the frontal brain asymmetry concept to provide a method for evaluating emotion recognition. According to the literature review, machine learning classifiers have been used frequently by researchers. SVMs classifier [13-15] was the most popular, followed by KNN [16-18] and NN [15, 17]. Other classifiers used were Logistic Regression (LR) [16], Random Forest (RF) [19, 20], and the Naive Bayes (NB) [21]. These methods have been used to classify emotions by using machine learning: (1) identifying discrete emotions such as happiness, fear, and disgust [15, 20, 22-25]; (2) identifying arousal and valence distinctions [21, 26-30]; (3) also, there have been some works that include positive emotions in one class and negative emotions in another, and sometimes with a neutral class included as well [14, 16].

The purpose of this study is to recognize four groups of music-induced emotions, namely pleasure, happiness, sadness, and stress, using EEG signals. For the first time, in accordance with Linguistic and cultural Iranians, vocal and non-vocal music excerpts have been selected and labeled. The present work used Principal Component Analysis (PCA) to reduce EEG features. The objective of this study is to identify which emotion is more induced in subjects and which classifier has the best performance among the most popular machine learning algorithms used in emotion recognition.

2. Materials and Methods

The present empirical study was carried out in six stages consisting of (1) inducing emotions, (2) recording EEG signals, (3) pre-processing data, (4) extracting EEG features, (5) reducing the EEG features via PCA, and finally, (6) classifying and recognizing the emotions (Figure 1).

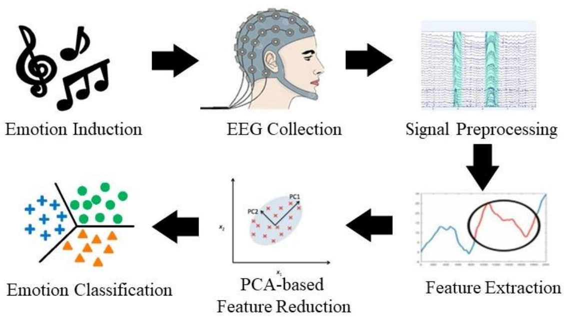

Figure 1. The schematic steps of the proposed method

2.1. Music-Induced Emotion

Respecting diversity during the selection of music tracks has a significant effect on the ability to induce a variety of emotions. In some databases, music tracks are labeled based on the type of emotion they induce [21, 31]. However, all the labeled tracks contain foreign music styles, which may not induce the intended emotions because of cultural and linguistic mismatch. Therefore, the music tracks were divided into three categories: Foreign non-vocal, native non-vocal, and native vocal. Each category contained four classes of music: happy, relaxing, stressful, and sad. Finally, to select the music tracks, 20 pieces of non-vocal foreign music, covering the four classes of emotion were first selected from databases. In addition, 60 music tracks were selected for the next two classes based on Iranian user comments on various websites. Consulting with an expert musician, 56 tracks were eliminated, leaving us with 24 tracks in the collection. A Telegram messenger bot was designed and implemented to gather comments on this collection and conduct a survey from 100 participants, about the severity of the induced emotion while listening to these 24 tracks (each taking 40 seconds). Finally, 12 music tracks, with the highest number of votes were selected under three classes of non-vocal foreign, native non-vocal, and native vocal, with four subclasses of happy, relaxing, stressful, and sad, which were used during the final EEG test.

Figure 2a represents the experimental procedure. At first, participants were instructed about the procedure. Ten seconds before playing each track, a notifier short beep informed the participants to be prepared for the playback and to stop moving. To prevent bias among the participants, the tracks were played randomly. Albeit when the music tracks were selected, there was a target emotion for each music stimulus, the feelings of the participant towards the same music could be subjective and may differ from person to person. In order to obtain the participants' true feelings, they need to complete a self-assessment. Self-Assessment Manikin (SAM) technique is a widely used one [32]. In this assessment, subjects are provided with a non-verbal pictorial evaluation of their emotions after they are exposed to the stimuli. Accordingly, each music track was then played for 40 seconds, at the end of which, the participants evaluated the level of valence and arousal they received from it on the SAM scale. The valence scale ranged from 1 (very pleasant) to 5 (very unpleasant). After each self-assessment, the participants could take a respite until they were notified by another beep to be prepared for the next track. The assessment and respite duration was 40 seconds in total.

2.2. Data Collection

Including Criteria for participants contained the absence of any hearing loss, sleep disorders, drug use background, and depression symptoms, based on the Beck test [33]. 20 volunteers in the age range of 24 to 34 years old (Mean = 27, SD = 3.2) were selected to participate in the tests. Data were recorded in the National Brain Mapping Laboratory (NBML). To ensure that the participants are not mentally or physically tired, all tests were conducted from 9:00 to 12:00 AM. Before starting the tests, the participants were familiarized with the test conditions. To avoid vision noise, the participants were asked to sit against a wall, keep their eyes open, and pay attention to a certain point on the wall. Noise-canceling headphones were used to make sure participants would only pay attention to music, and ambient sounds could not distract them. EEG data were recorded at a frequency of 256 Hz, using a 64-channel g-tech recorder device.

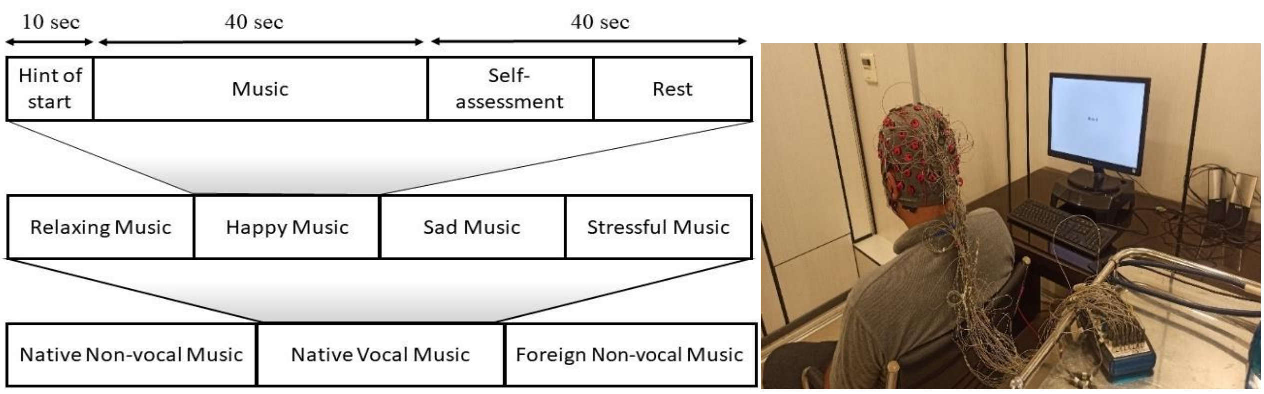

Figure 2. a) Experimental task, using music excerpts played at random, b) EEG signal recording

2.3. Data Pre-Processing

Data preprocessing was performed through the following steps [34]:

1. Signal extraction: Signal data was extracted from the moment a short beep has played for the audience (10 seconds before music playback begins) until the playback has finished.

2. Corrupt channel replacement: As the channels suffering impedance reduction, record the data with high noise, they were first removed and then replaced with the average values from adjacent channels.

3. Noise removal: Through Independent Component Analysis (ICA) the resource space was obtained. Noise components (such as ECG, EMG, and EOG) were removed from this space and the remaining components were combined, leaving a noise-free EEG signal.

4. Signal filtering: a 0.5 to 50 Hz Mid-pass filter was applied to all channels.

5. Baseline correction: The baseline was corrected using data from 5 seconds before the beginning.

The EEG data of one of the 20 participants were discarded, due to the many physical movements during the test, leading to a high-noised signal. The music takes 40 seconds to play during which the effectiveness of emotion induction increases as the playback nears the end; the last 10 seconds were selected for data analysis [35]. Data segmentation was carried out in compliance with Dar *et al.* [36], with a two-second window from the EEG signal, selected as a sample. The window is then tilted forward by one second, such that each window overlaps the adjacent window for one second, allowing 9 samples to be extracted from every 10 seconds.

2.4. Feature Extraction

In the present study, 62 channels were used to analyze the data. Linear and nonlinear statistical features were extracted based on Zangeneh *et al.* [7] and Rahman *et al.* [37]. All data were extracted in three frequency sub-bands, namely α (8~13 Hz), β (14~30 Hz), and Gamma (31~50 Hz). The features are detailed in Table 1.

2.5. Feature Reduction

On the one hand, a large number of features can cause the low efficiency of the classifier, and on the other hand, increase the number of calculations leading to an increase in the processing time [38]. The high number of channels and features seems to necessitate the use of a method to reduce the number of features. Principal Component Analysis (PCA) can reduce the number of dimensions in a dataset consisting of many interrelated variables. Such changes in the dataset were preserved as much as possible. The new variables lack any correlations among Principal Components (PC) and were arranged with respect to their effectiveness value. Then, the first few components, which maintain the most changes in all principal components were selected and used as input for classifiers [39].

Principal component extraction was carried out in six steps:

1. All components were arranged in one of the dimensions of a matrix. There are 12 music tracks and 46,872 features in total (28 channel features × 62 channels × 3 frequency bands × 9 samples). A 12 × 46,872 element feature matrix was thus created.

2. To ensure the accuracy of PCA, the feature average must be subtracted from all features. To execute this, the average for every row from the feature matrix was calculated and subtracted from all elements in that row.

3. The covariance matrix (or scatter matrix) was calculated for the entire dataset.

4. Eigenvectors and eigenvalues for the covariance matrix were calculated.

5. Eigenvectors were arranged in descending order and k eigenvectors were selected with the highest eigenvalue to form a W matrix with d × k dimensions, where each column represents an eigenvector.

6. The d × k eigenvalue matrix was used to convert samples to the secondary space.

After taking the steps above, the first ten components are selected as input for the classifiers.

Table 1. Linear and nonlinear features selected from Zangeneh *et al.* [7] and Rahman *et al.* [37]

Types	Names
Linear	Mean, Maximum, Minimum, Sum, Variance, Skewness, Standard Deviation, Interquartile Range, Log Detector, Average amplitude change, Kurtosis, Root mean square, Average of the power of signals, Peaks in periodic signals, Integrated signals, Simples square integral, Difference absolute standard deviation value,
Non-linear	Fuzzy Entropy, Shannon's Entropy, Permutation Entropy, Hjorth Parameters, Hurst Exponent, Detrended Fluctuation Analysis, Approximate Entropy, Largest Lyapunov exponent, Correlation dimension, Fractal dimension, Average time lag, Maximum length of diagonal structures

2.6. Classifiers

To classify the induced emotions, based on the extracted features, three algorithms of NN, KNN, and SVM were employed

For the neural network, the Multilayer Perceptron (MLP) consisted of one input layer, one hidden layer, and one output layer was chosen. The MLP's architecture comprises 10 neurons in the input layer, 7 neurons in the hidden layer, and 4 output neurons (each corresponding to one of the four emotional states). Based on half of the summation of the neurons in the input and output layers, the number of neurons in the hidden layer was empirically assigned. A sigmoid function was selected as the neural excitation function.

For KNN emotions classification, a value for "K", closest neighbor, should be specified. A range of "K" values from 2 to 12 was tried. In order to achieve the maximum classification performance, the optimal value of K is chosen. For most subjects, K = 5 produced the best results.

A multiclass SVM classifier was used. it is performed by a separating surface in the input space of the data set using different kernel functions as linear or non-linear such as quadratic, polynomials, and Radial Basis Functions (RBF). The RBF kernel has two regularization parameters, cost parameter C (penalty parameter for the hyperplanes' margin) and gamma γ (inversely proportional to the variance of the Gaussian function). A grid-search procedure was implemented to the whole dataset to choose an optimal parameter pair (γ, C) in the range from [-8, 8]. Parameter optimization of the nuclear function was achieved on the training and validation sets.

For the evaluation of the classifier, the k-fold cross-validation method with k=10 was applied. To analyze the effectiveness and efficacy of classifying emotions, a Confusion Matrix (CM) was used, generating the four class parameters of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The Accuracy (ACC), Sensitivity (SEN), and Specificity (SPC) parameters were determined through the following relations (Equations 1-3):

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$SEN = \frac{TP}{TP + FN} \tag{2}$$

$$SPC = \frac{TN}{TN + FP} \tag{3}$$

3. Results

Twelve tracks of foreign non-vocal, native non-vocal, and native vocal music were played back for each participant to induce the four emotions of relaxation, happiness, sadness, and stress in them. Average participant responses on the SAM scale were mapped to points one to five and were displayed on the valence-arousal diagram (Figure 3). As observed in the diagram, Happiness led to high levels of both valence and arousal, whereas sadness caused low levels of both valence and arousal. Moreover, the stress involved high arousal vs. low valence, while relaxation was accompanied by high valence vs. low arousal. Self-assessment results verify that the music tracks were well-selected.

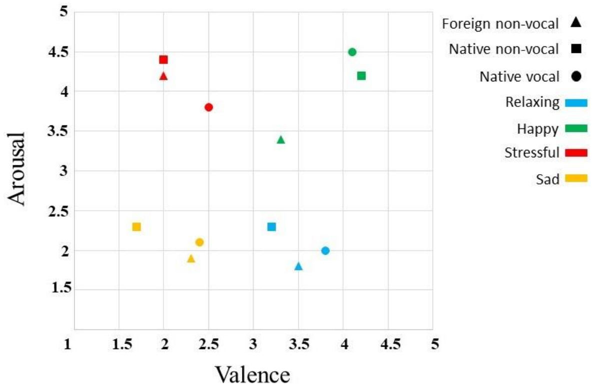

Figure 3. SAM scale scores on the valence-arousal plane

Figure 4 provides the CMs for the NN, KNN, and SVM classifiers, where the main diameter consists of TP values. As visible, happiness is the most pronounced emotion and has a higher TP in the SVM confusion matrix. The lowest FP value was observed for relaxation in the NN classifier matrix.

The performance of various methods of classification is displayed in Table 2. Overall, the emotion recognition performance of the SVM classifier is better than that of the other two classifiers. The highest accuracy (%89) was related to the feeling of happiness, in the SVM classifier results, whereas the lowest accuracy (%80) was related to the feeling of sadness for the KNN classifier. Moreover, it must be noted that the SVM classes have a higher sensitivity in detecting emotions, compared to the other two classifiers.

4. Discussion

In this paper, we performed a study that measures the brain activity of the participants via EEG signals, while listening to happy, sad, stressful, and relaxing music excerpts. Signals were collected through a 64-channel EEG recorder. During preprocessing, the obtained signals were filtered and divided into two-second pieces; and their alpha (α), beta (β), and gamma (γ) frequency sub-bands were extracted. During the next stage, several linear and non-linear features of three frequency sub-bands were extracted from all channels. The PCA method was employed to reduce the features, and the 10 components provided were obtained with the highest effectiveness. By using PCA, it is possible to reduce the dimensionality of a data set with many interrelated variables, while retaining as much variation as possible. Therefore, PCA has the advantage that the extracted features have the least correlation along the principal axes, but PCA cannot be used to identify emotion-specific features. In the end, an attempt was made to classify the induced emotions using NN, KNN, and SVM algorithms.

Table 2 shows the outcome of three classifiers of NN, KNN, and SVM via reduced features via PCA, where detecting positive emotions such as happiness with real positive rates above all three classes is easier. In contrast, the feeling of pleasure and sadness obtained the lowest score in the NN and KNN classifier results with 81% and 80% accuracies, respectively.

Table 2. The performance of various classification methods based on reduction features, according to PCA

Classifier		Relaxing	Happy	Sad	Stressful
NN	SEN	%65	%65	%67	%71
	SPC	%87	%90	%89	%89
	ACC	%81	%84	%83	%84
KNN	SEN	%65	%65	%65	%68
	SPC	%90	%91	%85	%88
	ACC	%84	%84	%80	%83
SVM	SEN	%71	%86	%71	%73
	SPC	%92	%90	%93	%91
	ACC	%87	%89	%88	%86

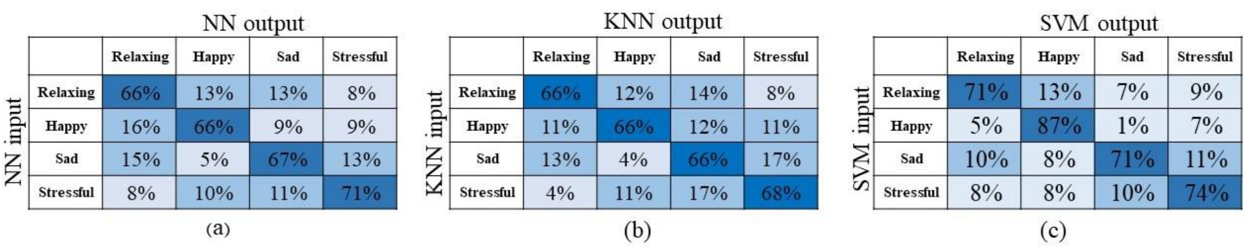

Figure 4. Average CMs for a) NN, b) KNN, and c) SVM classifiers

In our study, the best accuracy of all classifications is achieved with SVM, followed by NN, and lastly KNN. The results show that the SVM models outperform other models with higher mean accuracy and sensitivity. The SVM model achieves 4.5% higher accuracy than NN. Also, NN performance is slightly better than KNN. In Table 3, the accuracy of the proposed emotion recognition system was compared to that of other studies. Comparison is provided regarding the utilized stimulus, number of EEG channels, number of emotions recognized, classifiers employed, and classification accuracy. Previous studies have used images, non-vocal music tracks, and video clips to induce emotions, whereas the present study has used vocal music tracks as well as non-vocal native and foreign tracks. There are various types of stimuli used in emotion studies like film, music, and image. Based on Table 3, Films with emotional content perform better than others in terms of induction. Scenes and audio from emotional films can expose subjects to more real-life scenarios, eliciting strong changes in subjective and physiological responses. The SVM model of our study achieves 16.5% higher accuracy than the SVM model of the Bairavi study [40] with music stimuli. Different numbers of EEG channels were used in induced data, which may explain the difference in results.

The present study faced several limitations. As our EEG test takes time, the sensor gel will more likely begin to dry, causing the impedance and electrode noise to increase. The participant population was acceptable, compared to similar studies [10, 45]. But to generalize brain activity, a larger pool of volunteers must be tested, allowing similar patterns to be identified. We recommend further studies on this topic through other feature selection methods, such as evolutionary algorithm, genetic algorithm, and ant colony optimization, compared against PCA results. Moreover, as the participants may have listened to some of the music tracks before, their brains may have responded unexpectedly. Further studies on the relationship between music-induced emotions and memory are thus recommended.

Acknowledgments

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To comply with established principles of research ethics, before the beginning, participants were provided with an informed consent form, elaborating on the research objectives and procedures. The form

Table 3. Comparison between classifiers used in the present study vs other studies

Stimuli	# EEG channel	Classifier	Emotion type	Classification accuracy (%)	Ref
Music	62	SVM-KNN-NN	Relaxing, Happy, Stressful, Sad	The average accuracy of four emotions SVM: 87.5 KNN: 82.7 NN: 83	**Present**
Audio-Video Clip	32	Dempster-Shafer theory of evidence	Arousal-Valence	Overall accuracy: 92%	[41]
Audio-Video Clip	62	Autoencoder based Random Forest	Negative, Positive, Neutral	Overall accuracy: 94.4%	[42]
Audio-Video Clip	62	Deep Belief Network (DBN)- SVM-Logistic Regression (LR)- KNN	Positive, Neutral and Negative	Average accuracy DBN: 86.1 SVM: 84 LR: 82.1 KNN: 72.6	[43]
Music	1	Random Forest (RF)-SVM- Naïve Bayes (NB) -KNN	Arousal-valence	RF: 82 SVM: 71 NB: 67 KNN: 56	[40]
Image	18	SVM	Happiness and Sadness	Overall accuracy: 74.2%	[44]

explains the participant's right to abandon, at any stage of the tests. Participants were also assured that their information will remain confidential. The present study was granted the following ethical compliance ID by the Ethics Committee for Research at Iran University of Medical Sciences, Iran: [IR.IUMS.REC.1401.12].

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