Classification of Emotion Stimulation via Iranian Music Using Sparse Representation of EEG Signal

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Abstract. To interpret actions and communications in a correct way, emotion is very crucial. Emotion class recognition capability without using conventional approaches such as Self-Assessment Manikin (SAM) has been provided by Emotion Recognition EEG. Emotion Recognition with no medical and clinical examinations, as another merit for the EEG method, plays a key role in the completion of the structure of the Brain Computer Interface (BCI). One of the major challenges in this field is the selection of proper features of EEG signals in a way that makes an acceptable change among different emotion classes. Another challenge is the selection of a suitable classifier labeling algorithm for correct labeling and segregation of signals of every class. This article proposes a method based on compressed sensing (CS) theory, which resolves the mentioned challenges and provides the classifier performance results in accordance with sparse representation-based classification (SRC). Furthermore, recognition is assumed for two positive and negative classes according to valence-arousal emotion model (two of the three valence-arousal-dominance spaces). The results of the proposed method on the laboratory signal recorded by stimulating Iranian music show that the proposed method can compete with previous methods.

Keywords: Emotion classification · EEG signal · Compressed sensing · Dictionary learning · Sparse representation · Update dictionary · Classification

1 Introduction

Emotion Classification has had a major role in humankind's lifestyle, and most of the traditional research have been carried out using face expression, human sound, and body gestures in this field. The situation for obtaining information directly from the brain has been prepared with the advancement of science and technology. Among numerous methods used for emotion classification, three majors of them are Functional Magnetic

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Resonance Imaging (FMRI), Electroencephalography (EEG), and Near-Infrared Spectroscopy (NIRS). Among them, the utilization of electroencephalograph signals is more common due to its advantages of considering other signal obtaining methods. Electroencephalography benefits from three major advantages: high time-resolution, portability, and inexpensive measurement facilities. However, the multiplicity of the required channels for measurement can be a drawback of this method due to processing a colossal amount of information as well as complexity and signal nonstationarity [1]. The recognition accuracy depends on different parameters, which is still prone for research. This article has aimed to provide an acceptable conclusion in the correct emotion recognition (for two positive and negative emotion classes) without incorporating common features and classifiers into emotion.

The article first presents some information revolving around the EEG signal, which is the basis of this research. Then, the topic of emotion is discussed, and topics regarding music, particularly psychological music used for emotion stimulation of the participants, are expressed in the end [2].

1.1 Related Work

1.1.1 Models of Emotion

As a physiological stimulation state, emotion is perceived by a person under the emotional situation. Other cognitive evaluations can be confirmed based on this definition. Under the emotional occurrence, six dimensions of cognitive evaluation of circumstances are: pleasantness, responsibility, certainty, control, attentional activity, and expectance of the situation and pleasure [3]. Based on the theory of James Long, the experience of emotion is body response to physiological alterations [4]. Figure 1 shows the dimensional model used in the present study, which is interpreted in the next section.

1.1.2 Music and Emotion

Sound has physical and psychological components [5]. The physics of sound is the result of changes in pressure due to the changes in vibration of an object [6].

The figure shows the process of production and transmission of sound waves from musical instruments to passing through the ear to the mind regions involved in the

Fig. 1. Valence-arousal-dominance spaces [2].

evaluation as well as the process of excitations. Music is a tool for studying numerous aspects of neuroscience and learning dynamic-to-emotional skills [7]. Music delivers its emotional content directly to the audience and does not require mediators for receiving process. Music agitates our hearing sense. Therefore, it enters our perceptual domain without any resistance or selectivity. In other artistic phenomena, the audience uses sight and tone senses selectively [8].

1.1.3 EEG and Emotion

There have been abortive attempts to develop a new field of emotion recognition by electroencephalogram signal [9], the first of which stems from 1997 [10]. Attentions towards this topic have been increasing, and the word Affective BCI (aBCI) has been the result of this attention [11]. Feature selection, extraction, and electrode selection have been based on neuroscience theories. Hence power spectrums in different frequencies often come with different emotional moods. Alongside the assumptions of this science, signal processing application in the field of a BCI has been increasing [12, 13].

2 Materials

2.1 Stimulus Materials

Music effect depends on two basic factors. The first one is the theme of the music and the mood of the melodic rhythm surrounding it. The second is the emotional circumstances and the level of understanding of the audience [14]. Music theme has general and physiological effects and influences almost everybody irrespective of their emotional and mental mechanism. However, the magnitude and intensity of this influence is dependent on nerve cells, mental records, and the habits of the audience. Considering the participants' Iranian nationality, according to the investigations, sad and historical themes were selected to induce negative and positive emotions, respectively. For every emotional theme, Iranian music tracks were played.

Table 1 depicts the details of every selected music. Every music track was played for one minute with a fifteen-second pause between successive music tracks to prevent any emotion transfer. For better induction, the speaker was not used in this study, and between hands-free and headphones, we chose to use the second option due to less noise and participants' convenience. The highest level of computer sound volume with 70% of the player's sound volume was selected (the comfortability of the sound volume was confirmed by the participants).

2.2 Subjects

Sixteen participants, including six females and ten males, in the age range of 20 to 28 were recruited in this study. While listening to music, their EEG signal was recorded. Participants were asked to sign the consent form, and the following circumstances were considered for them.

Table 1. Details of each selected music

Music	Abbreviation	DE
Esfahan prologue by Mohammad Reza Lotfi	N1	First negative emotion
Hysterical music (Azerbaijan)	P1	First positive emotion induction
Homayoun prologue by Faramarz Payvar	N2	Second negative emotion
Hysterical music (Azerbaijan)	P2	Second positive emotion induction
Hysterical music (Bandari)	P3	Third positive emotion induction
Afshari piece by Sohrab Pournazeri	N3	Third negative emotion
Esfahan prologue MohammadReza Lotfi	N4	Fourth negative emotion
Hysterical music (Bandari)	P4	Fourth positive emotion induction
Dashti prologue by Hosein Alizade & Kayhan Kalhor	N5	Fifteenth negative emotion
Hysterical music (Persian)	P5	Fifteenth negative emotion

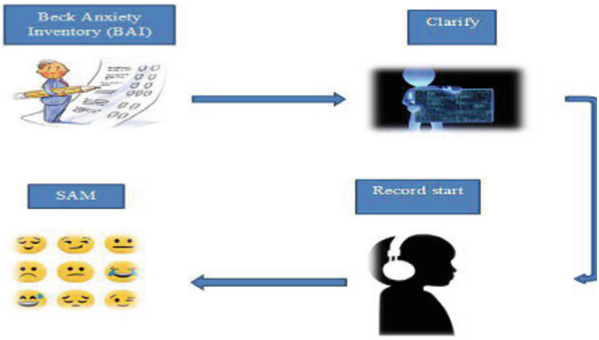

Fig. 2. Flowchart of the procedure.

- No mental sickness records.
- No sign of any sickness like epilepsy
- No record of usage of any kind of psychiatry drugs

Since physiological signals are strongly dependent on illnesses like anxiety and lifestyle, this study used healthy participants. The qualification of participants for being involved in tests was evaluated using the Beck Anxiety Inventory and Self-Assessment Manikin.

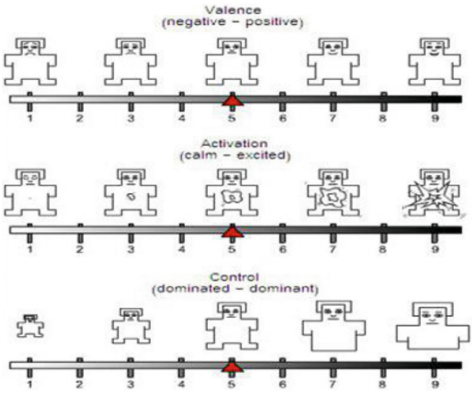

Fig. 3. Self-assessment manikin.

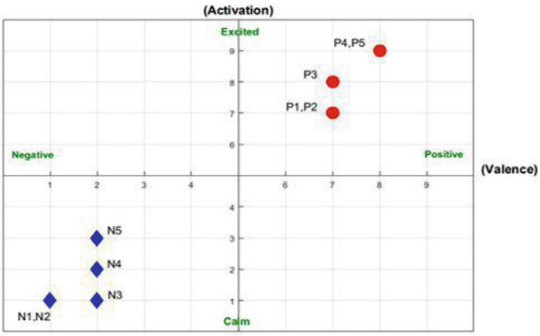

Fig. 4. SAM test results of the first participant.

2.3 Task

In addition to the proposed method based on SRC, [15] has revealed database for two positive and negative emotions. The proposed method was also tested on the reported data base, and a new database was formed for these two emotions. The recording process followed the same procedure of part A after silence for one minute and forty-five seconds to prevent signals of the first noise. Figure 2 shows the procedure of the experiment. The results of the self-assessment manikin test (Fig. 3) for the first participant and every part of the music track are displayed in a two-dimensional diagram in Fig. 4.

The following features were considered for the participants for a better record:

- Enough sleeping time before taking part in the test.
- Participants' washed hair before attending the test (no greasy hair).

Participants were asked to fill out the Beck Anxiety Inventory before the commencement of the process. Then the participants who achieved grades lower than 21 were removed from the process and conclusion.

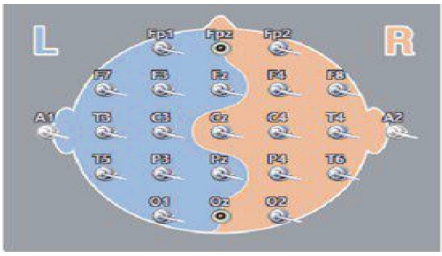

Fig. 5. The electrodes combination of placement.

2.4 EEG Recording

Time and local conditions are major factors of the test result. The signals were tried to be recorded before the launch meal when the participants did not feel sleepy or tired. Furthermore, participants were asked not to eat greasy or salty food during the day. The test room was checked for suitable light and sound conditions. Also, the participants' chairs were verified of proper conditions not to make noises during the test. To prevent any EEG noises, the participants were asked to close their eyes during the test.

The recorded signals were gathered in the EEG laboratory of Tabriz University in the faculty of Electrical Engineering.

The laboratory temperature was around 20 °C, and the participants were asked not to make any physical movements. To eliminate magnetic fields, cellphones were kept away from the electrodes. To reduce the noise made by electricity, the lights were turned off.

The system 10–20 standard was chosen for the placement of electrodes on the head, 21 electrodes were used for the process, and an especial hat was used for the ease of the process. Another important point that more often gets neglected is how the electrodes are assembled in the software. The standard Base Monopolar assembly was used in this paper. The number of the brain electrodes of the right hemisphere was subtracted from the number of electrodes in the right ear (A2). This calculation was also done for the left ear and brain hemisphere electrodes (A1). The electrodes' combination of placement is demonstrated in Fig. 5.

- Recording Device Sensitivity: 10 mV was selected.
- Electrodes Impedance: Maximum allowed impedance of any electrodes with respect to the head surface was considered to be 10 kohms.
- Sampling Rate: For the recorded data in this paper, sampling rate is considered to be 250 Hz.

3 Methods

In previous sections, the common methodologies used for emotion recognition were reviewed.

When signal feature complexity is combined with different methodologies, different moods are created. The main challenge in the previous methods was mostly around

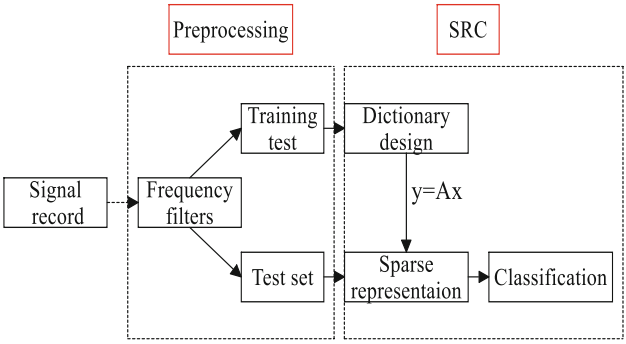

Fig. 6. Block diagram of the proposed method.

feature selection and extraction to segregate different emotion classes. This paper used a compressed sensor and a method of feature extraction to recognize emotions. Figure 6 shows the block diagram of the proposed method to classify the two emotion classes. The two following major challenges are proposed after reviewing the learning dictionary:

- For receiving any new data, all of the dictionary cells are updated. In the proposed method, we only try to update the dictionary cells involved in the new data sparse representation and its relevant data.

In the cost function, common methods have the same value and effect in updating the dictionary, while in the proposed method, the value and effect of each data were different in dictionary update.

3.1 Update Dictionary

In this part, we discuss the procedure of updating the dictionary shown in Fig. 6, which is the common aim between this paper and [16].

Here, we discuss CBW-RLS (Correlation Based Weighted Recursive Least Squares (CBW-RLS) Dictionary Learning Algorithm) method to develop the RLS-DLA method. RLS was proposed after MOD, which makes the calculation more complex in each inverse matrix. RLS learning dictionary method uses the Recursive Least Square and develops algorithm convergence by considering the Forgetting Factor. Furthermore, this Forgetting Factor controls the number of previous data. We want to use the new data correlation and the previous one instead of using the Forgetting Factor. In dictionary cells update, a corrective factor was used mentioned.

In the article [17]. If $Y \in \mathbb{R}^{m\times L}$ is electroencephalogram signal, $D \in \mathbb{R}^{m\times n}$ is matrix dictionary, and $X \in \mathbb{R}^{n\times L}$ is signal related to sparse factor, to relate the new data to the correlated data, we use the proposed method represented in [17, 18]. $Y\left(y_i\right)$ is the reduced dimension form of matrix Y, and its columns are the columns that correlate with y_i.

Algorithm 1 shows the procedure of the proposed CBW-RLS.

A. Parameters related to the proposed algorithm

Algorithm 1: CBW-RLS dictionary learning algorithm

1. **Initialize D and C**
2. **For (i=1: L)**
3. **Get the new training data y_i**
4. **Find x_i, sparse representation of y_i, using OMP**
5. **Find $\Omega(y_i)$, indices of previous signals which use common atoms in their sparse representation with y_i**
6. **Find $Y(y_i) \in \mathbb{R}^{m \times q_i}$, the set of all previous signals. Correlated with y_i**
7. **Find $D(y_i)$, the subset of D which deal with $Y(y_i)$**
8. **For (j=1: q)**
9. **Calculate $u_j(y_i) = C_{j-1}^{-1}(y_i) x_j(y_i)$**
10. **Calculate $r_j(y_i) = y_j(y_i) - D_{j-1}(y_i) x_j(y_i)$**
11. **Calculate $\omega_j(y_i)$, the weight correction using (17)**
12. **Calculate step size α_j using (23)**
13. **Update $D_j(y_i)$ using (25) and normalize its column**
14. **Update $C_j^{-1}(y_i)$ for next step using (26)**
15. **End**
16. **Replace the updated atoms of $D_j(y_i)$ into the original dictionary D**
17. **Update sparse coding of y_i using OMP**
18. **end**

To achieve any matrix dictionary related to each emotion, several variable and dependent parameters were defined. To find a proper form of combination, all the parameters, except the signal sparsity level, were considered to be constant. The parameters are as follows:

Segment Longitude:

In local correlation with the selection of different longitudes, we observed that by the increment of the segment longitude, the algorithm's processing speed and signal rebuilding accuracy were both developed. Therefore, we selected every segment equal to 1000 arrays shown in the figure.

- The number of channels: Nineteen channels were related to the laboratory recorded of this research.

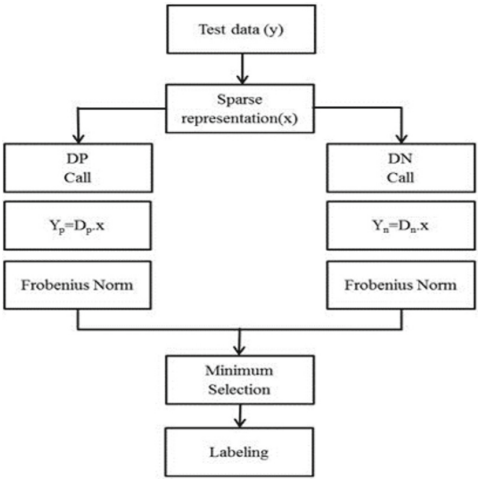

Fig. 7. The process of classification.

- Dictionary dimension: Dictionary dimension is the product of signal longitude and a random number.
- The number of train and test data: 60% of data was used for education and the rest for the test. Data selection for the train was done randomly.
- Signal Noise Ratio (SNR): White Gaussian noise to signal noise ratio was considered to be 30 dB to show the resistance of the proposed method.
- Sparsity Level: Considering the dictionary dimension and reviewing the related results, the sparse level of the education and test data was considered to be 40.
- The number of Algorithm Repeat: To form any matrix dictionary for each emotion, 60% of the data was used. For convergence of the matrix dictionary, the algorithm repeat cycle was selected to be 10.

3.2 Classifying Process

To generate Dictionary for each emotion, every test data was conducted in this paper by OMP algorithm. A sparse representation was achieved through this algorithm. Then, through the achieved sparse signal and two dictionaries related to two emotion classes, two buildings were formed. Through the Frobenius norm, the similarity (distance) between two signals was shown, and labeling was done. The process of this classifying is displayed in Fig. 7.

4 Results

This paper the removed feature extraction block from emotion recognition and proposed a method based on the compressed sensor. To verify the efficiency level of this method.

The results of the proposed method were gathered by testing seven participants and were shown in Table 2.

Table 2. The proposed method's results of the laboratory data base.

Subject	**Accuracy (%)**
1	75
4	75
8	91.66
13	83.33
12	83.33
14	75
16	83.33
Average	**80.95**

Table 3. The comparison of the proposed method's results via similar studies

Method reference	Number of emotion classes	**Stimuli**	Classification accuracy
This Research	2	Music	80.95%
[19]	2	Music video	70.1%
[20]	2	picture	85.41%
[21]	2	Film	79.16%

4.1 Comparison with Similar Works

From three criteria, only accuracy was mentioned in papers. Hence, this paper evaluated the results in accordance with this standard. The proposed method was compared with the results of three papers in Table 3.

Due to the lack of need for big data and the use of Sparse Representation, this method obviates the computational complexity and the need for powerful processors compared to other methods and can compete with similar methods in two classes in terms of classification accuracy.

Furthermore, the proposed method in the reference paper [15] has been simulated for a more thorough comparison. In [15], DWT has been used as a feature and SVM as a classifier.

5 Conclusion

The main challenge of emotion recognition is to select distinguishing features.

The advantage of the proposed algorithm is the removal of the feature selection block. However, feature selection is hidden in the SRC (Sparse Representation Classification). A dictionary has been extracted for each class from the train signals and then the test signals have been reconstructed through two existing dictionaries. Labeling has been

done based on the most similarity related to reconstruction through the dictionary, and no interaction has occurred between this algorithm and feature selection as it is clear from the steps of the algorithm.

Various classifying methods caused different results. However, the proposed method presented in this paper made a successful recognition of two positive and negative emotion classes without using complex classifying methods. Considering the correlation, atoms update was done through the related data, and the data which was not correlated had no effect on atom update. The forgetting factor for the correlated data and data with no correlation was considered to be one and zero, respectively, which occupied less RAM memory for saving previous data. The software processing speed increased by decreasing the data number. The volume of education data used in the RLS algorithm was influential in dictionary updates. The cost function was developed and modified by employing the correction factor.

The following are suggested for future work by the author:

1. To develop correction recognition, the extracted feature signal can be involved in the proposed algorithm process.
2. The number of emotion classes can be more than two.
3. Other algorithms can be used for the sparse signal, and its results can be compared with the OMP algorithm.

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