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COMBINING INDEPENDENT COMPONENT ANALYSIS WITH CHAOTIC QUANTIFIERS FOR THE RECOGNITION OF POSITIVE, NEGATIVE AND NEUTRAL EMOTIONS USING EEG SIGNALS

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ABSTRACT

Given the importance of recognizingemotions, the present study attempts to recognize emotions from the EEG signals. The main idea of this study is that the brain has independent sources with different functions. Thus, emotions would be observable in independent brain sources. These sources are obtained by Independent component Analysis (ICA) algorithm from recorded EEG signals. However, considering the ill-posed problem in ICA, the Shannon entropy was used to resolve this problem and sort outthe sources. Moreover, Recurrence Quantification Analysis (RQA) was used to extract chaotic features of each source and then, using a k-nearest neighbor (KNN) Classifier, the chaotic features of the three types of emotional state, i.e., positive, negative and neutral were analyzed, which yielded significant results. The results suggested that the greatest difference was observed in low-entropy sources while high- entropy sources showed no significant changes. Finally, for each emotional state, we established a relation between emotions and sources.

KEYWORDS: EEG, ICA, Emotion, Entropy, Chaos, RQA, KNN

Emotion is an important part of human communication, which marks one of the major differences between human and machine. Emotions can be expressed verbally or as a series of non-verbal behaviors like facial expressions, gestures or change in intonation of words[1]. Thus, the recognition of these behaviors or expressionsis critical to understanding human relations and providing a proportional reaction [2]. So far, great efforts have been made to build robots capable of imitatingemotions with the purpose of rendering these machines more human-like. The importance of emotion recognition arises from the fact that in human computer interface, machines should be able to recognize emotions so that they can provide appropriate reaction [3-4].

Recent studies on the emotion recognitionhave been focused on speech processing, facial expression analysis and biological effects such as heart rate, skin resistance, blood pressure and electrical activities of brain [5]. However, most conventional image and speech processing studies ignorecritical factors such as the fact that subjects may be hiding their internal emotions.

Biological effects, nonetheless, are able to estimate the true internal states of individuals without them being aware of it. Moreover, most studies use images to induce emotions, for it has been shown that the effect of visual on emotions is greater than other sensory modalities, and the amount of information transferred via an image is much larger than other ways of emotion induction [6-8].

The main idea of this study is that the brain is composed of different sources where each source is adapted to a specific job. Thus, there has to be an independent source or sources for any particular emotion in the brain. However, while the original source of information lies inside the brain, EEG recorded from the scalp may be the results of the interferences in different brain sources. Thus, such information cannot be easily extracted.

In other words, the original sources provide more accurate and precise information than the EEG recorded signals. Accordingly, specific changes in each source may be identified when analyzed separately.

Since we are unable to access these sources directly, we have no choice but to use the records from scalp or the methods that allow us access to the original sources based on observations. Independent Component Analysis (ICA) algorithms are able to guide us to the original source through some assumptions [9-10].The fastICA method is a useful method for decomposing EEG signals into its original sources [11]. Although ICA can extract information in the brain activity by independent components, the problem associated with ICA algorithms

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is that the order of extracted components is not specified, changing with each implementation of algorithm. That is, ICA is ill-posed [9]. To solve this problem, more information is needed, which should be related to original properties of system. In this study, we used the Shannon entropy for sorting the sources because it is assumed that emotion inductions cause changes in entropy of sources.

The traditional methods for analyzing biological signals include time series analysis and focusing on statistical propertiesof time or frequency domains, though those methods are useful for linear systems with very specific mathematical properties [12].While it has been asserted that biological systems, especially the brain system, have complex dynamics, this complexity can be interpreted as nonlinear chaotic dynamics of the system [13-14]. When assumed that brain is a complex dynamic system, EEG signals, which are directly proportional to the information processing capability, can be considered as a representation ofthe chaotic behavior of the human brain. To study the chaotic behavior of a system, Recurrence Quantification Analysis (RQA), which was proposed by Zbilut and Webber, appears to be a useful tool [15].

It is because RQA demonstrates the dynamic behavior of a system that is indicative of the recurrence of a trajectory in a given state in phase space. The quantitative measures of RQA enable us to decide about the deterministic or stochastic nature of the dynamic behavior of the system.To measure the quantitative measures of RQA, the phase space via time-delay embedding should be reconstructed [16].

Based on the assumption that emotions are produced in independent sources inside the brain, where each source displays chaotic behavior, the authors, combining ICA and chaotic features, introduced a new method based on ICA-Chaos to process EEG, which can be used for recognizing the nature of emotion and extracting features in emotion recognition. Moreover, this has improved the accurate recognition of emotions compared to other studies [5,17-19]. Therefore, the combination of ICA and chaos in EEG signal with the aim of emotion processing is the premise of this research.

MATERIALS AND METHOD

Subjects

In this paper, a new database consisting of 35 right-handed male volunteers, all of whom had been tested with standardized right-handedness test, with a mean age of 20.1 +1.4was constructed. All the participants were students who did not have any history of physical diseases or mental disorders, and had not usedany drug or alcohol 48 hours before the test. Additionally, depression, anxiety and alexithymia were testedusing German versions of the Self-Rating Depression Scale. The study was conducted based on the Declaration of Helsinki principles, which was approved by the ethics committee of the Islamic Azad University, Branch of Science and Research.All participants were also informed that they could leave the experiment at any time.

Visual Stimuli

Visual stimulation consisted of color pictures selected from the International Affective Picture System (IAPS). According to social constructivist point of view, all selected images, had already been evaluated by Iranian subjects who were different from the final participants and eliciting emotional responses similar to IAPS database. In this study, three types of positive, negative and neutral emotional pictures were used.

Stimulus Presentation

Visual stimuli were presented in monovalent blocks (positive, negative or neutral) randomly, followed by a 5-min cool-down period to eliminate the emotional effects of each block on other blocks. Each block consisted of 10 emotional images that have been presented with 5000 ms by 2000 ms intertribal intervals.

The stimuli were projected onto a 15.6 inch LED that had been placed 50 cm from the subjects in a soundproof room. After showing each monovalent block of the stimuli, the subjects were inquired about the elicited emotions to ensure the subjects were looking carefully at the images.

EEG Measurement

The electroencephalogram (EEG) was recorded by 15 scalp Ag-AgCl electrodes in accordance with international 10-20 system using a G-tec system (Austria) on left and right hemispheres locations as shown in Fig. 1.

(Electrode impedance <5 kΩ, 0.5-70 Hz, 512 samples / sec)

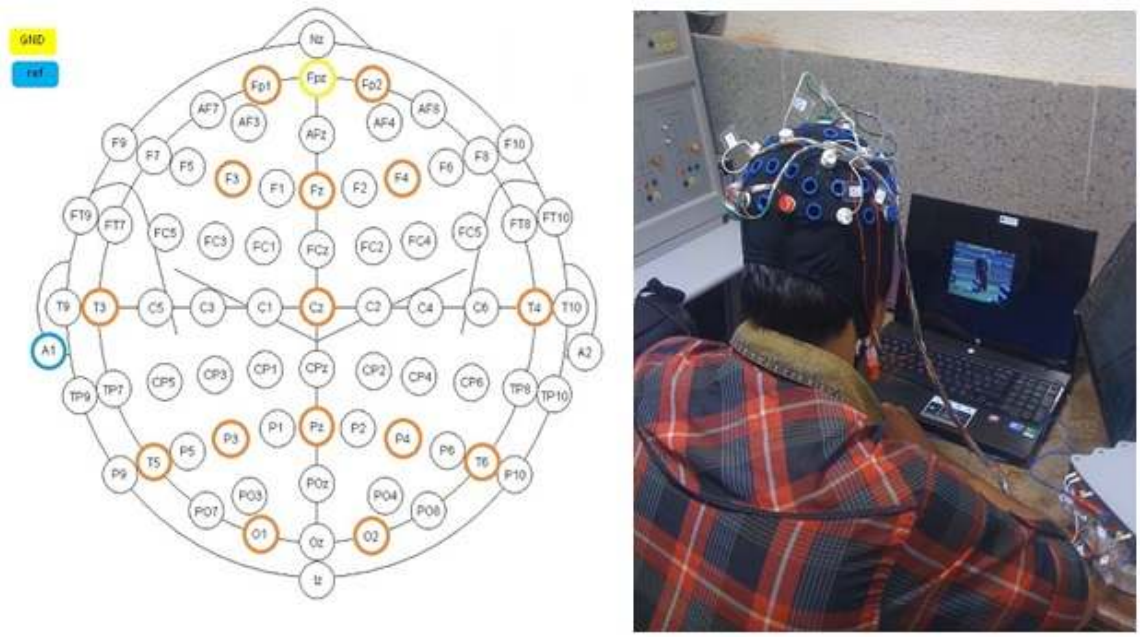

Figure 1: The place of the electrodes (left) and a subject recording signal (right)

The electrooculogram (EOG) was recorded byan additional electrode placed below the left eye (outer canthi) with A1 serving as the reference electrode.

METHODS

Based on the assumption that brain composed of various sources with each adapted for a specific activity, EEG signals recorded from scalp were decomposed into components by ICA algorithm, which were independent in terms of time. The fastICA method was used to separate 16 source components from 15 channels of EEG and one channel of EOG. The main problem of ICA algorithm is that it is ill-posed. In other words, in each run of ICA algorithm, the order of the independent components will change. To solve ill-posed problem, we need additional information proportional to the chaotic nature of the signals. Since the entropy of a variable can be interpreted as the degree of information provided by that variable, the entropy of sources was used as a criterion to handle ill-posed problem of ICA. Another problem associated with fastICA is that in each run of this method, after whitening, the number of converged sources of the output may not be the same as the number of observations in the input, which is equal to 16 in this test. Thus, we only used the trials in which the number of fastICA output was at least equal to 13 independent components and discarding the rest.

As reported in previous studies, ICA can effectively separates EEG artifact sources (such as blinks, muscle activity, electrical noise, and cardiac signals) from the original EEG, which is considered asindependent cortical source activities. Consequently, to remove these artifact components, first all the sources were sorted out based on descent order of entropy, and then the top ten independent components were retained for each trial with those with minimum entropy being discarded. It is because we have assumed that artifacts, especially EOG, have minimal entropy compared to other available sources in the brain. To verify this assumption, the correlation between discarded components (those with minimum entropy) and EOG was assessed, showing that in most cases, the correlation coefficient between the source and EOG signal was greater than 0.6.

Also, RQA was used for the remaining ten sources to study their chaotic behavior. Time delay was estimated as the first minimum of the Average Mutual Information, and embedding dimension was calculated by

the false nearest neighbor technique. The mean embedding dimension was equal to 3 and the mean time delay was equal to 4 that we considered them for all the trials. Finally, 12 features including Recurrence rate, Determinism, Averaged diagonal line length, Length of longest diagonal line, Entropy of diagonal line length, Laminarity, Trapping time, Length of longest vertical line, Recurrence time of 1st type, Recurrence time of 2nd type, Recurrence time entropy and transitivity were extracted for ten independent sources in each trial.

RESULTS AND DISCUSSION

After extracting RQA features for each source sorted by entropy, it was observed that the differences were insignificant for emotional states while the empirical results of each state were different. Accordingly, a simple classifier, based on RQA features, was used for clustering and forming the primary knowledge in positive, negative and neutral emotional states. A KNN Classifier with k = 1 was considered and the genetic algorithm was used to find the optimal feature space. 60% of the data was used for training, 20% for validation and the remaining 20% was used to test system performance. The results of the system performance have been shown in Table 1. In this table, the columns represent 10 independent sources that were sorted out based on maximum to minimum entropy. In other words, the first source has the maximum and the 10th source has the minimum entropy. Each row of the table represents the sensitivity, which is the number of the target emotional state identified accurately by KNN Classifier divided by the total data of the same emotional state.

Table 1: Performance of the system in recognizing three emotional states in independent sources by genetic algorithm and KNN

	1	2	3	4	5	6	7	8	9	10
Positive sensitivity	44.21±5.91	50.54±9.37	33.12±5.76	36.73±7.11	49.29±8.36	47.14±7.07	41.35±6.91	49.15±6.64	45.68±7.18	56.52±7.59
Negative sensitivity	41.72±9.12	44.29±7.47	40.52±7.01	38.89±7.88	57.23±9.29	41.09±7.4	49.54±7.41	55.80±6.89	56.27±6.48	42.54±6.86
Natural sensitivity	35.84±7.69	47.35±6.60	36.74±7.81	38.74±6.35	70.61±8.87	39.45±6.53	42.67±7.11	46.69±5.64	57.52±6.52	39.07±7.51
Overall accuracy	40.55±3.61	47.41±4.41	36.61±3.75	37.88±4.29	59.00±4.72	42.38±4.09	44.52±3.86	50.47±3.77	53.25±2.62	45.91±3.69

As shown in table 1, better results in recognizing positive emotional state were achieved at source 10 with a sensitivity of 56% .For the negative and neutral emotional states, the better results were achieved at sources 8 and 9 with a sensitivity of 56% and source 5 with a sensitivity of 70%, respectively.

According to the results, the better sensitivity for neutral, negative and positive states is found at source 5, 8 and 10, respectively. Accordingly, there seems to be a relation between neutral emotions and source 5, negative emotions and source 8 and positive emotions and source 10. To verify the accuracy of this interpretation, we compared various emotions in pairs.

To recognize both positive and negative emotional states, another KNN with a genetic algorithm was used.

The results of the classifier performance are shown in Table 2.

Table 2: Performance of the system in recognizing positive and negative emotional states in independent sources by genetic algorithm and KNN

	1	2	3	4	5	6	7	8	9	10
Positive sensitivity	59.60±7.33	65.01±8.35	53.53±8.78	53.46±7.16	68.41±6.45	58.35±7.45	70.01±6.46	70.45±6.85	59.95±6.47	80.42±7.35
Negative specificity	55.81±8.52	61.11±7.09	59.71±9.46	56.40±8.68	68.29±4.97	57.86±7.07	79.14±6.94	79.74±6.69	67.42±6.98	69.06±6.72
Overall accuracy	57.58±4.62	63.08±5.24	56.70±5.01	54.62±5.49	68.29±3.51	58.04±5.23	74.54±4.97	74.70±4.31	63.50±3.84	74.87±3.99

Table 3 presents the results of recognizing both positive and neutral emotions by a KNN along with genetic algorithm. In Table 4, the results of recognizing both negative and neutral emotions have been shown by a KNN and genetic algorithm.

Table 3: Performance of the system in recognizing positive and neutral emotional states in independent sources by genetic algorithm and KNN

	1	2	3	4	5	6	7	8	9	10
Positive sensitivity	59.41±7.44	65.23±7.59	53.74±8.86	51.63±7.86	68.53±5.46	64.69±6.44	55.45±6.20	63.83±8.00	78.08±7.64	82.55±7.11
Neutral specificity	59.33±7.53	69.51±7.63	49.68±6.96	57.66±6.89	76.74±6.91	58.29±7.42	53.93±7.51	66.97±7.03	74.05±6.23	76.09±7.02
Overall accuracy	59.12±4.12	67.25±5.99	51.58±5.86	54.62±5.31	72.58±3.29	61.45±4.82	54.41±4.22	65.54±5.39	76.00±5.24	78.87±4.96

Table 4: Performance of the system in recognizing negative and neutral emotional states in independent sources by genetic algorithm and KNN

	1	2	3	4	5	6	7	8	9	10
Negative sensitivity	63.40±8.64	52.39±6.54	60.34±8.75	64.63±6.54	77.06±7.37	59.59±6.71	73.34±6.71	79.51±7.09	79.30±8.43	52.47±6.84
Neutral specificity	59.11±8.44	59.60±7.80	56.31±6.11	57.81±8.21	82.78±6.57	59.60±6.69	71.54±7.69	68.05±6.75	76.01±8.30	56.98±8.09
Overall accuracy	61.20±4.57	55.87±4.21	58.29±4.94	61.04±4.47	80.04±4.20	59.41±3.72	72.54±4.04	73.58±4.35	77.41±5.18	54.79±5.38

The results of Tables 2, 3 and 4 also confirm the relation between emotions and sources. According to the Table 2, the best recognition forpositive emotional state was achieved at source with a sensitivity of 80%,whereas for negative emotional state, this was achieved at sources 7 and 8 with specificity of 79%.

Moreover, the results of Table 3 for positive and neutral states suggest source 10 with a sensitivity of 82% for positive state and source 5 with a specificity of 77% for neutral emotional state. The results of Table 4 also shows that for negative emotional states, the best sensitivity was achieved at source 8 with a valueof 79% and for neutral emotional state, the best specificity was achieved at source 5 with a value of 82%.

These results indicate that a simple KNN Classifier is able to recognize three emotional states with acceptable precision. This shows that Shannon entropy has been able to sort out the independent sources decomposed by the fastICA method and resolve ill-posed problem of this algorithm in recognizing emotional states. The results also suggest that there is a set of independent sources in human's brain which are related to emotions and can be represented using chaotic and non-linear dynamic methods. Moreover, it was found that sources representing neutral emotions had the highest entropy compared to the sources related to negative emotions while these emotions also had higher entropy than sources representing positive emotions. This means that higher order can be observed in positive and negative emotions, and that sources with lower entropy are capable of recognizing emotions.

In the previous studies, the proposed systems that used complex classifier with only EEG signals to recognize emotions had inadequate efficiency. Compared to them, although this study has used a simple classifier, better results were achieved. This approves the idea that emotions are produced in independent sources within the brain.

CONCLUSION

Similar to the human relations, human-machine interfaces have gained popularity these days. In this regard, emotion recognition in humans is attracting growing attention. In this study, a new method to evaluate the relationship between the independent sources of the brain and emotions was introduced. It appears that there are independent sources in the brain with chaotic behavior which are responsible of recognizing and producing emotions. In keeping with this idea, we obtained higher accuracy in recognition and classification of emotions, which presents a new method for automating brain

computer interface. Apparently, a more complex classifier yields higher accuracy in recognizing different emotional states.

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