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Evaluating the Determinism of Brain Signals Using Recurrence Chaotic Features in Positive, Negative and Neutral Emotional States in the Sources Achieved From ICA Algorithm

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ABSTRACT

Background: This study investigates electroencephalogram (EEG) signals in positive, negative and neutral emotion states.
Method: It is assumed that the brain draws on several independent sources in any activity that are observable by independent component algorithm (ICA). To overcome the problem of ill-posedness of extracted components from ICA algorithm, first these sources are sorted out by Shannon entropy and then based on these sources, the features of trapping time and determinism of Recurrence Quantification Analysis (RQA) are extracted as representative of determination.
Result: The results show that the degree of determinism of sorted sources related by emotions is significantly different over time and in three positive, negative and neutral states. The degree of determinism increases in neutral, positive and negative emotional states respectively.

Keywords: Emotion; Electroencephalogram (EEG); Independent Component Analysis (ICA); Recurrence Quantification Analysis (RQA); Determinism; trapping time

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INTRODUCTION

Emotion recognition, as a critical component of human communication and one of the major differences between humans and machines, is of utmost importance [1]. The importance of emotion recognition is especially visible in human-computer interface where machines need to recognize emotions and produce an appropriate reaction so that they can provide real efficiency. However, the main problem of an intelligent system in identifying emotions is that the factors involved in generation of different emotions are unknown [2,3]. Recent research on identifying the emotional states of individuals focus on sound processing, processing of facial movements and biological effects such as heart rate, skin resistance, blood pressure and brain electrical activity [4]. It seems that in the conventional sound and image processing methods used for identifying emotions, important factors such subjects' attempts to hide their inner feelings are not taken into account. It is claimed that critical signals such as brain signals are able to estimate true inner feelings of an individual without them being aware of it [5]. There are many ways to instill emotions including sound, film and demonstration of emotional images. However, in most studies, images are used to convey emotions. Visual stimulation has been shown to have the greatest effect on emotions, and the amount of information conveyed by a picture in a moment is much more than other methods [6-8].

The main idea of this study is that inside the brain, there are many different independent sources and brain activities are the produced by these sources and their interactions [9,10,11]. Thus, for each special emotion, there should be an independent source or the interaction of independent sources in the brain. Given the fact that in EEG signals are recorded from scalp sensors, and thus recorded signals represent the interference of various brain sources, it is not easy to extract information. In fact, main sources have more precise and accurate information than original EEG signals do and thus the changes in each source are more vivid when examined individually. Since these resources are not directly accessible, these scalp records or other methods used to achieve the main sources based on the recorded observations are the only available sources. Independent component algorithms (ICA) are able to rebuild main sources from the observations of sensor based on some assumptions [9,10].

ICA algorithm can extract brain activity information by independent components. One shortcoming of ICA algorithms in using extracted sources is that the order of these factors is not determined and it may vary in each implementation of algorithm [9]. To solve this problem, more information associated with the major features of the system and its resources is needed. One of the criteria related to the nature of the system is entropy, which presents the amount of information in a system or the degree of uncertainty. Previous studies have demonstrated that biological systems, especially brain systems, are characterized by complex dynamics [12]. These dynamic complexities could be demonstrated by spatial dimension occupied by the system data. Fractal dimension is a measure of how a fractal fills the entire space. Fractal dimension is used for the study of nonlinear dynamics. This dimension indicates the geometrical features of the absorption substrate. It can be said that as the absorption of the substrate increases, the degree of complexity and uncertainty of signal rises. Furthermore, the degree of this complexity can be achieved by the mutual information between samples of a signal. To do so, the delay in which mutual information functions observe their first relative minimum can be used. This delay can be identified based on the autocorrelation function where its value is closest to zero [13]. Such delay reveals that there is a minimum of the mutual information between a signal example and a few of its subsequent examples. Thus, the greater is the delay, the higher will be the signal certainty and the lower will be its complexity. In this study, first the emotional signals recorded by fast ICA algorithm are decomposed into independent sources and then sorted by the entropy. Finally, trapping time and determinism features of RQA for emotional signals are extracted and investigated in each source over time. In the rest of this paper, first, the study population, the method of emotion induction and the record of brain signals as described and then Recurrence Quantification Analysis (RQA) index, trapping time and determinism features extracted form RQA index are expressed. In the third section, using ICA algorithm and entropy criterion, independent sources are identified and sorted in each record and the results are presented. In the final section, the results of the study are discussed.

MATERIALS AND METHODS

Data recording protocol

This study was performed on 35 right-handed male volunteers with a mean age of 20.1+1.4. All participants were students without any history of physical or mental illness, who also had adequate rest in the last 24 hours. Moreover, they had not consumed any drug 48 hours before the test. All participants were informed that they could leave the trial whenever they desired.

Visual stimulation

Visual stimulations are colored images selected from the IAPS database. According to social structure theory, emotions are the outcome of intra-social interactions and regulations in each culture [14]. All images were evaluated by Iranian subjects, who were different from final participants of the study, and similar emotional responses in the selected images were received from the IAPS database. In this study, three sets of positive, negative and neutral images were used. Visual stimuli were presented randomly in positive, negative and neutral emotional blocks in each block with a 5 minutes break between emotional blocks to eliminate the emotional effects between blocks. Each blocks contained 10 emotional corresponding images and a show time of 5000 milliseconds for each image and a delay of 2000 milliseconds between images. Images were displayed on a 15.6 inch LED screen which was in a distance of 50 cm from the subjects. After displaying each block of emotional images, participants answered some questions about their feelings to ensure that they have observed the images carefully.

Signal recording

EEG signal was recorded by 15 Ag-AgCl electrodes in accordance with 10-20 international standard system by G-tec (Austria) system on the right and left hemispheres in channels Fp1, Fp2, F3, F4, Fz, T3, T4, T5, T6, Cz, P3, P4, Pz, O1, O2. Sampling frequency was equal to 512 with 0.5 to 70 Hz filters and electrode impedance was adjusted below 5 kilo ohm. EOG signal was taken from the left eye and A1 was considered as the reference electrode.

The main idea of this study is that the brain is composed of various sources each adjusted for a particular function. Accordingly, EEG signals recorded from the scalp are decomposed into time-independent components by ICA algorithm.

Fast ICA algorithm has been used to sort 16 elements of the source from 15 channels of EEG and a channel of EOG [9]. One of the problems of ICA algorithm is that in implementation of ICA algorithm, the order of independent component is not changed. To solve this problem, entropy criterion is used as a level of information available. As reported in the literature, ICA is able to effectively separate artifact sources of EEG, such as blinking, muscle activity, electrical interference and heart signals, from pure EEG which is considered as the activities of independent cortical sources. Therefore, to remove unwanted artifact components, first all resources are sorted based on maximum to minimum values of entropy. Then ten independent components of each signal record are kept and the rest of sources with minimum entropy is removed. It is supposed that artifacts, especially EOG, have the lowest chaos and entropy compared to other sources in the brain [17,18]. Thus, in each emotional stimulus, ten independent sources were obtained and sorted based on entropy.

According to Abdossalehi et al. research, the fifth, the eighth and the 10th source respectively relevant to neutral, negative and positive emotions for evaluating determinism of these three emotional states were considered [17].

To examine the degree of determinism of emotional signals, trapping time and determinism features of Recurrence Quantification Analysis (RQA) were extracted.

RQA is a method of nonlinear data analysis for the investigation of dynamical systems. It quantifies the number and duration of recurrences of a dynamical system presented by its phase space trajectory.

The recurrence quantification analysis was developed in order to quantify differently appearing recurrence plots (RPs) based on the small-scale structures therein. Recurrence plots are tools which visualize the recurrence behavior of the phase space trajectory of dynamical systems [15,16].

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 embedding dimension and time delay was calculated for each person by showing a special picture.

Determinism feature percent ratio between the number of the recurrence points forming diagonal lines longer than a fixed threshold and the total number of recurrence points. This variable discriminates between spurious recurrent points and those with specific diagonal line organization contain the information about the duration of a stable interaction. The longer the interactions are, the higher the Determinism value is. Processes with stochastic behavior cause none or very short diagonals, and thus we get low Determinism. Deterministic processes cause longer diagonals and less single, isolated recurrence points, and we get higher Determinism.

With trapping time feature we measure the mean time that the system will abide at a specific state (how long a state will be trapped).

RESULTS

At this stage, the determinism of emotional signals was ev1aluated by two criteria, trapping time and determinism features of RQA in a five-second duration. The variation of Determinism feature in all 3 independent sources, neutral, positive and negative emotional states are shown in Figure 1. For this feature, p_value results of ANOVA and T-test in positive-negative, positive-neutral and negative-neutral emotional states are shown. Table 1, 2 and 3 respectively shows the results for the 5th, the 8th and the 10th sources.

Besides, the variation of Determinism feature in the same sources are depicted in Figure 2. The vertical axis represents the mean and the range of variation around the mean in the measures obtained from each emotional recording, and the horizontal axis shows the beginning of calculation windows of the trapping time and Determinism features.

According to the Determinism feature's definition of RQA index, which is the distribution percentage of the lengths of diagonal structures, it is obvious that greater Determinism index between neighboring points increases the certainty of the signals. In the other word, an increase of the index results in a decrease in chaotic system property or the complexity of emotional brain activities. Therefore, it could be said that in the three independent sources, the determinism index in neutral emotional signals was greater than negative and positive emotional states in the same source and therefore, the complexity in the positive and negative states are higher

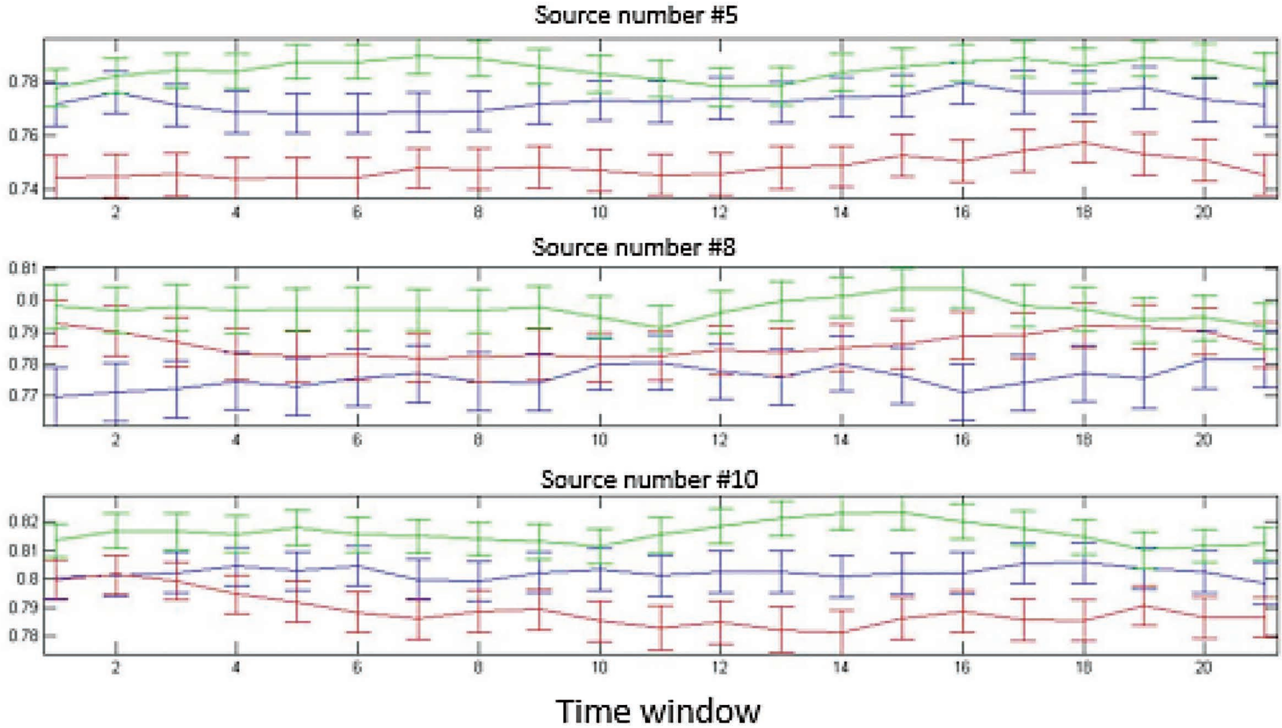

Figure 1. Determinism feature of RQA index for positive, neural and negative emotional states in 5, 8 and 10th sources achieved from ICA algorithm. The blue line for negative, green for neutral and red is shown positive states.

than the neutral states in the same source.

Moreover, in the 8th source that is related to the negative state, Determinism index of the negative state is in the lowest stage comparing to the positive and the neutral state; therefore, it reveals that the maximum of the complexity index according to positive and neutral state in this source.

Also, the minimum value of Determinism index in

Table 1. *P* value results of ANOVA and T test in making differences in positive-negative, positive-neutral and negative-neutral emotional states in the time windowed duration in the 5th source by Determinism feature

	***P* value**	**ANOVA**	**Positive-negative**	**Positive-neutral**	**Negative-neutral**
Time window	0-1000	0	0.02	0	0.54
	200-1200	0	0	0	0.52
	400-1400	0	0.02	0	0.17
	600-1600	0	0.02	0	0.11
	800-1800	0	0.02	0	0.03
	1000-2000	0	0.02	0	0.03
	1200-2200	0	0.05	0	0.02
	1400-2400	0	0.04	0	0.02
	1600-2600	0	0.03	0	0.11
	1800-2800	0	0.01	0	0.28
	2000-3000	0	0.01	0	0.38
	2200-3200	0	0.01	0	0.65
	2400-3400	0.01	0.03	0	0.55
	2600-3600	0	0.02	0	0.35
	2800-3800	0	0.05	0	0.29
	3000-4000	0	0	0	0.45
	3200-4200	0	0.04	0	0.22
	3400-4400	0.02	0.09	0	0.3
	3600-4600	0	0.02	0	0.25
	3800-4800	0	0.04	0	0.12
	4000-5000	0	0.01	0	0.16

Table 2. *P* value results of ANOVA and T test in making differences in positive-negative, positive-neutral and negative-neutral emotional states in the time windowed duration in the 8th source by Determinism feature

	P value	ANOVA	Positive-negative	Positive-neutral	Negative-neutral
Time window	0-1000	0.02	0.03	0.58	0
	200-1200	0.06	0.08	0.51	0.01
	400-1400	0.07	0.17	0.29	0.01
	600-1600	0.14	0.41	0.2	0.03
	800-1800	0.09	0.35	0.15	0.01
	1000-2000	0.14	0.49	0.15	0.03
	1200-2200	0.16	0.61	0.12	0.04
	1400-2400	0.12	0.45	0.14	0.03
	1600-2600	0.09	0.39	0.14	0.02
	1800-2800	0.34	0.85	0.2	0.14
	2000-3000	0.57	0.84	0.37	0.28
	2200-3200	0.22	0.53	0.22	0.06
	2400-3400	0.07	0.45	0.08	0.01
	2600-3600	0.12	0.6	0.09	0.03
	2800-3800	0.03	0.35	0.07	0
	3000-4000	0.01	0.09	0.12	0
	3200-4200	0.07	0.16	0.31	0.01
	3400-4400	0.15	0.14	0.6	0.05
	3600-4600	0.19	0.13	0.84	0.09
	3800-4800	0.49	0.44	0.66	0.23
	4000-5000	0.65	0.69	0.54	0.33

Table 3. *P* value results of ANOVA and T test in making differences in positive-negative, positive-neutral and negative-neutral emotional states in the time windowed duration in the 10th source by Determinism feature

	P value	ANOVA	Positive-negative	Positive-neutral	Negative-neutral
Time window	0-1000	0.26	0.92	0.1	0.11
	200-1200	0.16	0.97	0.07	0.06
	400-1400	0.14	0.72	0.04	0.09
	600-1600	0.07	0.24	0.01	0.14
	800-1800	0.02	0.19	0	0.05
	1000-2000	0.01	0.05	0	0.14
	1200-2200	0.01	0.1	0	0.04
	1400-2400	0.02	0.2	0	0.05
	1600-2600	0.04	0.14	0	0.17
	1800-2800	0.02	0.04	0	0.3
	2000-3000	0	0.04	0	0.09
	2200-3200	0	0.05	0	0.06
	2400-3400	0	0.02	0	0.02
	2600-3600	0	0.02	0	0
	2800-3800	0	0.06	0	0
	3000-4000	0	0.13	0	0.02
	3200-4200	0	0.02	0	0.12
	3400-4400	0	0.01	0	0.25
	3600-4600	0.12	0.13	0.01	0.42
	3800-4800	0.03	0.07	0	0.26
	4000-5000	0.02	0.17	0	0.07

the 10th source relates to the positive state results in an increase in the complexity in comparison to the neutral and the negative states.

Regarding the table 1, Although T test was done in 5th source related to neutral emotional state, maximum differences with $P<0.05$ threshold in determinism feature, is related to positive-negative and positive-neutral states. Moreover, difference between neutral and negative emotional states in this feature is just in the 800ms to 2400ms after presenting emotional picture.

The results of table 2 which is related to negative emotional states, illustrate maximum differences in

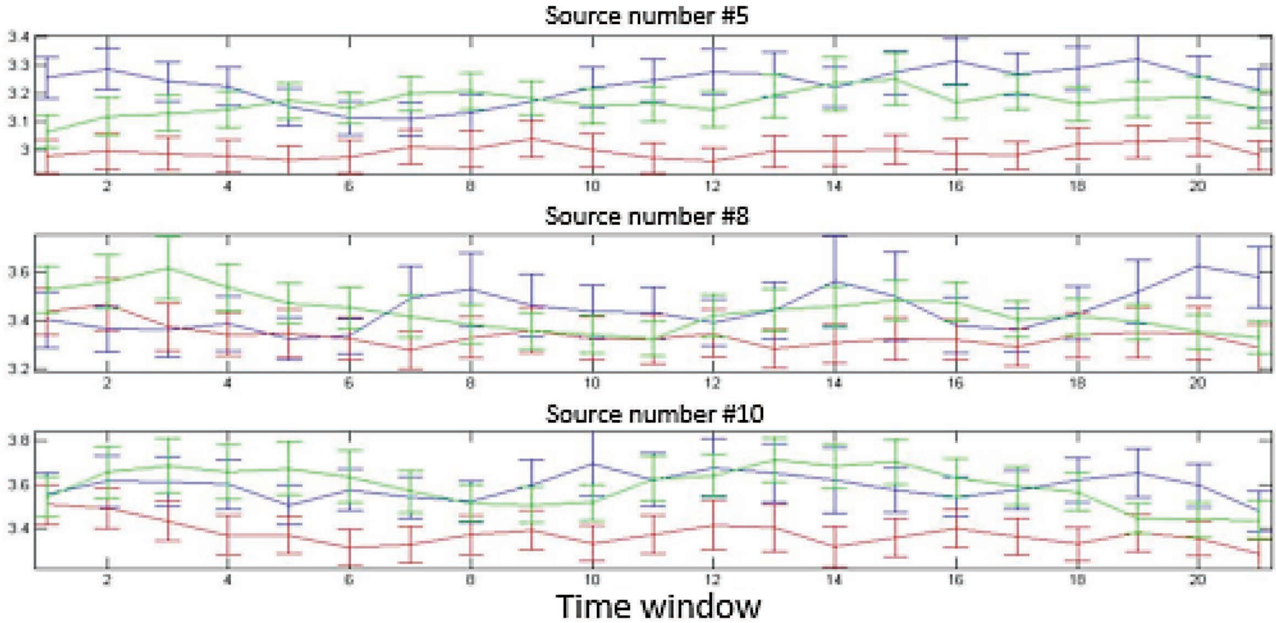

Figure 2. Trapping time feature of RQA index for positive, neural and negative emotional states in 5, 8 and 10th sources achieved from ICA algorithm. The blue line for negative, green for neutral and red is shown positive states.

negative states versus neutral states.Furthermore, the results of table 3 show maximum differences in positive states versus negative states. However, in the duration between 1800ms to 4400ms maximum differences is shown in positive states in comparison with negative ones and in 2300ms_400ms duration, maximum differences are shown in negative states vs neutral.

Trapping time feature in each source

The trapping time feature that results the mean of the length of the vertical line structures in a recurrence plot, is shown in figure 2 for 5th, 8th and 10th independent source related to neutral, negative and positive emotional states in 5 sec duration. Also for this feature, table 4 is shown the p_value in ANOVA and T test in positive-

Table 4. *P* value results of ANOVA and T test in making differences in positive-negative, positive-neutral and negative-neutral emotional states in the time windowed duration in the 5th source by trapping time feature

	P value	ANOVA	Positive-negative	Positive-neutral	Negative-neutral
Time window	0-1000	0	0	0.28	0.02
	200-1200	0.01	0	0.18	0.07
	400-1400	0.02	0	0.09	0.2
	600-1600	0.02	0	0.05	0.37
	800-1800	0.02	0.02	0	0.81
	1000-2000	0.08	0.09	0.03	0.66
	1200-2200	0.09	0.25	0.02	0.28
	1400-2400	0.08	0.16	0.02	0.39
	1600-2600	0.21	0.16	0.09	0.9
	1800-2800	0.04	0.02	0.06	0.5
	2000-3000	0	0	0.01	0.38
	2200-3200	0	0	0.01	0.2
	2400-3400	0.02	0	0.04	0.5
	2600-3600	0.04	0.01	0.03	0.92
	2800-3800	0.01	0	0.02	0.85
	3000-4000	0	0	0.01	0.15
	3200-4200	0	0	0	0.51
	3400-4400	0.01	0	0.07	0.2
	3600-4600	0	0	0.06	0.15
	3800-4800	0.06	0.02	0.09	0.47
	4000-5000	0.02	0	0.04	0.46

negative, positive-neutral and negative-neutral emotional states in the 5 sec duration and in the 5th source. Table 5 is shown the same relations in 8th source and table 6 shows the same relations in 10th sources.

According to definition of trapping time, increasing of this feature, means that duration of presenting a trajectory in a given phase space state was over the limit it causes equivalently increasing the system's intermittency. Hence, regarding figure 2 in 5th independent source, average of intermittency in negative emotional states was higher than average of this feature in positive and neutral states in the same source and intermittency of

Table 5. *P* value results of ANOVA and T test in making differences in positive-negative, positive-neutral and negative-neutral emotional states in the time windowed duration in the 8th source by trapping time feature

	***P* value**	**ANOVA**	**Positive-negative**	**Positive-neutral**	**Negative-neutral**
	0-1000	0.66	0.82	0.49	0.38
	200-1200	0.42	0.48	0.55	0.16
	400-1400	0.19	0.93	0.13	0.12
	600-1600	0.34	0.74	0.14	0.28
	800-1800	0.46	0.84	0.35	0.19
	1000-2000	0.47	0.91	0.31	0.27
	1200-2200	0.33	0.15	0.24	0.64
	1400-2400	0.43	0.24	0.66	0.4
	1600-2600	0.71	0.51	0.99	0.49
	1800-2800	0.66	0.42	0.88	0.47
Time window	2000-3000	0.65	0.45	0.98	0.4
	2200-3200	0.85	0.73	0.54	0.81
	2400-3400	0.38	0.24	0.15	0.98
	2600-3600	0.36	0.21	0.18	0.6
	2800-3800	0.55	0.39	0.16	0.93
	3000-4000	0.49	0.66	0.15	0.5
	3200-4200	0.59	0.55	0.22	0.69
	3400-4400	0.76	0.54	0.47	0.92
	3600-4600	0.51	0.33	0.72	0.41
	3800-4800	0.1	0.1	0.95	0.05
	4000-5000	0.07	0.06	0.67	0.05

Table 6. *P* value results of ANOVA and T test in making differences in positive-negative, positive-neutral and negative-neutral emotional states in the time windowed duration in the 10th source by trapping time feature

	***P* value**	**ANOVA**	**Positive-negative**	**Positive-neutral**	**Negative-neutral**
	0-1000	0.93	0.71	0.77	0.93
	200-1200	0.54	0.38	0.28	0.8
	400-1400	0.25	0.19	0.11	0.65
	600-1600	0.14	0.09	0.06	0.72
	800-1800	0.1	0.26	0.03	0.24
	1000-2000	0.04	0.03	0.02	0.66
	1200-2200	0.11	0.08	0.04	0.82
	1400-2400	0.39	0.24	0.22	0.95
	1600-2600	0.31	0.15	0.31	0.49
	1800-2800	0.05	0.02	0.08	0.27
Time window	2000-3000	0.15	0.06	0.06	0.96
	2200-3200	0.21	0.09	0.11	0.79
	2400-3400	0.13	0.12	0.02	0.71
	2600-3600	0.05	0.07	0	0.69
	2800-3800	0.04	0.06	0	0.31
	3000-4000	0.18	0.19	0.03	0.42
	3200-4200	0.11	0.05	0.03	0.86
	3400-4400	0.04	0.01	0.02	0.66
	3600-4600	0.08	0.03	0.49	0.1
	3800-4800	0.12	0.05	0.4	0.21
	4000-5000	0.22	0.08	0.15	0.75

neutral states was between positive and negative states.

Therefore, certainty in neutral state is less than negative and more than positive state in 5th source. In other words, complexity in natural state is less than positive and more than negative state in 5th source. Also in 10th source which is related to positive state, intermittency of positive state versus neutral and negative states is the least amount that means increasing the complexity of positive state in related source versus negative and neutral states. This result is as the same as the result of Determinism feature in 10th source.

Regarding result of table 4, Although T test was done in 5th source related to neutral emotional state, maximum differences with $P<0.05$ threshold in trapping time feature, is related to differences between positive-negative and positive-neutral states. Moreover, it didn't show any differences between neutral and negative emotional states in 5th source. Also the results of table 5 show no difference of trapping time feature in 8th source for each pair of emotional states.

In table 6 related to positive state (10^{th} source), trapping time feature could have done difference in positive versus neutral and negative state just in some durations.

DISCUSSION

Emotion recognition in humans is a key point in the relationship of humans and machines. In this study, a new evaluation of the complexity of different emotions in independent sources of brain was presented. It seems there are independent sources in the brain responsible for identifying and producing emotions, which demonstrate a chaotic behavior. This study shows that the degree of determinism in different brain sources in positive, negative and neutral emotional states makes a significant difference. These results indicate that the degree of complexity and uncertainty in signal with positive emotional state is higher than negative state. In other words, the degree of determinism in negative emotional state is greater than positive emotional state and the extent of determinism in neutral emotional states is higher than other emotional states. This can be due to the fact that when the brain is involved in positive or negative emotions, the minimum determinism is achieved. In other words, the complexity of the brain during the appearance of positive and negative emotions will have its highest value in comparison to the neutral state.

According to the results of Table 1 and 2, there was not a significant difference between negative and neutral emotional states in most independent sources, though this difference was significant between positive and negative emotional states as well as positive and neutral emotional states. Moreover, the diachronic investigation of three positive, negative and neutral emotional states based on the p-value <0.05 in Table 3 and in the time interval between 1400 and 3200 milliseconds revealed that the lowest significant difference was between negative and neutral emotional states and most significant differences were achieved from the results of paired t-test in sources with low entropy, especially in the seventh source. In other words, the highest degree of separation for the three emotional states was achieved at the seventh source. As shown in this table, the highest significant difference with respect to p-value quantities for separation of the positive emotional state was achieved at the tenth source whereas for the negative emotional state, it was achieved at seventh and eighth sources. This finding is consistent with the table 4-6 and literature. Thus, it can be concluded that the best time for emotional analysis is in the interval between 1800 and 3800 milliseconds, suggesting that emotions are completely recognized and a distinctions have been made between three states. Also, the best resources for emotion recognition are independent sources with minimal entropy.

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