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The relation of susceptibility levels of hypnosis and different mental tasks

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Abstract The analysis of electroencephalogram (EEG) signals plays an important role in a various applications. EEG during pure hypnosis has different characteristics compared to normal non-hypnotic EEG especially in the frontal area of the brain. The purpose of this paper is to examine whether there is any similarity between different levels of hypnosis susceptibility and mental tasks using Fuzzy Similarity Index (FSI) method. In the first step, some of nonlinear features of EEG signals extracted; the next part of this method is to calculate the similarity between the features set of the reference segment (mental tasks) and the test segment (hypnosis signal) using fuzzy measure. Our results demonstrate that FSI is suitable for discriminating the relations between different status of brain activity in the non-hypnotic and hypnosis EEG signals. The more complex mental task, the behavior of the brain is more like a hypnotic state. Our results confirm previous ones that more activity of the right hemisphere during hypnosis was reported in right-hand subjects.

Keywords Hypnosis · EEG · Fuzzy Similarity Index · Mental task · Hemisphere

1 Introduction

In clinical applications, hypnotherapy can give solutions to some of neurological disorders like schizophrenia, Parkinson, epilepsy, migraine, psycho-physiological diseases like anxiety, obsession, pain control, quitting unhealthy habits, weight loss and dietary control [1]. Throughout history, different aspects of hypnosis have been challenged. A review of recent studies in neuroscience filed, based on EEG signal processing, image processing including computerized tomography (CT) scans, positron emission tomography (PET) scans, magnetic resonance imaging (MRI) and other methods of research shows that hypnosis represents the operating states of the brain, in regard to selective attention and dis-attention processes [2].

During the hypnosis process, high hypnotizing subjects are more apt to show does not have any volition on their actions, and low hypnotizing subjects show more intentionally [2]. When receiving hypnotic suggestion, brain subsystems associated with automatic functions are more active in high hypnotizing subjects.

Nowadays, the hypnosis susceptibility level is determined based on some well-known subjective tests, which try to measure to what extent subjects adjust to the behavior of different hypnotizing groups [3–5]. However, these tests suffer from some disadvantages in the determination of hypnosis susceptibility levels such as:

(1) Some steps of these methods may prevent entering into deep hypnosis,
(2) Since these methods are subjective, the result depends on the subject's responses,
(3) The time duration of these clinical tests is too long, about 45 min, causing fatigue and inattention of subjects, which leads to reducing the depth of hypnosis trance.

Therefore, to avoid the drawbacks of these subjective clinical tests, researchers are looking for new methods to identify the hypnosis susceptibility level based on non-subjective

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measures, such as EEG [6]. Their method is based on EEG feature extraction. Some of these features were considered in previous studies [6,7].

A brief review of studies on hypnosis signals shows that researchers have long considered the behavior of the brain in this status and find interesting results. Sabourin and colleagues show that in high hypnotized subjects, the mean theta power is more pronounced than in low hypnotized subjects [7]. This theta activity was visible in frontal, central and occipital derivations during resting non-hypnotic baseline. Lubar and colleagues tried to find in which conditions there exist differences between high and low hypnotic susceptible subjects [8]. Their research was based on fast Fourier power spectral analysis of the EEG signal. The signals were recorded before and during hypnotic tasks from frontal–temporal and occipital–parietal locations. They found significant dependencies on electrode location, different frequency domains of EEG and hypnotic tasks. However, no main effect differences were obtained based on hypnotic susceptibility. Graffin and colleagues reported that highly susceptible individuals displayed a decrease in EEG theta activity whereas the low-susceptible subjects showed an increase in EEG theta activity after hypnosis induction, and similar to theta activity, alpha activity increased as the induction duration continued [9].

Results of previous research indicate that changes in different EEG-frequencies occur in association with hypnosis; however, their results cannot be compared with each other due to differences between processing methods and criteria in selecting subjects. These studies reported various differences between high and low hypnotized subjects, but there is no complete agreement between their findings. However, a considerable number of these approaches showed a strong relationship between theta and levels of hypnosis susceptibility [10,11].

Although so far several studies performed on hypnosis and its features, still there are some interesting aspects that remain unexplored. To the best of our knowledge, none of the above-mentioned studies assessed the relation of hypnosis and normal non-hypnotic mental tasks and their properties. Moreover, no previous study reports a reliable metric for tracking the mental status of the patients. Finding the relationship between different mental tasks and hypnosis levels of susceptibility can help the physicians using the mental tasks that show the similar behavior to hypnosis, in cases where hypnosis cannot be used to treat the patients.

In this study, we compared hypnosis signal with different mental tasks in normal EEG to examine the relation and the similarity between complex normal mental tasks and hypnosis. In addition, we analyzed the natural hypnosis in front–back and left–right hemispheres to find whether there is any significant relation between the levels of hypnosis susceptibility and activity of the brain's hemispheres. Due to the robustness and good results of Fuzzy Similarity Index method in processing of EEG [12,13], we decided to use it in our research.

In this paper, the characteristics of the data and the Fuzzy Similarity Index method are introduced in Sect. 2. Section 3 includes an explanation of extracting features. The introduction of the statistical analysis is in Sect. 4. The results and conclusion are brought in Sects. 5 and 6, respectively.

2 Data and method

2.1 Recordings and subjects

EEG data used in this study were collected by Nasrabadi [14] for his research on "quantitative and qualitative evaluation of consciousness variation and depth of hypnosis" [14]. The data were collected from 32 right-handed volunteer males and were sampled at 256 Hz. EEG data recorded from 19 channels according to the international 10–20 system (Fig. 1).

Hypnosis induction was performed by playing an audiotape based on the Waterloo–Stanford criterion [15,16]. Therefore, the method and duration of hypnosis induction were the same for all the subjects. To do so, a 45-min audio file was provided; therefore, all the subjects were placed under the equal circumstances. The first 15 min of audio file were assigned to the hypnosis induction and the remaining 30 min related to 12-item Waterloo–Stanford group scale (WSGS) of hypnosis susceptibility measuring. In WSGS method, the subjects fill in the form after their trance, and then based on their answer in the form, a hypnosis susceptibility score (a number between 12 and 60 according to the WSGS guidelines) is determined for each subject.

Based on these scores, the subjects were divided into the low (12< WSGS scores <22), medium (23< WSGS scores <41) and high (42< WSGS scores <60) hypnotized groups. In current database, four subjects were categorized as low, 18 subjects as medium and 10 subjects as high hypnotized.

Before starting the hypnosis suggestions, the subjects requested to execute three mental tasks and data from all of

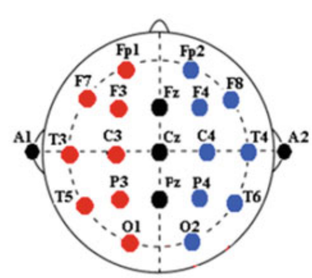

Fig. 1 Electrode positions based on 10–20 standards

the electrodes reordered during each task. These three tasks described as:

Task 1: Baseline measurement

No mental task performed; subjects told to be relaxed and try to think of nothing in particular.

Task 2: Numerical multiplication

A numerical multiplication was given to the subjects that should be solved mentally. It is important to mention that the subjects could not find the answer of the multiplication during the EEG recording.

Task 3: Geometric figure rotation

A 3D block figure was shown to the subject and instructed to visualizing rotation of the object about an axis (Fig. 2).

To explore the relation of hypnosis susceptibility levels and similarity of right–left and front–back hemispheres during the hypnosis procedure, 16 and 14 channels of electrodes placed at the Fp2, Fp1, F8, F4, F3, F7, T4, C4, C3, T3, T6, P4, P3, T5, O2, O1 (right-left) and Fp1, Fp2, F3, F4, Fz, Pz, P3, P4, F8, F7, T6, T5, O1 and O2 (front-back) locations were chosen, respectively.

2.2 Feature extraction

Although Similarity Index method is usually performed with two features (energy and entropy), we decided to find the best features, which could help us find whether there is any relation between hypnosis susceptibility levels (low, medium and high) and three different mental tasks. Therefore, we examined Similarity Index method with different sets of features which are summarized in Table 1.

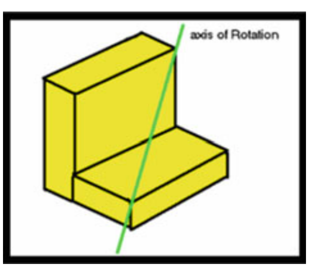

Fig. 2 3D block figure for visualizing rotation in Task 3

Table 1 Feature sets

Number of sets	Feature sets
1	Energy, entropy
2	Entropy, Higuchi
3	Energy, entropy, low frequency band
4	Energy, entropy, high frequency band
5	Energy, entropy, frequency band (both low & high)
6	High frequency band
7	Low frequency band

2.2.1 *Wavelet coefficients*

Often, there are five broad spectral bands of EEG signal from the clinical interest: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), which can be divided into two bands (beta1 and beta2). Above five frequency bands can be extracted by using a discrete wavelet transform. In this study, we consider the wavelet coefficients at each level ($j = 1, \ldots, 5$) to find the relation between the hypnosis signals (duration of 15 min) and three mental tasks (duration of 30 s).

For a given signal, $s(t)$ initially represented by means of its coefficients at resolution 0, the wavelet decomposition can be written as follows:

$$\begin{aligned} s(t) &= \sum_{k=-\infty}^{+\infty} c_0(k)\varphi(t-k) \\ &= \sum_{k=-\infty}^{+\infty} c_N(k)\varphi(2^{-N}t-k) \\ &\quad + \sum_{j=1}^{N}\sum_{k=-\infty}^{+\infty} d_j(k)\psi(2^{-j}t-k) \\ &= A_N(t) + \sum_{j=1}^{N} D_j(t) \end{aligned} \tag{1}$$

The first term in the right-hand member of Eq. (2) is the approximation at level N, while the second term is the sum of details. The quantities $d_j(k)$ are the wavelet coefficients. Functions $\varphi(t)$ and $\psi(t)$ named scaling function and wavelet function, respectively. The second represents the signal high frequencies, whereas the first describes smooth components. Eq. (1) implements a multiresolution analysis of the signal, i.e., the signal decomposed in N details and one approximation. The level of decomposition often chosen based on a desired cutoff frequency. If the analysis extended to all levels of details, we have the complete wavelet expansion:

$$s(t) = \sum_{j=1}^{N}\sum_{k=-\infty}^{+\infty} d_j(k)\psi(2^{-j}t-k) \tag{2}$$

2.2.2 *Energy*

According to Eq. (1), wavelet coefficients essentially quantify the strength of the contribution of each wavelet, at the sample time and scale j. The energy at different decomposition levels (from 1 to N) is the energy of wavelet coefficients $d_{j,k}$, and in order to simply description, the energy of scaling coefficients c_k is defined as the energy at decomposition level $N+1$. Thus, the energy at each decomposition level is defined as:

$$E_j = \sum_k |d_{j,k}|^2 \quad j = 1, \ldots, N \tag{3}$$

$$E_{N+1} = \sum_k |c_k|^2 \tag{4}$$

In this research, E_j of selected signals were considered as one of the features. The entire quantitative coded using MATLAB and the Wavelet Toolbox.

2.2.3 Entropy

A measure estimated by the wavelet coefficients to provide quantitative information about the order/complexity of the signals is the wavelet entropy. It has also been used in several works concerning several issues such as the neurological status of the brain following global cerebral ischemia by hypoxic-ischemic cardiac arrest [17], EEGs ordering/disordering during sleep [18,19] and seizures [19,20]. The Shannon entropy gives a useful criterion for analyzing and comparing probability distribution; it provides a measure of any distributions. Shannon's entropy computed directly from the EEG by examining the probability distribution of the amplitudes of the data values:

$$SE = -\sum_{i=1}^{M} p_i \log(p_i) \tag{5}$$

Where, M is the number of bins in which the amplitudes of the EEG are partitioned and p_i is the probability associated with the i_{th} bin.

2.2.4 Higuchi fractal dimension

Fractal dimension used as a feature to track the complexity and self-similarity of nonlinear signals. It has a relation with entropy, and entropy has a direct relationship with the amount of information in a signal. It can be interpreted simply as the degree meandering (or roughness or irregularity) of a signal. Applying Higuchi's algorithm, we calculated fractal dimension value [21,22].

If we consider an EEG signal as a time sequence $x(1), x(2), \ldots, x(N)$, we may construct $x(1), x(2), \ldots, x(N)$ new time series x_m^k as:

$$x_m^k = \{x(m), x(m+k), \ldots, x(m + \lfloor (N-m)/k \rfloor k\} \tag{6}$$

For $m = 1, 2, .., k$ where m indicates the initial time value, $x(1), x(2), \ldots, x(N)$ indicates the discrete time interval between points (the delay) and $\lfloor a \rfloor$ means the integer part of a. For each of the curves or time series x_m^k constructed, the average length $L_m(k)$ computed as:

$$L(m,k) = \frac{(N-1) \sum^{\lfloor (N-m)/K \rfloor} |x(m+ik) - x(m+(i-1)|}{\lfloor (N-m)/k \rfloor k} \tag{7}$$

Where N is the length of time sequence and $(N-1)$ / $\{\text{int}[(N-m)/k] \times k\}$ is a normalize factor. Total average length $L(k)$ computed for all time series having the same delay k, but different m as:

$$L(k) = \sum_{m=1}^{k} L_m(k) \tag{8}$$

This procedure is repeated for each k ranging from 1 to $k_{\max}$. The total average length for k as delay; $L(k)$ is proportional to k^{-D} where D is the fractal dimension by Higuchi's method [23].

2.2.5 Frequency band

As mentioned above, EEG contains different specific frequency components, which carry the discriminative information. Normally, most waves in the EEG classified as alpha, beta, theta and delta waves. The definition of the boundaries between the bands is somewhat arbitrary; however, in most of applications, these are defined as delta (less than 4 Hz), theta (4–8 Hz), alpha (8–13 Hz) and beta (13–30 Hz), which can be divided into two bands (beta1 and beta2).

When the person draws attention to some specific type of mental activity, the alpha waves are replaced by asynchronous, higher frequency beta waves. Beta waves occur at frequencies greater than 13 Hz. Theta waves have frequencies between 4 and 8 Hz. They occur normally in parietal and temporal regions in children, but they also occur during emotional stress in some adults. Theta waves also occur in many brain disorders, often in degenerative brain states. Delta waves include all the waves of the EEG with frequencies less than 4 Hz, and they occur in very deep sleep, in infancy and in serious organic brain disease. Therefore, EEG contains different specific frequency components, which carry the discriminative information [23].

These frequencies represent well-known features in EEG studies, and therefore, in this research, we used their power as one of our features and into two groups: low (delta, theta and alpha) and high (beta1, beta2) frequency bands.

3 Fuzzy Similarity Index (FSI)

Fuzzy logic is a worthwhile technique in signal processing and classification. Biomedical signals are not always strictly repeatable and may sometimes even be contradictory. One of the most useful properties of fuzzy logic systems is that contradictions in the data can be tolerated. Furthermore, it is possible to discover patterns in data using trainable fuzzy systems, which can not easily detect by other methods [24].

The concept of similarity cannot be formulated as a simple mathematical model. It should be faced as an elaborate cognitive process. When the evaluation of similarity is based on knowledge of a human observer and qualitative features, it is better to model it as a cognitive process that pretends human similarity perception. The Fuzzy Similarity Index is one of these methods that showed good results in EEG signal processing especially in epileptic seizure prediction [12,13]. One of the simplest methods to identify the change of the system state is to compare the feature sets of the present state and previous ones. If both states are very similar, it means that the feature sets do not show a large change.

After the feature extraction process, a fuzzy membership function transfers the present and previous features as two fuzzy sets. Then, a standard Gaussian membership function is used to describe features calculated for each coefficient level *(j=1, 2,..., 5)*. The features can determine the parameters of the fuzzy membership function. The Gaussian function employed in the Similarity Index method leads to soft boundary results. The Gaussian function represents a fuzzy similarity between the neighbors and the points around [25]. Obviously, by this way, the fuzzy similarity of the data points is neither hard nor binary. The symmetric Gaussian function depends on two parameters σ and c as given by $f(x;\sigma,c) = \exp(-(x-c)^2/(2\sigma)^2)$. The parameters σ and c are determined by the mean and deviation of each feature (for example energy or entropy). Six membership functions are applied to describe the fuzzy character of each feature.

Applying the fuzziness process for each selected feature set, fuzzy sets (set A—hypnosis signal; set B—mental Task 1; set C—mental Task 2; set D—mental Task 3; set E—EEG signal of front–back hemispheres; set F—EEG signal of left–right hemispheres) can be obtained. For example; if a segment from the set A was taken as a reference segment, the Fuzzy Similarity Index among sets $A, B, C, D, E and F$ can be 0.97, 0.35, 0.40, 0.85.,0.31 and 0.22, respectively. As expected, the first value indicating the similarity between the segments from the set A is close to 1. The fourth value is also close to 1, which shows sets A and D have more similarity. The other values are close to 0, and these values indicate the significant differences between set A and the other EEG sets.

The closer the data points are, the more similar they become. When the width of the Gaussian function or the lengths of the EEG windowed changed slightly, the similarity does not change abruptly. Fuzzy sets obtained from the feature sets of the signals under study by repeating the fuzziness process. Suppose two fuzzy sets A and B and each set includes N features $x_1, x_2, \ldots, x_N$, a reliable and simple method can be used to compute the similarity between the two fuzzy sets, A and B as follows:

$$S(A,B) = \frac{\sum_{i=1}^{N}(1-|\mu_A(x_i)-\mu_B(x_i)|)}{N} \tag{9}$$

Where μ_A and μ_B are membership functions and $1 - |\mu_A(x_i) - \mu_B(x_i)|$ can be regarded as the similarity degree of fuzzy sets A and B on the features x_i. $S(A,B)$ is the average of the similarity degree of fuzzy sets A and B, called Fuzzy Similarity Index. $S(A,B)$ ranges from 0 to 1, which corresponds to the different similarity degree [25]. The larger the value of $S(A,B)$, the greater the similarity between the fuzzy sets A and B.

Decision making is performed in two stages: feature extraction by computing the features of each signal and computing Fuzzy Similarity Index of feature sets between the reference EEG signals and the other classes of EEG signals.

4 Statistical analysis

4.1 Analysis of variance (ANOVA)

Since the number of result Tables arising from comparisons was large, visual inspection of these Tables needs more time, and may be associated with faults, we used the Statistical Package for the Social Science (SPSS) software. This software includes some statistical analyses such as ANOVA [26].

This analysis helps us understand the relationship between a "dependent variable" which is assumed to be the hypnosis susceptibility levels of subjects and an "independent variables" which is considered to be the similarity of mental tasks to hypnosis signals. The dependent variable is the variable that we are trying to predict from the values of the independent variables. Therefore, before making any decision or conclusion about applying method, the results were tested by one-way ANOVA to find whether the extracted features can make a significant difference between three hypnotized groups. The P value of less than 0.05 was considered statistically significant.

4.2 Receiver operating characteristic (ROC) curve

ROC curve is a graphical representation of the trade-offs between sensitivity and specificity. It allows comparing features to find the best performing one and to compare performance of selected features. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a particular decision threshold [27]. A larger area under a ROC curve means that high agreement or the relationship between selected subjects ($0 \leq$ area below an ROC curve ≤ 1). In our research, ROC curve can indicates the probability to predict the hypnosis scale of a randomly selected hypnotized subject.

5 Results

In this research, Fuzzy Similarity Index method was applied to hypnosis EEG signals using different feature sets. Using statistical tests, the feature sets that could not make a significant difference between mentioned groups were omitted. Therefore, based on statistical test results, only the best features (the features with small P values, $P < 0.05$) were selected to present as results in Tables. In this way, the features that have no significant role in discriminating the relations were excluded, and hence, the feature dimension decreased.

The EEG signal of each subject was examined to find whether there was any similarity between the hypnosis signal and each of the three described mental tasks. As the recording duration of three tasks was short (30 s) and the hypnosis signal's duration was not the same as task (15 min), we used a sliding window in the comparison process. The length of this sliding window was defined to be the same as the mental task duration. Furthermore, we evaluated the ability of FSI to discriminate three hypnosis susceptibility levels by means of ROC curves.

If the area under the ROC curve is more than 0.8, the results could be reliable; the closer it is to one, the more reliable the result is. Tables 2, 3 and 4 show the features, discriminated channels P and ROC curve value for three different tasks.

Although different sets of features (entropy-energy, entropy-Higuchi-frequency band (high) and entropy-Higuchi-frequency band (low and high) could discriminate some channels in Task 1, ROC curve did not show any acceptable value so these discriminated channels did not consider as discriminating features.

In Task 2, only Fp2 & T6 with entropy and Higuchi features have acceptable ROC curve value, and in Task 3 with the feature set of entropy-Higuchi, entropy-Higuchi-frequency band (both low and high), ROC curve has the acceptable values in T6, F4, PZ, P3, and O2. There should be a trade-off between features set, ANOVA and ROC curve results. Selected channels of both ANOVA and ROC curve analyses represented in Fig. 3.

After comparison of hypnosis and three mental tasks, we analyzed the hypnosis signal of each subject in another point of view. In this step, we examined whether there is any similarity between left–right and front–back hemispheres separately during the hypnosis. In fact, in this section, the hypnosis signals of symmetric pairs of channels in the left–right hemisphere (FP1 & FP2, F3 & F4, F7 & F8, T3 & T4, C3 & C4, P3 & P4, T5 & T6 and O1& O2) are compared together to analyze whether there is any similarity between them. This process is repeated for symmetric pairs of channels (F7 & T5, FP1 & O1, F3 & P3, FZ & PZ, FP2 & O2, F4 & P4, F8 & T6) in the front–back hemisphere. In the first step, all of the features were extracted to compare these channels, and just like the previous section, the best features were selected based on statistical analysis.

The set of entropy, Higuchi and frequency band (low and high) features could discriminate C3 & C4 channels in the left–right hemisphere, and ROC curve showed an acceptable value. In the front–back hemisphere, F8 & T6 with energy and entropy features have the acceptable ROC curve value. Selected channels in front–back hemispheres and left–right hemisphere for both ANOVA and ROC curve analyses shown in Fig. 4.

Table 5 represents the best results obtained at left–right and front–back hemispheres with highest discrimination. In

Table 2 Features, discriminated channels, P value and ROC curve value of Task 1

Features	Discriminate channels	$P < 0.05$	ROC
Energy, entropy	O2	0.011	0.645
Energy, entropy, frequency band (low & high)	Fp2	0.033	0.656

Table 3 Features, discriminated channels, P value and ROC curve value of Task 2

Features	Discriminate channels	$P < 0.05$	ROC
Entropy, Higuchi	Fp2 & T6	0.015–0.028	0.812–0.858

Table 4 Features, discriminated channels, P value and ROC curve value of Task 3

Features	Discriminate channels	$P < 0.05$	ROC
Entropy, Higuchi	T6, F4, PZ, P3, O2	0.031, 0.021, 0.002, 0.014, 0.015	0.821, 0.850, 0.834, 0.818, 0.821
Energy, entropy, frequency band (both low & high)	Fp2, F4, O1	0.014, 0.044, 0.024	0.679, 0.696, 0.687

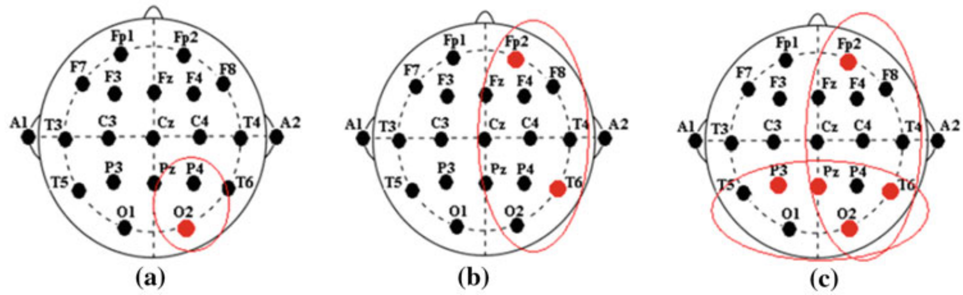

Fig. 3 Representation of selected channels with both ANOVA and ROC curve analyses, **a** Task 1 **b** Task 2 and **c** Task 3

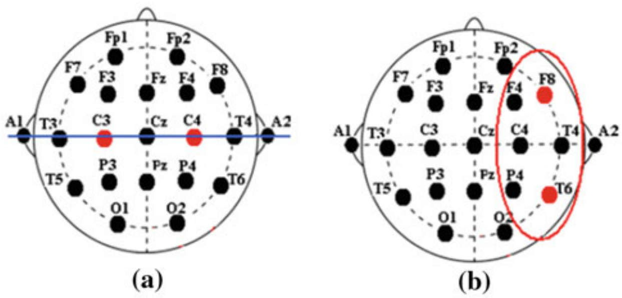

Fig. 4 Representation of selected channels with both ANOVA and ROC curve analyses, **a** *left–right* hemisphere **b** front–back hemispheres

the other word, this Table shows that during the hypnosis, which channels in left–right or front–back hemispheres have similar behaviors. The selected feature sets are the best features to show the similarity in the behavior of these channels in mentioned hemispheres.

6 Discussion

In current research, the EEG signal of each subject compared with three different mental tasks to find the significant similarity between hypnosis signal and these mental tasks.

In Task 1 (Baseline position): Results have shown that in Task 1, 1) Entropy & Higuchi, 2) Entropy, Higuchi and low frequency and 3) Entropy, Higuchi and low & high frequencies features are able to distinguish the various mental tasks. However, the other features have not shown acceptable results. Channels O2, P4 and C4 have been chosen more times regard other channels. Eventually, O2 was the selected channel by both ANOVA and ROC curve analyses using entropy & Higuchi features.

In Task 2 (Numerical multiplication): Entropy Higuchi features are able to differentiate the levels of susceptibility, and the discriminated channels are FP2 & T6. T6 electrode is located on the right side of the temporal lobe. Previous studies showed that temporal lobe activities and hypnotic susceptibility might share a common factor [28]. The temporal lobe is involved in auditory perception and is important in processing semantics in speech and vision.

In Task 3 (Geometric figure rotation): Entropy Higuchi were able to differentiate the three groups of susceptibility levels with T6, F4, PZ, P3 and O2 channels. It should be noted that in this task, more variety is seen in discriminated channels in comparison with the other two mental tasks. In addition, low frequency which includes theta band can discriminate some channels as a separate feature, but could not include in final selected channels due to the criteria choose for ROC curve analysis.

Theta band is associated with inhibition of elicited responses [29]. Moreover, it is reported that frontal functions become inhibited during hypnotic induction [30]. Therefore, it can be the reason to succeed of low frequency in the discrimination of channels.

If we divide the electrode positions into four equal parts by means of two imaginary lines in posterior–inferior and left–right directions, it can be expressed that the selected channels in all the tasks are mainly located in the right-posterior and right-inferior quarter. An important point that should be noticed is that hypnosis switches the brain electrical activities from left hemisphere to the right in right-handed subjects [31]. Therefore, this result expected, because all of the subjected in this study were right-handed. It can be also a proof to the fact that the right brain is more active during hypnosis.

On the other side, the results of Table 3 suggest that the complex activity generated by the brain in hypnosis may not be random, but indeed contain information concerning

Table 5 The best features, discriminated channels, *P* value and ROC curve values for left–right and front–back hemispheres

Features	Discriminate channels	$P < 0.05$	ROC	Hemispheres
Energy, entropy, frequency band (low)	C3 & C4	0.011	0.853	Left-right
Energy, entropy	F8 & T6	0.022	0.831	Front-back

the underlying nonlinear process of the brain. As the fractal dimension is an index of self-similarities in the signal, it can be suggested that hypnosis susceptibility levels have a significant effect on the EEG dynamics and can increase or decrease the signal's temporal correlations. It seems that as the latter activity is more complicated, the number of included brain areas is increased which behaved in a semi-hypnosis procedure.

Researchers have developed physiological markers of the stages of hypnotic induction and have shown that the hypnotic state characterized by left hemispheric frontal inhibition followed by the activation of right hemisphere posterior functions.

The frontal lobes are known as an emotional control center, and home to human personality [32]. These lobes are involved in motor function, problem solving, spontaneity, memory, language, initiation, judgment, impulse control and social-sexual behavior [33]. Moreover, there are important asymmetrical differences in the frontal lobes. The left-frontal lobe is involved in controlling language-related movement, whereas the right-frontal lobe plays a role in non-verbal abilities. Some researchers emphasize that this rule is not absolute, and in many people, both lobes are involved in nearly all behaviors.

In our research, significant similarities found between the front–back and left–right hemispheres separately in different hypnosis susceptibility levels. It means that during hypnosis, some of the channels show similar behaviors in the left–right and front–back hemispheres. We find the sets of features which can discriminate these channels.

At left–right hemispheres: The highest ROC curve results obtained in C3 & C4. It means that these channels have similar behaviors during hypnosis. These channels are located in posterior regions of the head, which is the origin of alpha wave with the frequency range of 8–13 Hz. This wave normally appears in conditions includes: relaxed/reflecting, closing the eyes and associated with inhibition control, seemingly with the purpose of timing inhibitory activity in different locations across the brain. Briefly, it is the brain wave state of mind associated with beginning of hypnosis.

Statistical analysis shows that C3 C4 channels were mostly selected ones in subjects with medium and high hypnosis susceptibility levels. It seems that our selected channels in the left–right hemispheres affirm the previous reports that as the hypnotic subjects begin to relax, the alpha brain wave state is achieved. It is mostly seen in high hypnotized subjects [3].

At front–back hemispheres: The highest ROC curve results achieved in F8 & T6 channels. Interestingly, these channels are focused in the right hemisphere of the brain. It was further confirmed that hypnosis switches the brain electrical activities from the left to the right hemisphere in right-handed subjects [34].

Location of T6 electrode and selection of this channel in the right hemisphere again reminds the role of frontal lobe in hypnosis induction [28]. Multiple brain areas including the lateral prefrontal cortex and posterior association cortex are functionally involved in working memory [34]. This area of the brain receives information from various lobes of the brain, and uses this information to carry out the body movements.

F8 is located in the back portion of the brain and is associated with interpreting visual stimuli and information. The primary visual cortex, which receives and interprets information from the retinas of the eyes, is located in this lobe of the brain.

The results of this research can be useful to clinicians and psychologists to choose the best treatment method based on the subject's hypnotic susceptibility level instead of using traditional subjective methods, due to wild application of hypnosis in treatments, changing the behaviors, overcoming bad habits, etc.

7 Conclusion

The analysis of EEG during hypnosis shows the switches of the brain electrical activities from the left hemisphere to the right in right-handed subjects as we expected. For continuing this research to clear other aspects of hypnosis, we have different suggestions that put under consideration for our future works:

The traditional clinical subjective methods have different problems in determining a subject's hypnosis susceptibility level. One of these problems is that these methods are subjective. Their results depend on the subject's answer and the reaction to the clinician's question. Therefore, inaccuracies of subjective answers make the results unreliable. The procedure of completing these questions and answers takes about 30 min, which may be boring for the subject and hypnotherapist. Moreover, the subject may be out of the hypnosis. Therefore, the EEG-based method could be a suitable replacement for these traditional subjective methods. Using this method can be considered in further research.

The database used in this research was included only male volunteers. It is suggested that more examination be done on women, to make a comparison between different genders. It should be clarified whether the sexuality can affect the results. To increase the credibility of the results, more signals should be used. It can be expected that by increasing the number of recorded data, the results can be judged better.

We recommend using most mental tasks to evaluate the relationship between complication of mental activities and hypnosis signal and finding a proper standard to classify the different susceptibility levels of hypnosis.

Higuchi as a nonlinear feature showed robust ability in the discrimination of various hypnosis susceptibility levels in this research. Therefore, it is recommended to check other nonlinear features by means of this method.

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