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INNOVATION

Recurrence quantification analysis of electroencephalograph signals during standard tasks of Waterloo-Stanford group scale of hypnotic susceptibility

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Abstract

The purpose of this study was to apply RQA (recurrence quantification analysis) on hypnotic electroencephalograph (EEG) signals recorded after hypnotic induction while subjects were doing standard tasks of the Waterloo-Stanford Group Scale (WSGS) of hypnotic susceptibility. Then recurrence quantifiers were used to analyse the influence of hypnotic depth on EEGs. By the application of this method, the capability of tasks to distinguish subjects of different hypnotizability levels was determined. Besides, medium hypnotizable subjects showed the highest disposition to be inducted by hypnotizer. Similarities between brain governing dynamics during tasks of the same type were also observed. The present study demonstrated two remarkable innovations; investigating the EEGs of the hypnotized as doing mental tasks of Waterloo-Stanford Group Scale (WSGS) and applying RQA on hypnotic EEGs.

Keywords

Electroencephalograph, hypnosis, hypnotizability/hypnotic susceptibility, recurrence quantification analysis, waterloo-stanford group scale of hypnotic susceptibility

History

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1. Introduction

Hypnosis is a mental state usually induced by a procedure known as hypnotic induction. There is a popular misconception that hypnosis is an unconsciousness state resembling sleep but contemporary neurological research indicate that it is actually a wakeful state of focused attention and extreme suggestibility with diminished peripheral awareness [1]—so-called altered state of consciousness [2].

To evaluate the hypnosis depth, various standards are employed. The most popular standards are as following: Stanford Hypnotic Susceptibility Scale (SHSS) [3], Stanford Hypnotic Clinical Scale (SHCS) [4], Waterloo-Stanford Group Scale of hypnotic susceptibility (WSGS) [5,6] and Hypnotic Induction Profile (HIP) [7]. Going through a standard scoring method, the patient undergoes the process of hypnosis. Then, he/she is asked to perform several tasks and the way the patient follows the orders and the extent of his/her submission to instructions lead the hypnotizer to assess the hypnotizability level of a patient and the hypnosis depth.

Due to the various physiological shifts the body may experience via hypnosis, a large number of scholars are doing research on hypnosis applying EEG, FMRI, PET, skin resistance measurement, heart rate, etc. In comparison with other methods, EEG signals recording have been applied the most since it is the most accessible and the simplest method. A great number of researchers concentrated on the power spectrum analysis of the hypnotic EEG signals [1,3,8–22]. According to the studies done so far, there exists the greatest solid relationship among EEG activity, hypnosis and hypnotizability in EEG theta frequency range [13,23,24]. However, some recent research did not apply the power spectrum analysis. Nasrabadi et al. [25] studied EEG signals in different mental status (baseline, tasks and hypnosis) in people with different hypnotizability levels. Lee [26] tried to make use of fractal analysis to examine EEG signals in both hypnotized and not-hypnotized states. Baghdadi [27] and Baghdadi and Nasarabi [28] looked into features extracted from hypnotic EEG using an improved empirical mode decomposing (EMD) algorithm. Ray [20] studied the difference between EEG signals' fractal dimension of lowly and highly hypnotizable subjects. Behbahani [29] and Behbahani and Nasrabadi [30] analysed the nature of hypnosis in right, left, back and frontal hemisphere in three groups of hypnotizable subjects by means of fuzzy similarity index method. Fingelkurts et al. [16] analysed operational synchrony in EEG signals between baseline, non-hypnotic and hypnotic metal states in highly hypnotizable virtuoso subject [16].

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So far, the majority of the research on EEG signals of the hypnotized subjects—regardless of the methods applied—have been performed during the induction period and the EEG signals of the hypnotized subjects while doing mental tasks of WSGS have not been examined. The current study intending to do so and studied the recorded EEG signals of three different hypnotizability levels (low, medium and high) while the subjects were engaged in performing some mental tasks (standard orders of WSGS). Therefore, the impacts of hypnosis depth and concentration rate on recorded signals of those three groups could be appropriately studied and dynamic variations of mental tasks could be detected and, to meet the purpose, recurrence quantification analysis (RQA) methods were employed.

Applying chaotic techniques of data analysis to EEG measurements is available in a great deal of research. Most of this research computed the correlation dimensions of EEG [31–34], while correlation dimensions are only well defined for a stationary time series generated by a low dimensional dynamical system moving around an attractor [35]. Therefore, these analyses do not suit EEG, which is a non-stationary signal. As opposed to the previously used methods, the new chaotic methods based on recurrence plots (RPs) provide us with the capability to analyse non-stationary signals [36–39]. Moreover, limitation of signals' length causes some errors in computing fractal dimensions [40]. While employing RQA, those limitations (stationarity, length and noise of signal) and errors are not encountered [39]. Thomasson [39] applied RPs on EEG to predict seizure. Marwan and Meinke [41], Schinkel et al. [42], Talebi [43] and Talebi and Nasrabadi [44] used RQA to study event-related potentials (ERPs). However, applying RQA on hypnotic EEG is performed in almost none of the reported investigations. By the means of RQA, the difference between the recorded EEG throughout the same activities but different hypnotizability depth-levels (low, medium and high) could be examined. Therefore, in this research, the existing difference of the dominant dynamics in these three groups with different hypnotizability and also the kind of differences were studied. Should any distinction of the extracted RQs between these three hypnotized groups be observed, those differences could serve as the criteria for hypnosis–depth determination to exert appropriate inductions; EEG examination during hypnosis provides the data for studying hypnosis stages and the transfer from one stage to another.

Therefore, the current study presented two important innovations in the analysis of hypnotic EEG; first, investigating the EEGs of the hypnotized subjects as doing mental tasks of WSGS and, second, applying RQA on hypnotic EEGs.

The subjects, the protocol followed in recording EEG signals applied in the current study and forming the RP of an EEG signal and estimation of its RQs are presented in section 2. In the Result and discussion section, the results of ANOVA among RQs of subjects with different hypnotizability levels while going through the same tasks are expressed. The conclusion includes a comparison between the obtained results and existing results of previous research carried out in the same field. Besides, suggestions to develop a detailed identification of a brain's governing dynamics during hypnosis are presented.

2. Method

In section 2.1 subjects are introduced and in section 2.2 features of the employed EEG are described. Then RQA is mentioned in section 2.3 and section 2.4 deals with surrogate data testing.

2.1. Subjects

The subjects of the study were 33 healthy men with an age range of 26–38 years, who were physician members of the Iranian Society of Clinical Hypnosis. All subjects featured in left hemisphere dominancy. The index to identify subjects as left hemisphere dominants was being right handed (writing with the right hand). They were volunteers and gave written consent to participate in this study, approved by the ethic committee of the Iranian Society of Clinical Hypnosis. Since all participants were physicians, there was no fear of signal recording instruments and it was assumed that their EEG signals would not be affected because of applying the recording apparatus. Besides, participants had enrolled in hypnosis teaching sessions and were hypnotized several times before this experiment, so there was no curiosity about or fear of hypnosis among them. They were also verbally informed about the details of the study and the point that no hypnotizability level (low, medium and high) is superior to others. Subjects were asked to take a good rest the night before the experiment day and not to do physical exercises during the day before the experiment to avoid being tired and falling asleep while they were hypnotized.

2.2. Material

In the present study, Nasrabadi's [25] database was applied. These EEG signals were recorded according to 10–20 international standards including 19 electrodes. Earlobe electrodes were used as references. Some features of the recording system are as follows: Ag-AgCl electrodes with impedances less than 5 KΩ, Frequency bandwidth of 0.1–100 Hz, Equal bandwidth and gain of all channels, Sampling frequency of 256 Hz and 12-bit analogue-to-digital convertor.

In order to avoid possible magnetic interference caused by current cables, instruments with a low energy level had to be used or all instruments had to be installed far away from the recording station and subjects had to be at the furthest possible position from the computer to ignore the field caused by the computer itself. Moreover, recordings were performed with all lamps turned off.

During the EEG signal recording, an electrooculograph (EOG) was also recorded to trace the eye movement, because visual induction may cause eyeball movement. The existence of EOG, imposed on EEG signals, was distinguished by a neurologist.

Signals were recorded at the same time of the day for every subject (16:00–20:00). The recording was carried out twice and in two different circumstances: once in a relaxed state with their eyes closed and no specific instructions were given to the subjects—serving as baseline signals (2 min), next time, the signals were recorded at the state of being hypnotized. To study the shifts occurring during hypnosis, a 45-min audio file was used applying the whole stages of WSGS. This file was

used for hypnotic induction in all the subjects and there existed no change in tone of speaking. Therefore, all subjects had almost the same situation. The subjects were sitting conscious with their eyes closed as the recording started. Following the baseline condition, the first 15 min of the audio file was devoted to the hypnosis induction. Further, to determine the hypnotizability score, he/she is required to do 12 different tasks, as it comes:

(1) Hand lowering (ideomotors),
(2) Moving hands together (ideomotors),
(3) Experience of mosquito (hallucination),
(4) Taste experience (hallucination),
(5) Arm rigidity (challenge),
(6) Dream (memory),
(7) Arm immobilization (challenge),
(8) Age regression (memory),
(9) Music hallucination (hallucination),
(10) Negative visual (hallucination),
(11) Post-hypnotic automatic writing (memory), and
(12) Amnesia (memory).

Ideomotor is human movement without volition that starts from the cerebellum. Actually metaphysical factors or factors beyond our senses may cause movement without volition. In the music hallucination task, a culturally well-known music was chosen. The subject was told that the music would be played with different volumes and he was asked to hold up his right hand when hearing the music satisfactorily. However, in reality no music was played at all [5]. In negative visual hallucination, the subject was told to open his eyes and see two balls on the floor. However, in reality there were three balls, not two of them [5].

There was a period of silence between induction periods of consecutive tasks. Therefore, there was no confounding from completing prior tasks. When tasks-performance finished, the scores of hypnotic susceptibility and the depth of hypnosis were determined based on each individual performance [5,6]. Each task was rated from 1–5 and, to produce the total scale scores ranging from 12–60, these ratings were summed: low hypnotic susceptibility (12–21), medium hypnotic susceptibility (22–41) and high hypnotic susceptibility (42–60). The EEG signals of all 19 electrodes were recorded throughout all tasks. In the present research EEG signals of tasks 1–10 were chosen to investigate and the last two tasks were not examined because both tasks were inter-woven and it was not possible to determine the task time of each individually.

It is necessary to mention that WSGS samples a greater variety of suggested experiences than do other scoring systems and, in particular, responses to the more difficult suggestions (e.g. age regression and positive/negative hallucination in several sensory modalities) are more adequately tapped, that is why WSGS is widely considered the gold standard in measuring hypnotic susceptibility [45,46]. In the following different task types, ideomotors, hallucination, challenge and memory are called IDE, HAL, CHA and MEM, respectively.

2.3. Recurrence quantification analysis

By plotting the recurrence matrix (equation 1), the RP is acquired. Different colours are applied for its binary entries, for instance a black dot for its binary entries if $R_{i,j}$ $R_{i,j}^{m,\varepsilon_i} = 1$ and a white dot, if $R_{i,j}^{m,\varepsilon_i} = 0$.

$$R_{i,j}^{m,\varepsilon_i} = \Theta\left(\varepsilon_i - \left\|\vec{x}_i - \vec{x}_j\right\|\right) \tag{1}$$

where Θ is the heaviside function, ε is the distance threshold and $\left\|\vec{x}_i - \vec{x}_j\right\|$ represents the distance between $\vec{x}_i, \vec{x}_j$. $\vec{x}_i, \vec{x}_j$ are phase space trajectories in an m-dimension phase space [47,48]. These trajectories can be reconstructed from a single time series u_i by using an embedding dimension m and a time delay τ [49,50] $\vec{x}_i = \left(u_i, u_{i+\tau}, \ldots, u_{i+(m-1)\tau}\right)^T$. To analyse the time series, both embedding parameters, the dimension m and the delay τ are of great importance and have to be chosen appropriately. To choose the delay, there are two dominant methods: choosing the lag at which the first zero-crossing of the autocorrelation function for the data occurs or selecting the first local minimum of the average mutual information function [51]. Correlation dimension and false nearest neighbour are two common approaches to estimate the proper embedding dimension [43,44]. In the present study, the false nearest neighbour method and first local minimum of the average mutual information function were employed to estimate the dimension m and the delay τ, respectively. Needless to say that the base of RP (equation 1) is the distance matrix

$$D_{i,j}^{m,\varepsilon_i} = \left\|\vec{x}_i - \vec{x}_j\right\| \tag{2}$$

The ε is a pre-defined distance threshold and for states in an ε-neighbourhood $R_{i,j}^{m,\varepsilon_i} = 1$. There are various methods to estimate ε [52–57], but the most frequent technique is to choose ε as 10% of the maximum phase space diameter. If ε is selected too small, there may be almost no recurrence states and nothing will be learnt about the recurrence structures of the underlying systems. On the other hand, if ε is adapted too large, almost every point is the neighbour of every other point, which results in a lot of artifacts. Therefore ε is the most important parameter in obtaining the RP.

In a RP, there are three small scale structures: single points which can occur if states are rare, a diagonal line of length l which occurs when a segment of the trajectory runs almost in parallel to another segment and a vertical (horizontal) line (with v the length of the vertical line) marks a time interval in which a state does not change or changes very slowly [43,44].

In order to go beyond the visual impression of RPs, several measures of complexity which quantify the small scale structures in RPs were proposed [58–60] and are known as RQ. The most common RQs are presented in the following paragraphs.

Recurrence rate (RR) is a measure of the density of recurrence points. In the limit $N \to \infty$, RR reveals the probability that a state returns to its ε-neighbourhood in phase space [61]

$$RR = \frac{1}{N^2} \sum_{i,j=1}^{N} R_{i,j}^{m,\varepsilon} \tag{3}$$

RP of uncorrelated, weakly correlated stochastic or chaotic processes include none or very short diagonals, while processes with deterministic behaviour include longer diagonals and less single isolated recurrence points in their PR.

Therefore, the ratio of recurrence points located on connected diagonal structures in the RP is defined as the determinism (a measure of system's predictability) [43,62].

$$DET = \frac{\sum_{l=l_{min}}^{N} lP^{\varepsilon}(l)}{\sum_{i,j}^{N} R_{i,j}^{m,\varepsilon}} \quad (4)$$

where $P^{\varepsilon}(l) = \{l_i; i = 1 \ldots N_l\}$ is the frequency lengths l of diagonal structures and N_l is the absolute number of diagonal lines.

Considering the length L_{max} of the longest diagonal line in the RP and the inverse of that, divergence, other RQA measures are obtained [43,54].

$$L_{max} = \max(\{l_i; i = 1 \ldots N_l\}) \text{ respective } DIV = \frac{1}{L_{max}} \quad (5)$$

These measures correspond to the exponential divergence of the phase space trajectory. The faster the trajectory segments diverge, the shorter are the diagonal lines and the greater is the *DIV*.

Entropy is the Shannon entropy of the probability $p(l)$ to find a diagonal line of an exact length equal to l. *ENTR* shows the complexity of the RP in respect of the diagonal lines, as an example *ENTR* of an uncorrelated noise is rather small, reflecting its low complexity [43,52]

$$ENTR = -\sum_{l=l_{min}}^{N} p(l) ln p(l) \quad \text{with} \quad p(l) = \frac{p^{\varepsilon}(l)}{\sum_{l=l_{min}}^{N} p^{\varepsilon}(l)} \quad (6)$$

The ratio between the recurrence points forming the vertical structures and the whole set of recurrence points given by

$$LAM = \frac{\sum_{v=v_{min}}^{N} vp^{\varepsilon}(v)}{\sum_{v=1}^{N} vp^{\varepsilon}(v)} \quad (7)$$

is called laminarity (analogous to determinism definition). To decline the tangential motion effect, just those v that are greater than a minimal length v_{min} are considered in the computation of *LAM*. *LAM* shows the occurrence of laminar phase without describing the length of these laminar states in the system. Having more single recurrence points than vertical structures in the RP results in a *LAM* decrease [59], where $p^{\varepsilon}(v) = \{v_i; i = 1 \ldots N_v\}$. denotes the frequency distribution of lengths l of vertical structures.

The average length of vertical structures is computed by

$$TT = \frac{\sum_{v=v_{min}}^{N} vp^{\varepsilon}(v)}{\sum_{v=v_{min}}^{N} p^{\varepsilon}(v)} \quad (8)$$

and is named trapping time. As in the case of *LAM*, calculation of *TT* also requires the consideration of a minimal length v_{min}. *TT* makes an estimate of the mean time that the system abides at a particular state or how long the state is trapped [63].

- Recurrence time of first type [64]:

$$T_j^1 = \left|\{i,j : \vec{x}_i, \vec{x}_j \in R_i\}\right| \quad (9)$$

- Recurrence time of second type [64]

$$T_j^2 = \left|\{i,j : \vec{x}_i, \vec{x}_j \in R_i; \vec{x}_{j-1} \notin R_i\}\right| \quad (10)$$

where R_i are the recurrence point which belong to the state $\vec{x}_i$.

RR, DET, L, Lmax and ENTR are mainly based on diagonal structures in RPs, while LAM, TT, Vmax, recurrence time of first type and recurrence time of second type are mainly based on vertical structures in RPs.

2.4. Surrogate data testing

Chaos can only happen in non-linear dynamical systems, but filtered noise signals fabricate low dimensional dynamics and chaotic behaviour without any non-linearity exists. Hence, before interpreting non-linear measures, it is necessary to check if it is factitive or real chaotic behaviour [65,66]. Using surrogate signals is one of the most crucial tools for this purpose [67]. Surrogate signals are built in a way to present the same linear features (power spectrum or autocorrelation function) as the main signal but not non-linear features. The fundamental principle is as follows: a non-linear measure, for example an RQ, is calculated for both the main signal and control or surrogate signals. A typical statistical test can then be applied on the measures of main signal and surrogate signals, not one surrogate signal but a whole set of them. The statistical test determines whether the feature value of the main signal lies within the value distribution of surrogate signals' features or not. Difference between measures of main signal and surrogate ones validates the existence of non-linear dynamics in the system producing the main signal and the chaotic behaviour is not a fabricated one.

There are various ways to construct surrogate signals. The most frequent way is to preserve the power spectrum. A simple procedure to generate surrogate signals with the same power spectrum as the main signal is to apply a Fourier transform, shuffle the phase and at the end apply inverse Fourier transform [68,69].

While surrogate data testing offers a great advance in comparison to uncontrolled studies, it may convey false results. A good example of this is that, if the main signal does not have an amplitude distribution of a Gaussian type, simple phase randomization results in Gaussian distribution. This also fabricates differences between the main signal and surrogate ones [66]. To control this problem, amplitude adjusted surrogate signals are suggested [69–71]. Schreiber and Schmitz [71] proposed an iterative approach to have both the power spectrum and the amplitude distribution preserved. Another issue is that non-stationarity alone or in combination with non-linearity can contribute to significant differences between the main signal and surrogate signals [72–74]. A possible solution to this problem is using wavelets to generate surrogate signals [75]. In addition, in the case of signals with strong periodic components, difficulties emerge. To solve this and also the issue of non-stationarity, time reverse copies of the main signal are used as surrogate ones [76].

Considering all the above-mentioned problems, in the current investigation, two methods were used to produce surrogate signals: (1) an iterative procedure which preserved

both the power spectrum and the amplitude–distribution; and (2) time reverse copies of the main signal. Results of applying the non-linear analysis on the main signals and their surrogate signals were significantly different, which indicates the existence of non-linear dynamics in the underlying system.

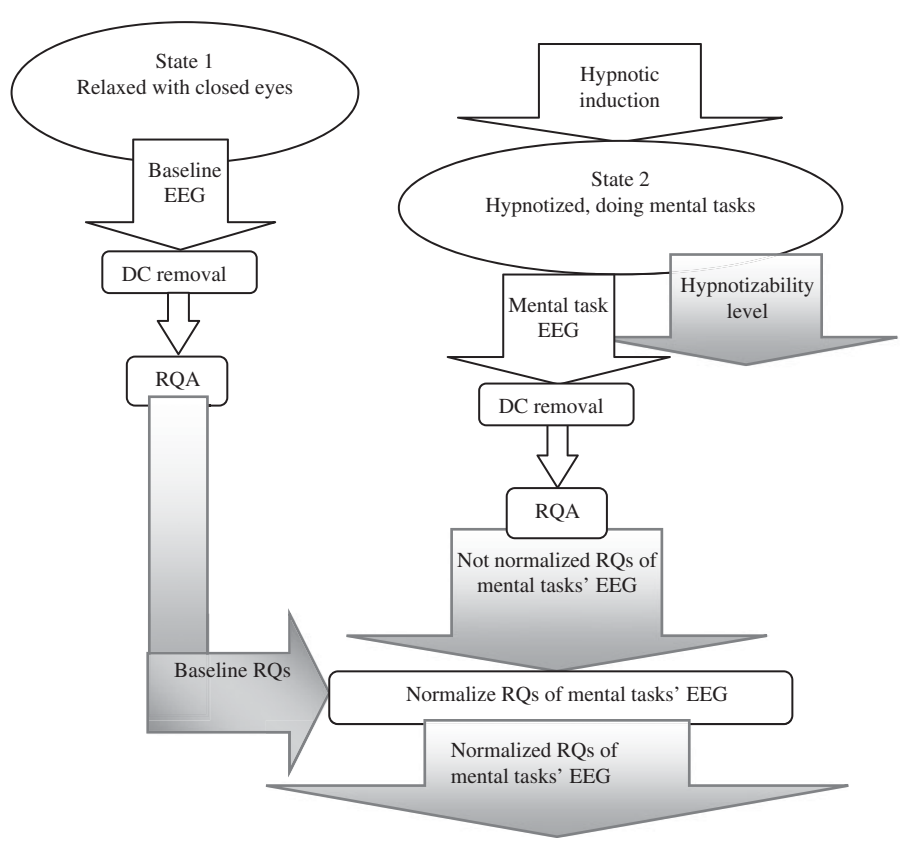
3. Results and discussion

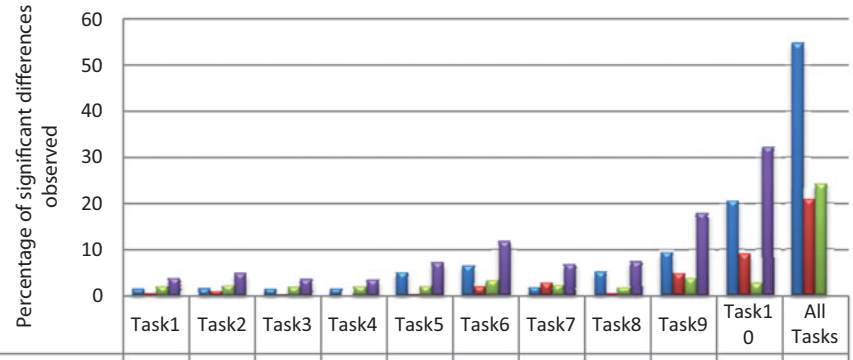
As can be seen in Figure 1, EEG signals were recorded in two different states: state 1 (relaxed with closed eyes) and state 2 (hypnotized, doing mental tasks). It is necessary to mention that state 2 was produced by applying the hypnotic induction and, in addition to recording EEG signals during mental tasks, in state 2, the hypnotizability level of subjects was recognized by considering how he/she followed hypnotic instructions and inductions. In the next step, the DC part of all recorded EEG signals was removed and RQs (recurrence rate, determinism, average diagonal length, length of longest diagonal length, entropy of diagonal length, laminarity, trapping time, length of longest vertical length, recurrence time of 1st type, recurrence time of 2nd type) of both baseline and hypnotic signals were calculated.

We computed RQs of signals recorded from 19 EEG channels in 33 men during 11 different states (10 hypnotic tasks and baseline), so 19*33*11 = 6897 signals were at hand to have their RQs assessed. First, the dimension m and the delay τ were determined by applying the false nearest neighbour method and the first local minimum of average mutual information method, respectively, to reconstruct the phase space. Moreover, ε was chosen as 10% of the maximum phase space diameter. This procedure was crucial because, if the same threshold was used for all signals, amplitude variations might conceal dynamic variations. Then all required parameters (6897 vectors of parameter values [m, τ, ε]) were ready to obtain the recurrence matrix ($R_{i,j}^{m,\varepsilon_i}$), plot the RP and calculate RQs of each signal. In the next stage, with the purpose of normalizing the RQs of hypnotic signals, those of baseline signals were employed. After feature extraction, ANOVA statistic analysis was applied to find out if there was a significant difference of normalized RQs among three hypnotizable groups (low, medium and high) while going through the same tasks. Analysis results of tasks 1–10, including channels whose normalized RPs showed p values less than 0.05, enabled us to differentiate three hypnotizable groups. In the following, significant differences among channels' EEG features of three hypnotizable groups are just called significant difference and the most efficient task is the one which shows the highest percentage of significant differences (p values less than 0.05).

Figure 2 shows the percentage of significant differences observed in each task. According to Figure 2 tasks can be sorted from the most efficient (based on percentage of significant differences observed) to the least efficient ones: (Task 10, Task 9, Task 6, Task 8, Task 5, Task 7, Task 2, Task 1, Task 3 and Task 4). This order shows the measure of tasks' difficulty and the measure of subjects' performance dependence on hypnosis depth in these tasks (e.g. subjects' performance in Task 10 depends on the hypnosis depth the most so it is the best task to distinguish subjects of different hypnotizability levels). It is also necessary to notice that the percentage of significant differences observed in Task 10, Task 9 and Task 6 are remarkably greater than those observed in other tasks. One could not suggest that the last tasks are more difficult just because they were in the end of the

Figure 1. The process of feature extractions.





	Task1	Task2	Task3	Task4	Task5	Task6	Task7	Task8	Task9	Task10	All Tasks
(Low, Medium)	1.32	1.61	1.46	1.46	5.12	6.58	1.75	5.26	9.5	20.76	54.82
(Low, High)	0.44	1.02	0.29	0	0.15	1.9	2.78	0.44	4.82	9.06	20.91
(Medium, High)	2.05	2.34	1.9	2.05	2.05	3.36	2.34	1.75	3.8	2.63	24.27
Total	3.8	4.97	3.66	3.51	7.31	11.84	6.87	7.46	18.13	32.46	

Figure 2. Percentage of significant differences between different hypnotizable groups in each task.

experiment and the subjects were tired. It is believed that they are inherently more difficult because results of experiments which followed the WSGS protocol are consistent with results of experiments which followed shorter protocols. (The WSGS is an adaptation of the Stanford Hypnotic Susceptibility Scale, Form C (SHSS:C), they both include 12 tasks [5] and results of SHSS:C showed high level of consistency with results of Stanford Hypnotic Clinical Scale (SHCS), a shorter protocol that includes five tasks [4]. Looking more closely at the above order, it can be seen that different task types can also be sorted from the most to the least efficient ones: (HAL (Task 10, Task 9), MEM, CHA, IDE, HAL (Task 3, Task 4)). This means that HAL (Task 10, Task 9) and memory tasks are the most difficult tasks and they are possible in enough depth of hypnosis but HAL (Tasks3, Task4) and IDE tasks are the least difficult tasks and they are well performed by subjects from all three different hypnotizability levels.

Moreover, Figure 2 demonstrates the percentage of significant differences between different hypnotizable groups in each task. According to Figure 2, for (Low, High) and (Low, Medium) group pairs, the most observed significant differences belonged to Task 10 and for (Medium, High) the most observed significant differences belonged to Task 9. Besides, in tasks 1–4 the most observed significant differences belonged to the (Medium, High) group pair, while in tasks 5, 6, 8, 9 and 10 the most observed significant differences belonged to the (Low, Medium) group pair and in task 7 the most observed significant differences belonged to the (Low, High) group pair. Therefore, during the first four tasks, the main difference is between the medium and high hypnotizable subjects, but, during the six final tasks, the main difference is between the low hypnotizable subjects and others. The reason is that the low hypnotizable subjects have the lowest hypnotic susceptibility and they experience the least depth of hypnosis so, as time passes further from the primitive inductions and suggestions (first 15 min of hypnosis before performing tasks), there is a rise in the possibility of their hypnosis depth decreasing and getting closer to not-hypnosis state. Therefore, as it gets nearer to the end time of hypnosis, more significant differences between low hypnotizable ones and subjects from other groups are observed.

Figure 2 also represents the percentage of significant differences between different hypnotizable groups. According to Figure 2, group pairs of significant differences can be sorted from the most to the least frequent: (Low, Medium), (Medium, High) and (Low, High). The reason for observing this order of group pairs is that, when extracting various features of all 10 tasks in all 19 channels, the features' variance of the medium hypnotizable group was the least and the low hypnotizable group showed the maximum variance in each extracted feature. This means that the medium hypnotizable subjects were under the effects of inductions and instructions of the hypnotizer the most (more than low or high hypnotizable subjects) and the low hypnotizable subjects showed the least affectability because of their low hypnotic susceptibility, while the high hypnotizable subjects stood in between (it is known from previous studies that the perception of high hypnotizable subjects will sometimes be altered to coincide with suggestions that do not accurately reflect the stimuli applied [5]), less affectability than medium hypnotizable subjects and more affectability than low hypnotizable ones.

As was mentioned, there were four HAL tasks: Task 3 (experience of mosquito), Task 4 (taste experience), Task 9 (music hallucination) and Task 10 (negative visual); and there were the overall similarities among all HAL tasks, but there were also some differences and it seemed that HAL tasks could be divided into two sub-divisions; tasks (3, 4) and tasks (9, 10). Task 3 (experience of mosquito) includes hallucination of both hearing and touching senses (hearing the sound of a mosquito and feeling its existence on your skin) and Task 9 (music hallucination) includes hallucination of hearing sense. So, both Task 3 and Task 9 include hallucination of hearing sense, but their results were not as similar to each other as HAL tasks from a sub-division and this leads us to this conclusion that hallucination of touching sense might be the dominant dynamic in Task 3 (not the hallucination of hearing sense). Considering this conclusion beside the sub-divisions of HAL tasks, it seems that governing dynamics of touching and tasting hallucination (Task 3 and Task 4) are similar and visual and hearing hallucination (Task 9 and Task 10) also involve similar governing dynamics.

4. Conclusion

Employing the RQA methods, the current study attempted to find out the impact, if any, of hypnosis depth on EEG signals recorded while the individuals were doing mental tasks under the hypnosis.

Results determined the capability of tasks to distinguish subjects of different hypnotizability levels (measure of tasks' difficulty and the subjects' performance dependence on hypnosis depth in tasks) and it was identified which tasks revealed the most percentage of significant differences between different hypnotizable group pairs, (Low, High), (Low, Medium) and (Medium, High). Another remarkable finding was that the medium hypnotizable subjects were identified to be under the effects of inductions and instructions of the hypnotizer the most (more than low or high hypnotizable subjects). In tasks of the same types (IDE, HAL, CHA and MEM) there were similarities in group pairs which significant differences belonged to and the level of tasks' difficulty. All these point to similarities of governing dynamics in the brain during tasks of the same type. Considering the analysis results of four HAL tasks (experience of mosquito, taste experience, music hallucination and negative visual), beside the overall similarities among all HAL tasks, there were some differences and it seemed that HAL tasks could be divided into two sub-divisions tasks (experience of mosquito, taste experience) and tasks (music hallucination, negative visual).

It is necessary to mention that, due to no existence of a previous study over EEG signals of WSGS, the results of the present study cannot be compared with any other research. However, a comparison of the two closest approaches shows:

- Solhjoo et al. [77] applied fractal dimensions and spectral features to classify mental tasks done in hypnosis state, but all their subjects belonged to a high hypnotizability group.
- Lee et al. [26] employed fractal analysis on EEG signals during hand rising in the state of hypnosis. They reported that features of analysed EEG signals are similar to those of white noise and different from those of EEG signals in not-hypnosis state or sleep, but their research did not include any investigation on hypnotizability variation.

To improve the quality of research, the following suggestions may work:

- In order to increase the validity of results, more subjects should be involved in signal recordings. It this way, we can make sure that the reported results are totally independent from the set of examined subjects.
- More investigation on finding a suitable mental task to alternate the baseline signals with.
- Having a longer signal recording in each task, beside a longer rest time between consecutive tasks (in order to have subjects completely returned to relaxation state) makes the more accurate study of tasks' dynamics possible.
- Considering the capability of non-linear features in distinguishing subjects from different hypnotizable groups, applying other non-linear features is strongly suggested.
- As the final suggestion, recording signals during the same tasks in both hypnosis and not-hypnosis states provides the chance to study and compare the dynamics governing the brain in those situations.

Declaration of interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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