The impacts of hypnotic susceptibility on chaotic dynamics of EEG signals during standard tasks of Waterloo-Stanford Group Scale

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Abstract

Chaotic features of hypnotic EEG (electroencephalograph), recorded during standard tasks of Waterloo-Stanford Group Scale of hypnotic susceptibility (WSGS), were used to investigate the underlying dynamic of tasks and analyse the effect of hypnotic depth and concentration on EEG signals. Results demonstrate: 1) More efficiency of Higuchi dimension in comparison with Correlation dimension to distinguish subjects from different hypnotizable groups, 2) Channels with significantly different chaotic features among people from various hypnotizability levels in tasks, 3) High level of consistency among discriminating channels of tasks with function of brain's lobes, 4) Most affectability of medium hypnotizable subjects, 5) Rise in fractal dimensions due to increase in hypnosis depth.

Keywords: hypnosis, hypnotizability/ hypnotic susceptibility, Waterloo-Stanford Group Scale of hypnosis susceptibility, EEG, fractal dimension.

1. Introduction

Hypnosis is defined as a mental state created via induction. Some scholars regard it as a kind of hypnoidal anesthesia; however, there are some other neurological researchers to define hypnosis as a state of consciousness [1] in which the hypnotized own high degree of concentration while being dissociated from his/her peripheral environment and in this state s/he is highly suggestible [2].

Hypnosis is presently employed in various fields such as medicine, psychology, dentistry and …. In case hypnosis is applied as a therapeutic means, it necessitates the patient's receptivity of hypnosis to reach the required, effective hypnotic depth. This is the depth in which, the therapeutic instructions as well as inductions are actively received and acted by the patients.

To assess the depth of hypnosis, different standards have been suggested. Some of those standards are as follows: 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]. Following a standard method, the patient is hypnotized. Then, s/he is asked to do special tasks. How the patient follows the instructions of the hypnotizer and the extent of his/her submission to the inductions and instructions of the hypnotizer determines the levels of a patient hypnotic susceptibility. But employing these methods may cause a decrease in hypnosis depth so finding more objective methods based on physiological shifts are of great interest.

In the state of hypnosis, the body may experience a variety of physiological changes; change of heart rhythm, hypotension, peripheral vessels resistance, skin electrical resistance, basic metabolism, body temperature, breathing rate and depth and … are instances of those physiological shifts. The inductions may also change the tone of muscles and the release of endocrine glands. Due to the various changes occurring via hypnosis, many scientists have been doing researches on hypnosis employing EEG, FMRI, PET, skin resistance measurement, heart rate and … . Thanks to accessibility and simple application of recording EEG signals in comparison with other methods, it has been applied by lots of experts involved in hypnosis studies.

The focus in a large number of researches, has been on the power spectrum of the hypnotic EEG signals [2]-[3], [8]-[22], results report the existence of a great relationship among EEG activity, hypnosis and hypnotizability in EEG theta frequency range [15], [23]-[24]; whereas, there are new researches in the area not applying the power spectrum. Nasrabadi et al. investigated EEG signals in various status of mind (baseline, tasks and hypnosis) in subjects with different levels of hypnotizability [25]. Lee et al. studied the fractal attributes of EEG signals in both states of hypnotized and not-hypnotized [26]. Baghdadi et al. examined the features of hypnotic EEG employing improved empirical mode decomposing (EMD) method [27]-[28]. Ray et al looked into the difference between fractal dimension extracted from EEG signals of subjects with low and high level of hypnotizability [8]. Behbahani et al. used fuzzy similarity index to analyze the hypnosis nature in right, left, back and frontal hemisphere in three groups of hypnotizable subjects [29]-[30].

So far, most of the studies on EEG signals of the hypnotized subjects- regardless of their methods- have been performed during hypnotic induction and the EEG signals of the hypnotized subjects during mental tasks like those of WSGS have not been examined. The present research looked into the EEG signals of subjects with 3 different hypnotizability levels- low, medium and high- as the subjects were performing some mental tasks (standard tasks of WSGS). Therefore, the effects of hypnosis depth and concentration rate on EEGs of those 3 groups could be studied and changes of mental tasks dynamics could be detected as well. To do so, chaotic methods were applied.

"Chaos", a new technique from non-linear dynamic view, points that a time series could be analysed to reflect all the variables taking part in dynamics of a system. "Chaotic approach" into EEG interpretation would provide the researchers with new insights for further investigation [31]-[32]. Chaotic measures such as fractal dimensions, Hausdorff dimensions, Lyapunov exponents, Kolmogrove entropy and others reveal that the complex activity generated by the brain -viewed by some as noise- may not be occur randomly and it includes specific information, indeed, which concerns the prime and underlying process of the brain, though in an ordered not-predictable pattern, identified as chaotic [33]. Moreover, the researches carried out in the 2 last decades show the presence of chaotic dynamics in both microscopic (neuron performance) and macroscopic levels (brain activities during sleep) [34]-[35] therefore, accurate and comprehensive results by chaotic methods application to EEG investigation of the hypnotized subjects is highly expected. The recorded EEG signal differences of 3 hypnotizability groups (low, medium and high) while doing the same tasks could be detected via extraction and comparison of chaotic features.

The present study also made an attempt to perceive the dominant dynamics of 3 groups with different hypnotizability levels. By the results and potentially-existing distinction among chaotic features of 3 groups some criteria could be defined for hypnosis- depth determination so that the appropriate induction would be used. In short, through examination during hypnosis, the required information to study different hypnosis stages and also the transfer from one stage to another are obtained.

Material

Nasrabadi's database [25] was used in current study. For EEG signal recording, 10-20 international standard with 19 electrodes were utilized. (figure 1)

The earlobes electrodes were reference ones. The EEG recording system features are as follows:

Ag-AgCl electrodes with impedances less than 5KΩ,

Frequency bandwidth of 0.1 to 100 Hz,

Equal bandwidth and gain of all channels,

Sampling frequency of 256 Hz and

12-bit analog to digital convertor.

To prevent magnetic interference the following instructions were applied:

Using current cables and instruments with low energy level

Installing all instruments far away from the recording station

Placing subjects at the furthest possible position

Having all lamps turned off during the experience

Since visual induction may cause movement of eyeballs, Electrooculography (EOG) was recorded in addition to recording EEG signals.

33 healthy male subjects with age range 32±6 participated the study. They were physician members of Iranian Society of Clinical Hypnosis. All subjects were right handed (writing with the right hand) so their left brain hemisphere was dominant over the right brain hemisphere. They voluntarily attended in the study and signed the consent, verified by the ethic committee of Iranian Society of Clinical Hypnosis. There was no fear or stress of signal recording apparatus, because all subjects were physician. Besides, it was assumed that applying the signal recording instruments would not affect the EEG signals. Moreover, subjects attended teaching sessions of hypnosis and were hypnotized several times before launching the study, so they were not curious about or afraid of hypnosis. Research details were also described to them and subjects were informed that no level of hypnotizability (low, medium and high) is superior/ inferior to others. Participants were asked/required to sleep well the night before the experiment day and refrain from doing physical exercises before the experiment, in order not to be tired or sleepy during the signal recording period and hypnosis process.

The time of experiment was fixed (16:00-20:00) for each subject. The recording had 2 parts: 1- baseline signal (subjects were asked to close their eyes and be relaxed for 2 minutes) and 2- hypnotic signals. To hypnotize the subjects an audio file encompassing all

stages of WSGS was played for 45 minutes. The same file was played for all subjects, so there was no change of/in speaking tone of hypnotic inducer and all participants sat the same and equal situation. The experiment begun as subjects were in conscious and normal state and they were sitting with closed eyes continuously after the baseline recordings. After hypnotic induction subjects were asked to perform 12 various tasks as it follows:

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. Posthypnotic automatic writing (memory) and

12. Amnesia (memory).

Between consecutive tasks induction, there was a period of silence to avoid confounding from completing prior tasks.

After finishing all 12 tasks, hypnotic susceptibility score/ hypnotic depth was determined based on each individual performance [5], [36]. Each task put a value on from 1 to 5 and these values were summed the total scale scoring varying between 12 and 60: low hypnotic susceptibility (12 to 21), medium hypnotic susceptibility (21 to 42) and high hypnotic susceptibility (42-60). All 19 electrodes of 10-20 international standards were used to record EEG signals. In current study task 1 to 10 were selected to be analysed and the last two tasks were not dealt with because both task 11 and task 12 were interwoven and it was not possible to separate the time of each task individually.

Since WSGS includes a greater variety of suggested experiences than other standard scorings and involves harder suggestions (e.g. age regression and positive/ negative hallucination in several sensory modalities), it is widely accepted as a gold standard for measuring hypnotic susceptibility [37]-[38].

Insert figure 1 about here

Method

In section 3.1, fractal dimensions including Higuchi and correlation dimensions are introduced. Evaluating the normality of the data is discussed in section 3.2 and Section 3.3 deals with surrogate data testing.

3.1 Fractal Dimensions

Chaotic behaviour is presented by two sets of parameters. The first category demonstrates the dynamic behaviour - behaviour of a system on nearby trajectories- like Maximum Lyapunov Exponent (MLE). The second category represents the geometric properties of the basin of attraction. Fractal dimensions (FDs) belong to this class of parameters. In present research, Higuchi and correlation dimensions - two FDs- were employed.

Higuchi Dimension (HD)

Considering the under study signal as *x(1), x(2), …, x(N)*, *K* new time series are produced using that:

$$x_m^k = \{x(m), x(m+k), x(m+2k), \dots, x(m+\left[\frac{N-m}{k}\right]k)\} \qquad \text{for } m = 1, 2, \dots, k \qquad (1).$$

Where m and k show the initial time value, and the discrete time interval between points, orderly. For each of the k time series x_m^k, the $L_m(k)$ is computed:

$$L_m(k) = \frac{\sum_{i=1}|x(m+ik)-x(m+(i-1)k)|\ \ (N-1)}{\left[\frac{N-m}{k}\right]k} \qquad (2).$$

Where *N* represents the total length of the signal $x(1), x(2), \dots, x(N)$. The mean of the k lengths $L_m(k)$ (for $m = 1, 2, \dots, k$) counts for an average length. This procedure is repeated for each k between 1 to k_{max}, calculating an average length for every k. The slope of the least square best fit line to the curve of $ln(L(k))$ versus $ln(1/k)$ is the Higuchi fractal dimension= $ln(L(k))/ln(1/k)$ [39].

Correlation Dimension (CD)

Considering the under study signal as *x(1), x(2), ..., x(N)*, new d dimensional vector are produced using that:

$$\overrightarrow{x_i} = (x_i, x_{i+t_L}, x_{i+2t_L}, \dots, x_{i+(d-1)t_L}) \quad (3).$$

Where t_L is the time lag. It shows the time interval between the consecutive sample values which build the vector $\overrightarrow{x_i}$. To select the time lag t_L there are two famous methods. One method is to adopt the first zero-crossing of the autocorrelation function as the lag time [40]-[42]. The other approach is to choose the first local minimum of the average mutual information function [43]. In present study the later algorithm was used.

After embedding the signal, to obtain the CD, the correlation sum is calculated firstly:

$$C^{(d)}(R) = \frac{1}{N(N-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \Theta[R - |\overrightarrow{x_i} - \overrightarrow{x_j}|] \quad (4).$$

Where d is the number of embedding dimension and x values show vectors in that embedding dimension. The correlation sum represents the relative number of point pairs that are within the distance of R of each other in this space. $D_c(d)$ is the value that satisfies $C^{(d)}(R) = kR^{-D_c(d)}$. For $d > d_{sat}$ (a saturation value), D_c is not dependent on the embedding dimension d anymore and this is the estimate of CD (figure 2) [40]-[42].

Insert figure 2 about here

3.2 Evaluating the normality of the data

ANOVA test, used to determine the significant differences among features extracted (CDs), assumes variables to have normal distributions. Therefore, it is necessary to investigate the

normality of features before applying the ANOVA. There are different statistical methods like Lilliefors, Jarque-Bera, Kolmogorov-Smirnov and … to test this null hypothesis and determine whether features are samples of a normal population. If the observed significance level is small then the features normality assumption is skeptical. Applying these tests, it is assessed by what significance level the null hypothesis (normality of distribution) is accepted or rejected.

Kolmogorov-Smirnov test requires prior knowledge of features' probability density function and extracting that function using the features itself does not lead to good results [44]. Besides, Jarque-Bera test is too sensitive to outliers and presence of a single outlier may result in a worthless test [45]. Therefore, in the present study, the Lilliefors test was employed to evaluate the normality of features which does not confront the before mentioned limitations of Jarque-Bera, Kolmogorov-Smirnov test [44].

3.3 Surrogate data testing

As chaos can simply occur in nonlinear dynamical systems, nonlinearity is of vital importance to exist. Filtered noise signals fabricate some low dimensional dynamics and chaos. It could occasionally result in problems as for interpreting nonlinear measures [46]-[47]. The shortcoming could be sorted out by employing surrogate signals- a highly effective means to avoid interpreting problems [48]. The principle framework, in doing so, is as follows: a nonlinear measure e.g. dimensions entropy or …, is calculated- the calculation includes both the main signal and control or surrogate signals. Surrogate signals are produced so as to present linear features (power spectrum or autocorrelation) similar to

those of the main signal but no nonlinear properties. In the case the nonlinear analysis introduces different results for main and surrogate signals, the existence of nonlinear structures in main signal is presumed. To verify whether the feature values of the main signal can be placed within the value distribution of surrogate signal features, a conventional statistical test is applied to a whole set of the main signal and surrogate signals.

Various methods are employed to build to build surrogate signals. The most frequently used method is to retain the power spectrum. An elementary, straight forward procedure to produce surrogate signals with the identical power spectrum as the main signal is application of a Fourier transform, jumbling the phase and finally using inverse Fourier transform [49]-[51].

Although compared to uncontrolled studies, surrogate data testing introduces major advances in this field of study; it may bring false results as well. If the major signal, for instance, does not have amplitude distribution of a Gaussian type, simple phase shuffling produces Gaussian distribution. It could also fabricate differences between main signal and surrogate ones [47]. Amplitude adjusted surrogate signals have been proposed to overcome the shortcoming [50]-[52]. Schreiber and Schmitz developed an iterative approach which preserves the power spectrum as well as the amplitude distribution. The other drawback is that nonstationarity just by itself or in combination with nonlinearity makes substantial contribution to differences between the main and surrogate signals [53]-[55]. Generating surrogate signals by the help of wavelets is a possible solution to defeat the nuisance [56]. There are further difficulties in consequence of signals with strong periodic components.

To deal with this issue and the matter of nonstationarity as well, time reverse copies of the main signals are taken as surrogate signals [57].

In the present study, concerning the stated problems, two methods were exercised to produce surrogate signals: 1) the iterative procedure to preserve both the power spectrum and the amplitude distribution. 2) time reverse copies of the main signals. Results of the nonlinear analysis application upon main signals and the surrogate signals exhibit substantial differences, indicating, in turn, the existence of nonlinear dynamics in the underlying system.

4. Results

FDs of both baseline and hypnotic signals were assessed. We calculated FDs of recorded signals from 33 subjects in 19 EEG channels during 11 various states (baseline plus 10 hypnotic tasks), so there were 33*19*11=6897 signals. At first stage, the DC part of each signal was removed. Then FDs for each and every of these 6897 signals were calculated. In the following stage, in order to normalize the FDs of hypnotic signals, those of baseline signals were applied. In advance to performing the statistic analysis, the normality of features was tested. The Lilliefors test was applied to determine how well the features fit the normal distribution [58]. Considering the test's result, it was assumed that the features has a normal distribution at significance level 0.05. The next stage employed ANOVA statistic analysis to find out if there is a significant difference of their not-normalized and normalized FDs among three hypnotizable groups (low, medium and high) while going through the same tasks. Three hypnotizable groups were differentiated by analysis results

of task 1 to 10, including channels whose not-normalized or normalized FDs showed p-values less than 0.05. At the end the surrogate data testing was performed.

Insert figure 3 about here

As figure 3, there are two different EEG signal recording states: state1 (relaxed with closed eyes) and state2 (hypnotized, doing mental tasks). It should be noticed that state2 is performed after hypnotic induction and in this stage, beside recording hypnotic EEG signals (while doing mental tasks of WSGS), hypnotic susceptibility of subjects was also determined based on how s/he follows instructions and inductions of hypnotizer. Thereafter, DC part of all signal was removed and FDs were computed which led to have baseline FDs and not normalized FDs of mental tasks' EEG. Then FDs of mental tasks' EEG were normalized. Hereafter, Lilliefors and ANOVA tests are performed.

In this paper, significant difference among channels' EEG features of three hypnotizable groups are just called significant difference and the most efficient item (task/channel/FD) is the one which represents the most number of significant differences (p-values less than 0.05).

Insert table 1 about here.

According to table 1 in ideomotor tasks, task1(lowering hand) and task2(moving hands together), channels of right hemisphere and parietal lobe were more efficient and this is consistent with function of parietal lobe associated with movement and orientation [59].

Insert table 2, table 3 and table 4 about here.

As table 2 of task3(experience of mosquito) and task4(taste experience), table 3 of task9(music hallucination) and table 4 of task10(negative visual) show, in hallucination tasks, channels of left hemisphere (except task3)and frontal lobe were more efficient and this is consistent with function of frontal lobe concerned with the reception and processing of sensory information from the body [59]. Results of investigating hallucination tasks were previously reported in [60] and are brought here again to make the comparison of all kinds of tasks possible.

According to table 5 of task5(arm rigidity) and task7(arm immobilization), in challenge tasks, channels of left hemisphere and frontal and temporal lobes (just in task7) were more efficient.

Insert table 5 about here.

As table 6 task6(dream) and task8(age regression) shows, in memory tasks, channels of left hemisphere, frontal lobe and temporal lobe were more efficient and this is consistent with function of frontal lobe as above-mentioned and function of temporal lobe which is the memory centre of brain [59].

Insert table 6 about here.

5. Discussion and conclusion

Applying the chaotic methods, current study was going to understand the influence, if any, of hypnosis depth on EEG signals recorded while the individuals were doing the same mental tasks under the hypnosis.

Comparing the results obtained using Higuchi and Correlation dimensions, it can be clearly observed that Higuchi dimension was more efficient to distinguish subjects from different hypnotizable groups and showed more significant differences (77 times) while Correlation dimension presents less significant differences (48 times). This efficiency of Higuchi dimension is due to no requirement of phase space reconstruction as computing this dimension so the limit lengths of signals and different errors which may exist as calculating Correlation dimension are not faced in estimating Higuchi dimension. Besides in applying Higuchi dimension, normalized dimensions were more efficient and this shows the dominance of relative dynamic in this feature.

The results of the analysis show just a few number of channels, not all, distinguish people with various levels of hypnotic susceptibility. Considering the results, Channels can be sorted from the most efficient in distinguishing different hypnotizable groups to the least ones (based on number of significant differences shown): (P_3, F_3, C_3, F_7, F_z, T_6, P_4, P_z, C_z, O_2, O_1, T_4, C_4, T_5, F_4, T_3). As can be seen, none of the first 5 channels in this list, belongs to right hemisphere. Looking closely at the results, it can also be noticed that in all tasks except ideomotor ones, channels of left hemisphere were more efficient (based on number of significant differences shown). These may be due to subjects being right-handed and left hemisphere dominancy and recent neuroimaging researches also confirm special changes in activity of left hemisphere neurons during hypnosis [61]-[65]. It is also necessary to

mention that signal features of channels (F_8, F_{p2}, F_{p1}) did not show any significant difference, this may be due to the effect of EOG (electrooculogram) signal on EEG signals of these 3 channels.

Similarities among discriminating channels of the same task types are also considerable. Moreover, a great consistency exists between channels involved with corresponding brain lobes:

- tasks1 and task2 of ideomotor type; channels of parietal lobe,
- task3, task4, task9 and task10 of taste hallucination type; channels of frontal lobe,
- task6 and task8 of memory type; channels of frontal and temporal lobes.

Besides, tasks can be sorted from the most efficient (based on number of significant differences shown) in distinguishing different hypnotizable groups to the least ones: (10, 9, 8, 6, 7, 1, 4, 2, 5, 3).

In current study, feature, channels and tasks which significantly discriminate subjects from different hypnotizability groups, are determined. Then, for further study these feature, channels and tasks could be employed for designing different types of classifiers in order to plan more objective hypnosis scoring techniques.

Studying the significant differences between FDs of subjects from different hypnotizability groups, it was observed that:

- In 95% (36 out of 38) of significant differences between FDs of subjects from low and medium hypnotizability groups, FDs of low hypnotizable subjects were less than those of medium hypnotizable ones.
- In 87% (42 out of 48) of significant differences between FDs of subjects from low and high hypnotizability groups, FDs of low hypnotizable subjects were less than those of high hypnotizable ones.

This means that an increase in the depth of hypnosis results in a rise in FDs and brain's more chaotic behaviour.

An amazing result obtained through the statistic analysis was that the variance of FDs extracted from all 10 tasks and all 19 channels was the least in medium hypnotizable group and the most in low hypnotizable group. This finding means that subjects with medium hypnotizability level 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 while the high hypnotizable subjects were in between, less affectability than medium hypnotizable subjects and more affectability than low hypnotizable ones.

It should be noticed that no previous researches on EEG signals of WSGS exists, therefore the result of the current research can't be compared with any reported study.

There are some suggestions to improve the research quality:

- Involving more subjects in the experiment, the result's validity will increase and this makes the research results independent from the group of subjects examined.

- Increasing both the time of each task and the time of rest between successive tasks permit subjects to return the relaxation state, so the dynamic of tasks will be investigated much more accurately.

- Employing more non-linear features may lead to better results due to capability of this category of features.

- Finally, analyzing the signals recorded during the same tasks in both hypnotic and not-hypnotic states, it will be possible to compare the brain's governing dynamics of two conditions.

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Table 1. Task 1 and task2.

Task1					
HD- Not normalized		***CD- Not normalized***		***CD- Normalized***	
Ch[a]	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**
C_Z	M[b](0.853)-H(0.794)	F_3	M(7.935)-H(6.744)	T_4	L(5.054)-H(2.439)
T_6	M(0.856)-H(0.763)	C_3	M(8.308)-H(6.788)		
P_4	M(0.875)-H(0.812)	P_4	M(8.652)-H(6.566)		
		P_z	M(8.271)-H(6.461)		
		P_3	M(8.170)-H(6.831)		
		O_2	M(7.898)-H(5.775)		

Task2					
HD- Not normalized		***CD- Not normalized***		***CD- Normalized***	
Ch	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**
C_Z	M(0.852)-H(0.794)	P_4	L(44.553)-M(7.797) L(44.553)-H(6.770)	P_4	L(19.494)-M(4.421) L(19.494)-H(3.576)
		P_Z	M(8.538)-H(5.463)	P_Z	M(5.331)-H(2.081)
		O_2	L(9.051)-H(6.007)		

a. Channel: Ch LOW: L, MEDIUM: M AND HIGH: H.

Table 2. Task 3 and task4.

Task3			
HD- Normalized		***CD- Normalized***	
Ch	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**
F_3	L(0.963)-H(1.060)	F_4	M(5.248)-H(3.074)
		T_4	L(5.099)-H(2.051)
		T_4	M(4.073)-H(2.051)

Task4			
HD- Normalized		***CD- Not normalized***	
Ch	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**
F_Z	L(0.957)-M(1.009)	C_4	M(8.398)-H(6.758)
F_3	L(0.958)-H(1.079) M(1.019)-H(1.079)		
F_7	L(0.961)-H(1.071) M(0.998)-H(1.071)		

C_3	L(0.981)-H(1.054)		
P_3	M(0.995)-H(1.041)		

Table 3. Task 9.

Task9							
HD-Not normalized		***HD- Normalized***		***CD- Not normalized***		***CD- Normalized***	
Ch	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**
P_3	L(0.736)-M(0.858)	F_Z	L(0.914)-M(1.0199) L(0.914)-H(1.063)	C_4	L(5.893)-M(8.543)	T_6	L(1.562)-M(4.549)
		F_3	L(0.906)-H(1.092) M(1.020)-H(1.092)	T_6	L(2.275)-M(7.661) L(2.275)-H(7.160)		
		F_7	L(0.964)-H(1.084) M(1.020)-H(1.084)	P_3	L(4.212)-M(7.628) L(4.212)-H(7.590)		
		C_3	L(0.972)-H(1.069) M(1.013)-H(1.069)	O_2	L(3.842)-M(8.967)		
		T_6	L(0.908)-M(1.015) L(0.908)-H(1.094) M(1.015)-H(1.094)				
		P_3	L(0.875)-M(0.997) L(0.875)-H(1.056) M(0.997)-H(1.056)				

Table 4. Task 10.

Task10							
HD- Not normalized		***HD- Normalized***		***CD- Not normalized***		***CD- Normalized***	
Ch	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**
P_3	L(0.715)-M(0.854)	F_Z	L(0.910)-M(1.004)	F_4	L(3.666)-M(8.050) L(3.666)-H(7.096)	F_3	L(1.310)-M(4.068) L(1.310)-H(3.586)
		F_3	L(0.894)-H(1.070) M(1.000)-H(1.070)	F_Z	L(5.039)-M(8.423)	C_3	L(2.305)-M(5.431)
		F_7	L(0.939)-H(1.052)	F_3	L(3.510)-M(7.683) L(3.510)-H(7.532)	P_z	M(5.077)-H(3.011)
		P_3	L(0.850)-M(0.992) L(0.850)-H(1.030)	F_7	L(4.763)-M(7.546)		
				C_4	L(5.117)-M(8.374)		
				C_Z	L(4.838)-M(8.534) L(4.838)-H(8.348)		
				C_3	L(5.277)-M(8.976)		
				P_z	L(4.484)-M(8.260) M(8.260)-H(6.454)		
				P_3	L(3.419)-M(8.842) L(3.419)-H(8.022)		
				O_2	L(3.694)-M(8.608)		
				O_1	L(5.112)-M(9.186)		

Table 5. Task 5 and task 7.

Task5	
HD- Normalized	
Ch	**Distinguished groups(mean)**
F_3	L(0.961)-H(1.077) M(1.016)-H(1.077)
C_3	L(0.991)-H(1.051)
P_3	L(0.971)-H(1.045) M(1.000)-H(1.045)

Task7					
HD- Normalized		*CD- Not normalized*		*CD- Normalized*	
Ch	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**
F_Z	L(0.897)-M(0.993)	C_Z	M(8.913)-H(7.497)	T_4	L(5.319)-H(2.792)
F_3	L(0.897)-H(1.045)				
F_7	L(0.940)-H(1.032)				
C_3	L(0.936)-H(1.027)				
T_3	L(0.933)-H(1.031)				
P_3	L(0.895)-M(0.981) L(0.895)-H(1.022)				
T_5	M(0.998)-H(1.101)				
O_1	L(0.925)-H(1.030)				

Table 6. Task 6 and task 8.

Task6			
HD- Normalized		*CD- Not normalized*	
Ch	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**
F_Z	L(0.922)-M(1.001)	C_Z	M(10.738)-H(7.956)
F_3	L(0.912)-H(1.063) M(0.994)-H(1.063)		
F_7	L(0.946)-H(1.029)		
C_3	L(0.960)-H(1.039) M(1.001)-H(1.039)		
T_3	L(0.945)-H(1.036)		
P_3	L(0.924)-M(0.986) L(0.924)-H(1.039) M(0.986)-H(1.039)		
T_5	M(1.007)-H(1.102)		
O_1	L(0.946)-H(1.046) M(0.985)-H(1.046)		

Task8			
HD- Not normalized		*HD- Normalized*	
Ch	**Distinguished groups(mean)**	**Ch**	**Distinguished groups(mean)**
F_3	L(0.732)-M(0.846) L(0.732)-H(0.854)	F_Z	L(0.918)-M(1.034) L(0.918)-H(1.079)
P_3	L(0.759)-M(0.874)	F_3	L(0.895)-M(1.040) L(0.895)-H(1.100) M(1.040)-H(1.100)
		F_7	K(0.955)-H(1.076) M(1.010)-H(1.076)
		C_4	L(0.933)-M(1.037)
		C_3	L(0.967)-H(1.073) M(1.024)-H(1.073)
		P_3	L(0.902)-M(1.018) L(0.902)-H(1.055)
		T_5	L(0.960)-H(1.072)

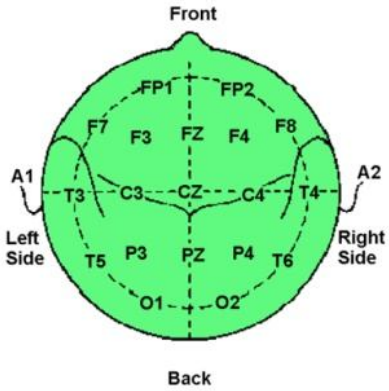

Figure 1. Location of electrodes in 10-20 standard

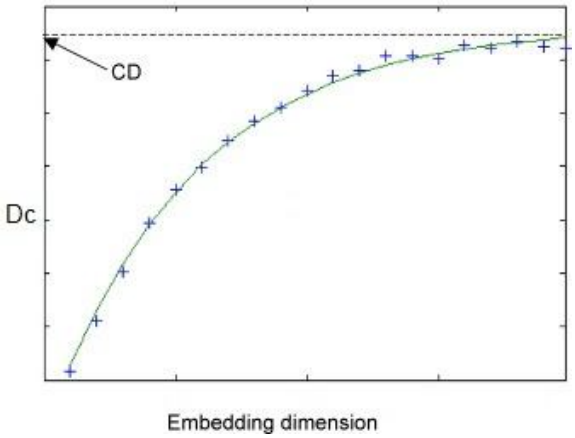

Figure 2. D_c as a function of embedding dimension.

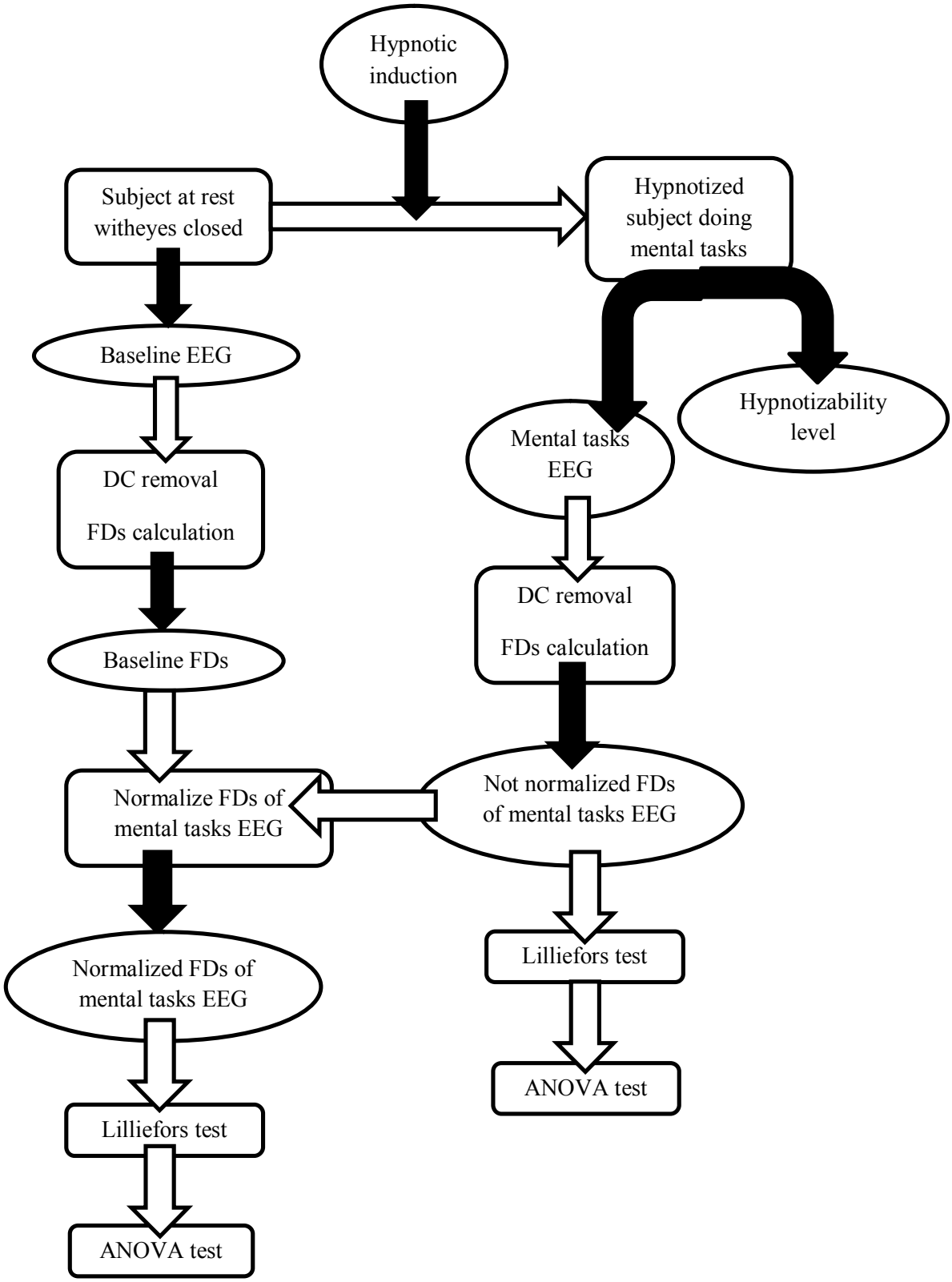

Figure 3. The process of feature extractions and analysis.