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Classifying Hypnotizable Groups Using EEG Weighted Regional Frequency

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Abstract. *Determination of hypnotizability is important, before prescribing any hypnotic treatment. Existing methods for measuring the level of hypnotic susceptibility are subjective, with some problems. In this study, a feature based on EEG weighted regional frequency was introduced, which can characterize the level of the subject's hypnotizability objectively. The ability of this feature for making a significant difference between three hypnotizable groups at the end of hypnotic suggestion was shown using statistical analyses. This feature was calculated based on the empirical mode decomposition method and the Hilbert transform. The EEG signals that were used in this study were recorded during hypnotic suggestion from 32 subjects. A K-nearest neighborhood-based classifier was designed for classification of the hypnotizable groups. The performance of the classifier was validated using the leave-one-out method, which showed the mean error of 3.13% in determination of the subject's hypnotic susceptibility level. This evaluation and obtaining the error were done by comparing the new method's results with the score of hypnotizability that was determined for each subject, using the subjective Waterloo-Stanford criterion. The new method, as opposed to common subjective clinical methods, represents a real time and objective procedure for determining hypnotic susceptibility.*

Keywords: *Hypnosis; Hypnotizability; Empirical mode decomposition; Hilbert transform; Classification; K-nearest neighborhood.*

INTRODUCTION

In recent years, much research has been devoted to processing EEG signals that can be recorded from the brain in different situations such as sleep, anesthesia and hypnosis. Hypnosis is a trance-like state of mind. The purpose of hypnosis is to help the subject gain more control over his behavior, emotions or physical well-being. Hypnotherapists say that hypnosis creates a state of deep relaxation and quiets the mind. When a person is hypnotized, he can concentrate intensely on a specific thought, memory, feeling or sensation, while blocking out distractions, and this can be used to change his behavior and, thereby, improve his health and well-being. However, these changes can only be done when the subject is more open than usual to suggestion. In other words, the best effect of hypnotherapy is on subjects who are more hypnotizable. Hypnotizability is the ability to experience a hypnotic trance. People vary in their ability to go into a trance at will and on purpose. Nowadays, the current method for determination of hypnotizability is the use of different standard tests that measure how well a subject conforms to the behavior of a classically hypnotized person [1-7]. Using the results of these tests, some people are found to be markedly more hypnotizable. There are different international tests, such as the Stanford Hypnotic Susceptibility Scale (SHSS) [8,9], the Hypnotic Induction Profile (HIP) [6] and the Waterloo-Stanford Group Scale of hypnotic susceptibility (WSGS) [2-5], which were designed in order to characterize the hypnotic susceptibility of a subject based on different questions and activities that a hypnotizer wants a subject to answer and perform. These standard clinical tests are subjective, so, they have some problems. As an example, clinical and subjective evaluations take time and are boring, which sometimes makes the subject tired and reduces the level of hypnotic trance. Also, sometimes the subjects try to cheat the hypnotherapist, so he has to investigate the reactions of the subject to the tests in order to obtain a real hypnotizability level. Because of these problems, researchers try to find an

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objective method for determining the hypnotizability level. In this way, they try to investigate the effect of hypnosis on different biological signals [10-18]. In this study, we focus on hypnosis and its effects on the EEG signal, in order to determine the level of hypnotizability.

Several studies have been directed to the identification of the hypnosis effect on EEG signals. Initial studies [19-21] suggested that highly hypnotizable people produced more EEG alpha under resting conditions than low-hypnotizable people. However, Evans [22] did not show this difference and suggested that previous results were biased by demand characteristics, and Dumas [23] suggested that the alpha-hypnotizability relationship resulted from biased subject selection [23]. Perlini and Spanos [24], in their critical review of alpha and hypnotizability, concluded that there is little support for an alpha-hypnotizability relationship. Graffin et al. [25] showed that following a standardized hypnotic induction, low susceptible participants displayed an increase in theta activity, whereas high-susceptible participants displayed a decrease.

Ray [26], using fractal dimensionality measures, reported that highly hypnotizable individuals display underlying brain patterns associated with imagery, whereas low hypnotizable individuals show patterns consistent with cognitive activity.

Abootalebi et al. [27] investigated and found the relation between hypnotizability and higher order spectra of EEG signals. The findings of these studies have not been consistently replicated either. One explanation is that perhaps the subject's personal preferences, and the hypnotic techniques used in different studies vary widely; by the fact that brain activity differs in hypnosis depending on the nature of the suggestions. Nasrabadi [28] represents a method for estimating the hypnotizability score based on EEG feature extraction.

Horton et al. [29] performed the first MRI study to report differences in brain structure size between low and highly hypnotizable, healthy, right-handed young adults. They imported that highly hypnotizable subjects had a significantly larger rostrum (a corpus callosum area involved in the allocation of attention and transfer of information between prefrontal cortices) than low hypnotizable subjects.

Lee et al. [30] investigated the correlation between HIP-induction scores and the scaling exponent of DFA, but he found no relation between this feature and hypnotizability.

Baghdadi & Nasrabadi [31] showed that some EEG fractal features have a significant relationship with the final depth of the hypnosis or hypnotizability level.

Behbahani and Nasrabadi [32] propose a method for classifying hypnotizable groups, based on the fuzzy similarity index of hypnosis EEG signals. Behbahani reported that based on a fuzzy similarity index feature we can classify the highly hypnotizable subjects from other subjects with high accuracy.

The mentioned studies, except [26,31], tried to find the effect of hypnosis on different brain wave features, not to classify the subjects into different hypnotizable groups. In this way, the studies are continued in order to find an objective general method for classifying subjects into more hypnotic susceptibility levels, such as very low, low, medium, high and very high.

This paper offers a promising method for classifying three hypnotizable groups (Low, medium and high) using calculation of the weighted regional frequencies based on an Empirical Mode Decomposition method (EMD) and Hilbert Transformation (HT). A combination of these two algorithms, which is called the Hilbert Huang Transform (HHT), was used for analyzing EEG signals during different brain activities [33-37]. Empirical mode decomposition is a new method for analyzing nonlinear and non-stationary data. By this method, any complicated data set can be decomposed into a finite and often small number of intrinsic mode functions that admit well-behaved Hilbert transforms. This decomposition method is adaptive and, therefore, highly efficient. Since the decomposition is based on the local characteristic time scale of the data, it is applicable to nonlinear and non-stationary processes. The EMD method was initially proposed for the study of ocean waves [38], and found immediate applications in biomedical engineering [39,40]. In this study, the EMD method was implemented in a study of the hypnotizability of different subjects and an effort was made to find out if there is a significant difference between three hypnotizable groups (low, medium and high) using a weighted regional frequency instead of common and earlier subjective clinical methods, such as WSGS.

MATERIALS AND METHODS

Data and Subjects

The data includes EEG signals that were recorded from 32 right-handed men during hypnosis. EEG data were recorded from 19 channels and were sampled with 256 Hz based on a 10-20 system of electrode placement. Hypnosis induction was done by playing a recorded sound on a tape, so, the method and time of the hypnosis induction were the same for all subjects. This tape was based on the Waterloo-Stanford criterion [2-5]. An EEG was recorded for 15 minutes during the hypnosis induction. In order to evaluate and compare the new method's results with a subjective

Table 1. Demographic and clinical characteristics of subjects.

Gender	Male
Number of hypnosis sessions	3-6 times
Physical features of subjects before recording	No high physical activity Enough relaxation Right handed
Duration of hypnosis	15 mins
Time of recording	Afternoon (about 4 to 8 o'clock)
Score of hypnotizability in Waterloo-Stanford criterion	12 to 52
Number of low hypnotizable subjects	4
Number of medium hypnotizable subjects	18
Number of high hypnotizable subjects	10

method, a score of hypnotizability was determined for each subject based on the subjective Waterloo-Stanford criterion. The WSGS scores are between 12-60. Based on these scores, the subjects divided into three groups, low (WSGS scores are between 12 and 22), medium (WSGS scores are between 23 and 41) and high (WSGS scores are between 42 and 60). Table 1 shows the demographic and clinical characteristics of subjects.

Empirical Mode Decomposition (EMD)

Huang et al. [38] have introduced the EMD method for nonlinear and nonstationary signal analysis. The general idea of this method is the sifting process to decompose any given signal into its intrinsic oscillations. With the EMD approach, the basic functions themselves are nonlinear, which can be derived directly from the data. Hence, the analysis is adaptive. The adaptive basis is called the Intrinsic Mode Function (IMF) and this method decomposes a time series into a finite and often small number of IMFs each of which must satisfy the following definition:

1. Number of extreme and number of zero-crossings must differ at most by one.
2. At any point, the mean value of the upper and lower envelope is zero.

The IMFs, $x_i(t)$, of a signal $y(t)$, is found by the following loop:

1. Compute the mean of upper and lower envelopes of signal, $m(t)$,
2. Subtract from the signal to obtain $z_i(t) = y(t) - m(t)$.
3. Check if $z_i(t)$ is an IMF, then, $z_i(t)$ is the first IMF of $y(t)$. If it is not an IMF, $z_i(t)$ is treated as the original signal and steps 1 to 3 are repeated;
4. Separating $z_i(t)$ from $y(t)$, we get $y_i(t) = y(t) - z_i(t)$. $y_i(t)$ is treated as the original data and, by repeating the above processes, the second IMF of $y(t)$ could be obtained [41-43].

The second step is applying the Hilbert transform to each IMF, in order to compute the instantaneous frequency and amplitude at each time [38,44]. $X(t)$ in the following equation is the Hilbert transform of $Y(t)$.

$$X(t) = \text{Hilbert Tranform}\{Y(t)\} = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{Y(t)}{t - t'} dt'. \tag{1}$$

Using Equation 1, instantaneous frequency, $If(t)$, and instantaneous amplitude, $a(t)$, are defined as [38,44,45]:

$$a(t) = \sqrt{Y^2(t) + X^2(t)}, \tag{2}$$

$$\begin{cases} If(t) = \frac{d\theta(t)}{2\pi dt} \\ \theta(t) = \arctan\left[\frac{X(T)}{Y(T)}\right]. \end{cases} \tag{3}$$

Weighted Instantaneous and Regional Frequency

Equations 2 and 3 give the frequencies and their amplitudes that make a signal in each time. Investigating the time-frequency-amplitude spectrum of a signal shows that a number of frequencies have larger amplitude, and this subject offers that these frequencies are more dominant in each time. However, a simple average of all obtained frequencies in each time does not consider the larger effect of the dominant frequencies. This problem can be solved by considering a larger weight for the dominant frequencies in calculating the average frequency in each time. In this study, the weight of each instantaneous frequency, $If_j(t)$, is

the instantaneous amplitude of this frequency, $a_j(t)$, divided by the summation of all instantaneous frequency amplitudes (see Equation 4). Therefore, the weight of the instantaneous frequencies that have the larger amplitude is greater than of those with lower amplitudes.

$$WIF(t) = \sum_{j=1}^{n} a_j(t) If_j(t) / \sum_{j=1}^{n} a_j(t), \quad (4)$$

where n is the number of the IMFs of a signal that is recorded from one of the brain channels. $If_j(t)$ and $a_j(t)$ is the series of the estimated instantaneous frequency and amplitude for each IMF [44]. $WIF(t)$ is a series of weighted instantaneous frequencies. In this study, we used the average of $WIF(t)$ in different time windows of the hypnosis EEG, so we have used a weighted regional frequency instead of an instantaneous frequency (see Equation 5).

$$RF = \sum_{t=t'}^{t'+T} WIF(t). \quad (5)$$

Therefore, RF is the average of $WIFs$ in a time window whose duration is T. In this paper, the ability of this feature in different brain channels is investigated in order to classify the hypnotizable groups.

Statistical Analysis and Area Under ROC Curve

Before designing and using any classifier, it was tested whether or not a feature based on a weighted regional frequency can make a significant difference between three hypnotizable groups. This investigation was performed using some statistical analyses, such as ANOVA [46] and MANOVA [47,48]. The normality of the data was investigated before performing the analyses. ANOVA was used when one feature was employed for making a difference between three hypnotizable groups and MANOVA was used in a situation where the ability of the simultaneous usage of different features was investigated. The MANOVA can also give a linear combination of the different features that make the largest separation between groups. Calculation of the coefficients of this linear combination was done by maximizing the F ratio:

$$F = \frac{\vec{W}^T \sum_b \vec{W}}{\vec{W}^T \sum \vec{W}}. \quad (6)$$

This ratio represents the between groups variability, Σ_b, with respect to within the groups variability, Σ. This means that when $\vec{W}$ is an eigenvector of $\Sigma^{-1}\Sigma_b$, the separation will be equal to the corresponding eigenvalue. Therefore, the coefficients of the linear combination maximize the ratio of between-groups to within-groups variance.

For more confidence about the results of the statistical analyses, we calculated the area under the ROC curve, abbreviated as AUC. The ROC curve is a two-dimensional depiction of the classifier performance. The two axes of this graph represent tradeoffs between errors (false positives) and benefits (true positives) that a classifier makes between two classes [49]. In this project, we have used an ROC analysis before implementing the data into a classifier, so, false positive and true positive rates are obtained from the data distribution of each class. The other point is that a ROC analysis is commonly employed in problems with two classes. For calculating AUC in a problem with more than two classes, the following equation is introduced [46]:

$$AUC_{\text{total}} = \frac{2}{|C|(|C|-1)} \sum_{(c_i,c_j)\in C} AUC(c_i, c_j), \quad (7)$$

where $|C|$ is the number of classes, (in this investigation, we have three hypnotizable groups) and AUC (c_i, c_j) is the area under the two-class ROC curve involving classes c_i and c_j.

KNN Algorithm and Cross Validation Method

The K-Nearest Neighbors (K-NN) algorithm is a method which does not need to calculate any parameter for making a classifier, in which, like the neural network based classifier, we are not required to estimate classifier parameters, for example the weight of the neurons. We just select an appropriate K and start the classification. In this method, the proximity of neighboring input (x) observations in the training data set and their corresponding output values (y) are used to predict (score) the output values of cases in the validation data set. The measuring of the adjacency of the neighboring input (x) is done using some distance function. In this project, the Euclidean distance function was used. For evaluating the performance of the KNN-based classifier, we have used the leave-one-out (LOO) cross validation method. When using the leave-one-out method, the learning algorithm is trained multiple times using all but one of the training set data points. Then, the removed data point is tested and the error is calculated. This procedure is repeated R times where R is the number of training set points. Then, the mean error is calculated over all R data points. Leave-one-out cross validation is useful, because it uses all data in the test and training stages. Therefore, its result is essentially the same as using all data points in the training stage. This method

is very appropriate when the size of the data set is small.

RESULTS

As mentioned before, our goal is determination of hypnotizability at the end of hypnotic suggestion; using calculations of the weighted regional frequency from hypnosis EEG, instead of using different standard subjective clinical tests, such as WSGS. So, the RF in Equation 5 was calculated in the last three minute time window of the EEG signals that were recorded from different brain channels during hypnosis induction. Then, it was investigated if whether or not the calculated RF in the last time window of the hypnosis induction in different brain channels can separate three hypnotizable groups. This investigation was performed using statistical analyses and AUC.

The ANOVA showed that the calculated RF in the last time window of a single channel could not make a significant difference between three groups. The MANOVA also showed that the simultaneous use of the calculated RF of all brain channels (19 channels) could not separate three hypnotizable groups significantly. However, a linear combination of the RFs of all channels was found that could make a significant difference between three hypnotizable groups in the last time window of the hypnosis EEG. So, the new feature can be obtained as follows:

$$\text{The feature in one channel} = RF = \sum_{t=t'}^{t'+T} WIF(t),$$

$$\text{Linear combination of } RF \text{ in all channel} = \sum_{i=1}^{19} M_i \times RF_i. \quad (8)$$

In this relation $[t', t'+T]$ is the last time window of the hypnosis EEG. So, T is equal to three minutes and is considered the same for all channels, and M_is are the coefficients of making this linear combination. These coefficients are obtained from MANOVA by the procedure introduced in previous sections. In this study, calculated coefficients (M_i) are validated using the LOO cross validation method.

The ANOVA results of investigating the ability of this linear combination for making a significant difference between three hypnotizable groups were shown in Table 2. The null hypothesis is that there is no significant difference between groups. The statistical significance for rejecting the null hypothesis was determat 0.05.

According to the recorded p-value in Table 2, the null hypothesis is rejected and we can report that this linear combination can separate three hypnotizable groups significantly (p-value $\approx$ 1.1e-011 $<<$ 0.05) during the last time window (last 3 minutes) of the hypnosis EEG. The distributions of this feature, in different three minute time windows during hypnosis suggestion, were represented in Figure 1 using a box plot [50]. This figure allows us to visually follow the changes of the obtained feature in three groups during hypnosis induction. It should be noted that the last 3 minutes of hypnosis EEG were considered for calculating the mentioned linear combination, but the obtained coefficients (M_i) have been used for the other time windows.

Table 2. The ANOVA results of investigating the ability of the linear combination of the RFs of all brain channels (19 channels) for making a significant difference between three hypnotizable groups.

ANOVA Table					
Source	SS	df	MS	F	Prob >F
Groups	136.198	2	68.099	68.1	1.10586e-011
Error	29	29	1		
Total	165.198	31			

According to Figure 1, it is obvious that the distributions of the obtained feature in three groups have an overlap in different time windows during hypnosis induction. However, in the last time windows of the hypnosis, the distributions of the three groups are nearly separated from each other. Therefore,

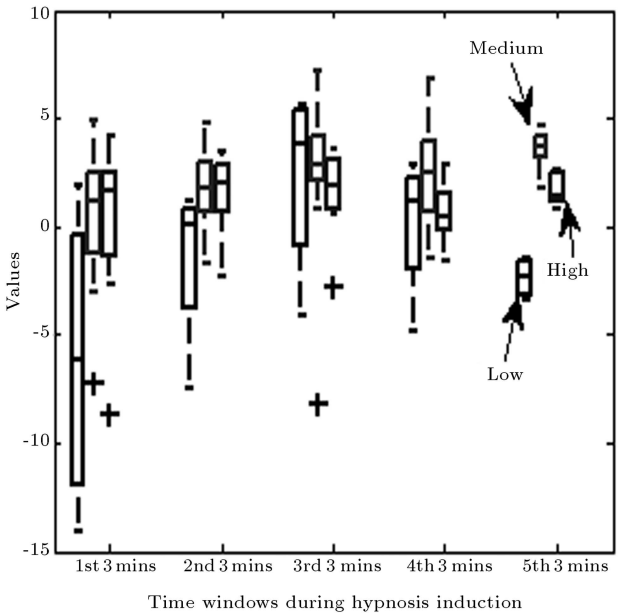

Figure 1. The box plots of the distributions of the linear combination of the RFs of all brain channels in three hypnotizable groups in different three minute time windows during hypnosis suggestion.

we can state that the obtained feature, based on weighted regional frequency, can be used as a feature for classifying three hypnotizable groups at the end of hypnosis induction.

This claim was proved by implementing the feature in a KNN-based classifier. In this study, we deal with a problem with three classes: low, medium and high hypnotizable. The obtained feature values in three hypnotizable groups were entered to the classifier as inputs. The desired output of the classifier that was the level of each subject's hypnotizability, was determined by WSGS. The number of low hypnotizable subjects in our data was four, and we have used the LOO cross validation method for evaluating the results. Thus, we have set $K = 3$, because at least 3 numbers of the values of this group exist in the training data set. Also, by a trial and error technique, $K = 3$ had the best result. Using the LOO cross validation method, the average classification error is obtained as 3.13%. It should be mentioned that this error is the mean error of the classification error of all three groups.

Then, it is investigated if whether or not a lower number of channels can make such a difference between groups. This investigation was done by looking for channels that were more effective than those of others in the linear combination. The level of each channel's efficacy could be shown by its coefficient (M_i) in the obtained linear combination. The values of the obtained M_i were shown in Figure 2; these values are validated by the LOO method. The low tolerance of the channel coefficients shows that we can use the obtained coefficients for making the mentioned linear combination confidently.

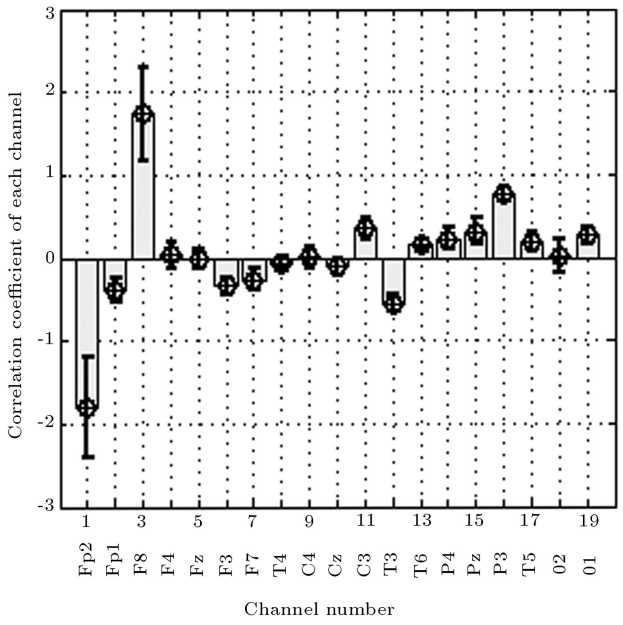

Figure 2. The coefficient values of each channel in order to make the linear combination of the *RF* values of all channels using LOO cross validation method.

These coefficients can show the effectiveness of each channel in the mentioned linear combination. According to these coefficients, we can report that channels (FP2) and (F8) have the most effect in this linear combination. The coefficient values of the channels (O2, C4, Fz, F4) and (T4), respectively, are between 0.0027 and 0.0606, so, we have considered them unimportant. Then, the linear combination was made without them, and the previous analysis was done in order to investigate the new linear combination. It was observed that the results do not have any considerable difference from when we considered all channels in the linear combination (see the first and second rows of Table 3).

Channels (Cz, T6, T5) and (P4) are the next channels whose coefficients are less than the remaining channels. In the next stage, these channels were, respectively, removed from the linear combination, and the result of the ability of the newly produced linear combination in separating three hypnotizable groups was investigated by different analyses whose results were recorded in Table 3.

According to the recorded results in Table 3, it is seen that elimination of channel (Cz) does not have any significant effect on the result, too. However, removing channels (T6) and (T5) makes a considerable increase in classification error. Therefore, it is resulted that the 13 channels highlighted in Table 3 are the most effective channels in the linear combination. In other words, these are the channels whose *RF* linear combination can determine the level of hypnotizability with the lowest error. Thus, the linear combination of these 13 channels can be replaced with the linear combination of all 19 channels. Therefore, the number of electrodes will reduce. Table 4 shows the classification error of each hypnotizable group separately using the LOO cross validation method. Figure 3 shows the scatter plot of the values of the newly obtained linear combination in three hypnotizable groups.

According to the classification errors in Table 4, it is resulted that the error comes from a miss-classification in high hypnotizable groups and in accordance with Figure 3, this mistake is because of the proximity of two data in high and medium hypnotizable groups (two data that are located in a circle). These data belong to two subjects whose WSGS score is 41 and 42. So, this closeness may be because of the nearness of their hypnotizability.

CONCLUSION

In this study, we introduced a feature based on weighted regional frequency, which allows determina-

Table 3. The results of investigating the ability of the linear combination of the RFs in different brain channels for making significant difference between three hypnotizable groups.

The Channels Which Contributed in the Linear Combination	p-value[1]	AUC[2]	Classifier Error[3]
All channels (19 channels)	1.1059e-011	0.9944	3.13%
Fp1,Fp2,F8,F3,F7,Cz,C3,T3,T6,P4,Pz,P3,T5,O1	2.0230e-011	0.9944	3.13%
Fp1,Fp2,F8,F3,F7,C3,T3,T6,P4,Pz,P3,T5,O1	9.6434e-011	0.9907	3.13%
Fp1,Fp2,F8,F3,F7,C3,T3,P4,Pz,P3,T5,O1	3.4886e-010	0.9852	18.75%
Fp1,Fp2,F8,F3,F7,C3,T3,P4,Pz,P3,O1	6.1038e-008	0.9602	37.5%
Fp1,Fp2,F8,F3,F7,C3,T3,Pz,P3,O1	5.004e-006	0.9102	40.63%

1-The p-values are obtained from the ANOVA, and the null hypothesis said that there is no significant difference between groups.

2-The values of the AUC are obtained before performing the KNN classification.

3-The classifier is based on KNN algorithm, the average error is the result of LOO validating method, and this error is the mean error of the classification error of all three groups.

Table 4. The resulting errors of the KNN based classifier in each hypnotizable group using LOO cross validation.

Feature	Hypnotizable Group	Classifier Error
The linear combination of the RFs	Low	0%
values of the channels	Medium	0%
Fp2, Fp1, F8, F3, F7, C3, T3, T6, P4, Pz, P3, T5 and O1	High	10%

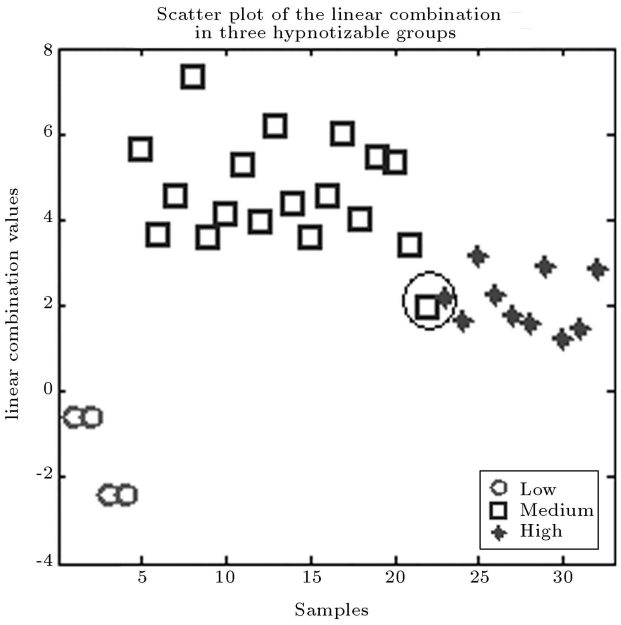

Figure 3. The scatter plot of the linear combination of the RFs values of the channels Fp2, Fp1, F8, F3, F7, C3, T3, T6, P4, Pz, P3, T5 and O1 in three hypnotizable groups.

tion of the level of hypnotic susceptibility of a subject by an average error of 3.13%. The separation of groups was possible only during the final 3 minutes of hypnotic induction. Before obtaining this result, we also expected that the best separation would be done at around the end of the hypnosis induction, because from the beginning of the hypnosis induction to the end, the hypnosis depth of the subjects would increase and at about the end of the hypnosis induction the subjects would be in the final level of hypnotizability. In other words, during the first time windows of hypnosis induction, the hypnosis depth of the subjects are near each other and, at about the end of hypnosis induction (final 3 minutes), the different hypnotizable groups stay at a different hypnotic depth. Thus, the separation can be done during the last time window of the hypnotic induction.

Instead of the study of Ray [26] and Behbahani [31], who used classifier algorithms for hypnotizability level determination, the other previously EEG based studies only paid attention to finding the relation between some features and hypnotizability using statistical analyses. Therefore, we can compare our results only to the study results of Ray

and Behbahani. Ray found an average precision of 94% (without any cross validation) in separating the low hypnotizable groups from the high hypnotizable subjects. Behbahani reports an average precision of 93% (LOO cross validation method) in separating high hypnotizable subjects from medium and low ones. In classifying low hypnotizability, she reported high error. But, in the current study, using the obtained procedure, three hypnotizable groups can separate from each other significantly, by an average precision of 96.9% (using LOO cross validation method). Moreover, the error is not because of the low hypnotizable subject's classification, it is related to a high hypnotizable subject whose hypnotizability score is close to medium hypnotizable subjects. In other words, the RF values of high hypnotizable subjects that have medium behavior are close to medium RF values.

Calculation of the introduced feature in the current study takes about 90 seconds (using a Pentium4 with 3.2 GHz CPU). So, just after hypnosis suggestion, we can say that the subject has low, 2medium or high hypnotizability. Common clinical methods based on behavioral assessment take time to determine the level of hypnotizability and are usually boring. Also, sometimes these assessments bring the subject out from hypnosis. Therefore, in comparison with common clinical methods such as (WSGS), the introduced procedure is a real time method for measuring hypnotic susceptibility. Another problem in clinical methods is that they are subjective and the subject's answers need to be trusted. But, the new method offers an objective procedure for determination of the hypnotizability level by measuring EEG weighted regional frequencies.

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