# Investigation of Spatial Characteristics of Meditation EEG: Using Wavelet and Fuzzy Classifier

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***Abstract* — The aim of this study is to propose a method for detecting α wave in EEG (electroencephalograph) and find the characteristics of EEG spatial distribution. We also investigated the difference of spatial characteristics between Zen-meditation practitioners (experimental group) and non-practitioners (control group).**

**We firstly adopted wavelet transform to decompose EEG signals and reconstruct waves in each frequency band using wavelet coefficients. From the power ratio, we selected the candidates (normalized α-power vectors) for further spatial analysis. Fuzzy C-means based algorithm was applied to the normalized vectors to explore various brain spatial characteristics during meditation (or, at rest). Here we evaluated correlation coefficients to decide the number of clusters.**

**From the results we found (1) the α power in the control group decreased dramatically but not in the experimental group, (2) after meditation, α power in the frontal area of meditators increased more than that of the control subjects (after resting-EEG recording). From the literatures, activating medial prefrontal cortex and anterior cingulated cortex during meditation may be the reason of increasing frontal α power.**

## I. Introduction

Numerous studies have examined various aspects of the physiology of meditation, and substantial investigations have been discovered. For instance, under meditation the activation of the autonomic and endocrine system is decreased, that is, the levels of respiration rate, heart rate, spontaneous skin conductance response and cortisol are lower [1] [2]. Other researches reported that meditation was useful in treating some medical problems such as hypertension [3] [4] anxiety [5], pressure [6] and tumors [7]. In the view of psychophysiology, researches focused on the effects of meditation taking place on the neural systems. Some related studies found that under meditation the alpha amplitude and coherence were higher [8] [9] , and the power of theta and lower alpha were larger [10] [11]. Sensory evoked potential assessment of concentrative meditation yields amplitude and latency changes for some components and practices [12] [13]. Although plentiful of EEG studies have been developed, but few focus on the topography distribution. Owing to specific component of frequency band stands for particular cognitive meaning, investigating the distribution of the specific band could help us to observe the spatial effects on the cortex of meditation.

The spatial features of alpha waves have been investigated for some researchers. Lehmann assumed that three stationary, semi-independent generators can account for the main features of alpha fields [14]. José Luis Cantero and et al. provided evidence for an alpha power modulation and a different scalp distribution according to the cerebral arousal state [15]. Basar E and et al. assumed that a ‘diffuse and distributed alpha system’ exists [16]. However, this issue is rarely discussed under meditation. The aim of this study is to investigate the spatial characteristics of alpha waves under meditation, and compared that to the control subjects under relaxation.

In this paper we utilized wavelet transform to find out the sections of alpha-dominant EEG, normalized the alpha-power vectors, and classified the feature vectors using Fuzzy C-means based algorithm. Finally we discuss the difference of results between experimental group (Zen meditatators) and control group (non-meditators)

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## II. Method

### A. Wavelet Transform

In the past studies of EEG analysis, spectrum analysis is the most popular method. However, the Fourier Transform is not adequate for non-stationary signals and the temporal information of the frequency patterns might be lost. To solve this problem, numbers of approaches have been developed, including the Wavelet Transform. The Wavelet Transform decomposes the signal into shift and scaled of the wavelets. The Wavelet Transform provided some advantages: its ability to perform local analysis, the high flexibility in terms of scalability in resolution and distortion, and furthermore, it does need require stationary. Due to the EEG signal is not stationary, that is, the frequency characteristic is not consistent all the time, we adopted the Wavelet Transform to localize the temporal features. Choosing the suitable wavelet is an important issue for EEG analysis. It is advantageous to choose wavelets that match the shapes of the extracting components (in this study, the interesting components are alpha waves). The wave shape of the Daubechies 6 (Db 6) low-pass filter’s wave shape was similar to the sum of neuron action potentials [17], so it was used to analyze the EEG.

### B. *Alpha Wave Detection*

In the bibliography of meditation EEG research, alpha wave has been the subject of much investigation [18]. Some researches that combined EEG and fMRI found that increased alpha power related to decreased blood flow in the inferior frontal, cingulated, superior temporal, and occipital cortices [19]. Due to the role of alpha has been investigated in many studies of meditation, we chose it as the object to study. Here we first developed a wavelet-based algorithm to extract alpha waves from meditation EEG.

When applying discrete wavelet transform, the window-size was 1-sec with no overlap. We applied wavelet transform to decompose the EEG using the typical pyramidal structure (order 2). After calculating the wavelet coefficients of delta (0~4.03Hz), theta (4.03~8.06 Hz), alpha (8.06~15.6 Hz), beta (15.6~31.3 Hz) and gamma (31.3~62.5 Hz) band, we reconstructed these waves by up-sampling and filtering respectively. Here we defined the ratio of the alpha-power as below.

$$\rho = \frac{p_\alpha}{p_\delta + p_\theta + p_\alpha + p_\beta + p_\gamma} \times 100\% \qquad (1)$$

where $p_\alpha$ means the power of the reconstructed alpha wave, and so on.

If the ratio of the alpha-power $\rho$ is greater than the threshold $\theta_1$ (here we set $\theta_1$ = 50%), this 1-sec section of EEG will be viewed as alpha-domination. Figure 1 is a example of detecting alpha wave.

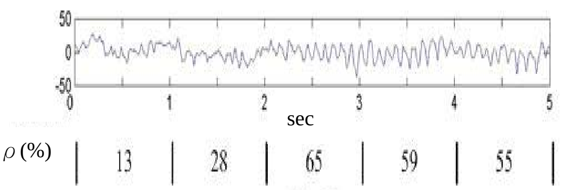


Fig. 1. A section of 5-sec long EEG. The numbers listed below are the ratios of alpha-power in each window.

From figure 1 we can find that alpha is dominant in the last 3 seconds, and by our method we extracted these three sections successfully ( $\rho$ > 50%).

All the 30-channels of EEG were examined whether alpha existed respectively. We extracted those sections of EEG with alpha-domination, and define the vector with the alpha-power of each channel as its elements (see as below).

$$p_{\alpha i} = [\, p_{\alpha i1} \quad p_{\alpha i2} \quad p_{\alpha i3} \quad \cdots \quad p_{\alpha i30} \,] \qquad (2)$$

where $p_{\alpha i}$ is a vector containing the alpha-power of the $i_{th}$ section of alpha-dominant EEG, and $p_{\alpha ij}$ means the alpha-power of the $j_{th}$ channel (total 30 channels in our recording) in the $i_{th}$ section. We then normalized each alpha-power vector as the feature vector.

### C. *Fuzzy C-means*

Fuzzy c-means (FCM) is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership-value. It was developed by Bezdek in 1973 [20]. Here we utilized FCM to classify the input feature vectors (normalized alpha-power vectors). Deciding the number of clusters is the first step while using FCM. Here we proposed a new method using correlation coefficients to determine the number of clusters. First we use an initial number to classify (larger than 5 in general), and we would get the membership value of each sample using the calculation below.

$$\chi_{ij} = \left[ \sum_{l=1}^{c} \left[ \frac{d_{ij}}{d_{lj}} \right]^{\frac{2}{\beta-1}} \right]^{-1} \qquad (3)$$

Where $\chi_{ij}$ is the membership value of the sample $x_j$ to the center $y_i$, $d_{ij}$ is the distance between $x_j$ and $y_i$, c is the number of clusters, and $\beta$ is the fuzzyness coefficient. Each center $y_i$ has its membership-value vector as follow.

$$\chi_i = [\chi_{i1} \quad \chi_{i2} \cdots \chi_{im}]$$

We then calculated the correlation coefficients by the formula below.

$$R(\chi_i, \chi_j) = \frac{C(\chi_i, \chi_j)}{\sqrt{C(\chi_i, \chi_i) C(\chi_j, \chi_j)}} \qquad (4)$$

where $C(\chi_i, \chi_j) = E[(\chi_i - \mu_i)(\chi_j - \mu_j)]$ is the covariance matrix.

If $R(\chi_i, \chi_j)$ is larger than the threshold $\theta_2$ (here we set $\theta_2$ =0.3), we considered that $y_i$ and $y_j$ are too close, and the number of cluster c must minus 1.

To test the performance, we applied the algorithm to a section of EEG (30 channels). In figure 2, we classified the EEG data into 4 clusters. Table 1 is the correlation coefficients of each center's membership-value vector.

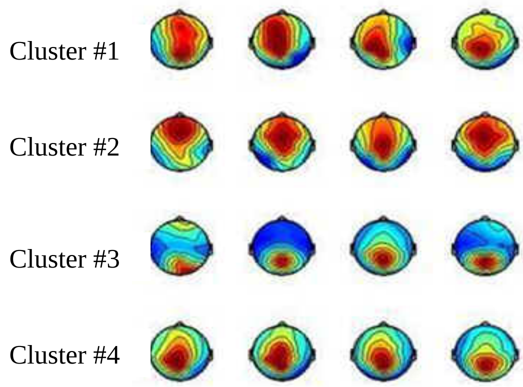


Fig. 2. The results of 4 clusters

Table 1
The correlation coefficients of each center's membership-value vector (4 clusters)

| Cluster | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1 | | 0.67 | -0.86 | -0.32 |
| 2 | 0.67 | | -0.73 | -0.64 |
| 3 | -0.86 | -0.73 | | 0.04 |
| 4 | -0.32 | -0.64 | 0.04 | |

We found that the samples in cluster #1 are very similar to that in cluster #2, and the correlation coefficient $R(\chi_1, \chi_2) = 0.67$ that is too high. The number of clusters should be decreased. Below is the result that we classified the same data into 3 clusters.

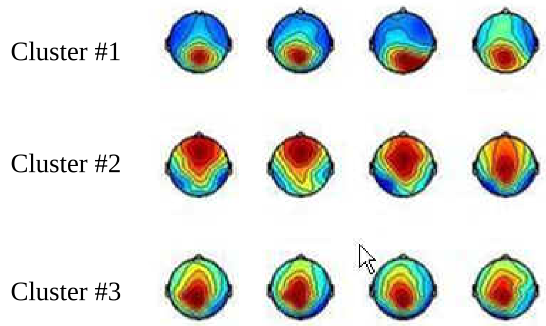

Fig. 3. The results of 3 clusters

Table 2
The correlation coefficients of each center's membership-value vector (3 clusters)

| Cluster | 1 | 2 | 3 |
|---|---|---|---|
| 1 | | -0.8 | -0.51 |
| 2 | -0.8 | | -0.11 |
| 3 | -0.51 | -0.11 | |

The results above show that it's better to class the data into 3 clusters. The flowchart of this algorithm is shown as figure 4.

### D. *Subjects and Recording Setup*

This study involves 10 experimental subjects (meditators) and 10 control subjects (normal, healthy people without any experience in meditation). In the experimental group, 3 females and 7 males at the mean age of 28.9±3.2 years participated. Their experiences in Zen-Buddhist practice span 7.6±4.5 years. The control group consists of 4 females and 6 males at the mean age of 25.9±5.2 year

The EEG was recorded within the frequency range from 0.15Hz to 50Hz. The sampling rate is 1000Hz. We applied the 30-channel recording montage with the ground at the forehead and the reference as the linked mastoids (using 10-20 system).

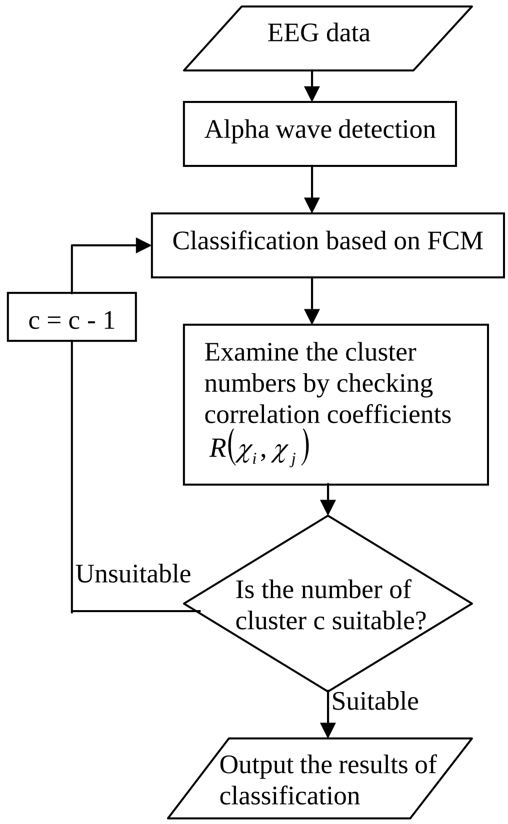

Fig. 4. The flowchart of the proposed algorithm

Subjects sat in a isolated space during the recording. Each recording lasted for about 32 minutes. The course included 2min pre-session, 40min main-session, and 2min post-session recording.

In the main-session period, experimental subjects practiced the Zen meditation, while control subjects sat in normal relaxed position with eyes closed. During the meditation, the subject sat, with eyes closed, in the full-lotus or half-lotus position. In the 2min pre-session and post-session, experimental and control subjects closed their eyes and relaxed.

## III. Result

### A. *The results of classification*

Figure 5 to 7 are the results of the classification of one experimental subject. Here the optimal number of clusters is 3. Owing to the space limitation, we only showed the selected samples of each cluster. Note we have normalized every feature vector into 0 to 1.

### B. *The performance of FCM*

Table 3 shows the Euclidean distances between each center, and table 4 is the standard deviation of the distances of each sample to its center. From these two tables we found that the distances are greater than three times of the standard deviations, thus FCM separated these cluster successfully.

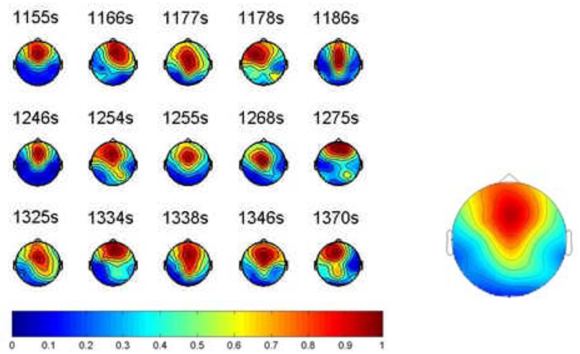


Fig. 5. Selected samples (three rows) and the center of Cluster #1. The numbers above the samples are the time indices (in sec).

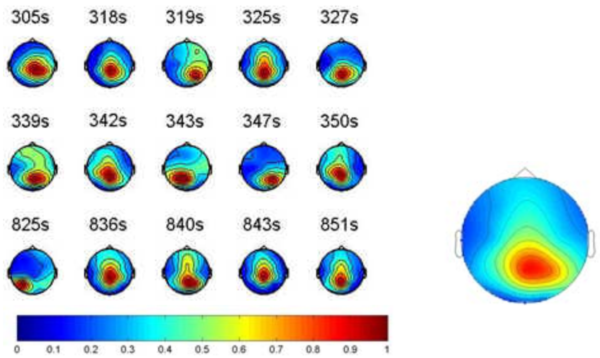


Fig. 6. Selected samples (three rows) and the center of Cluster #2. The numbers above the samples are the time indices (in sec).

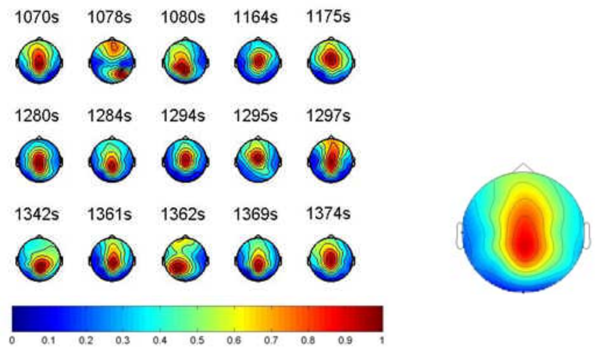


Fig. 7. Selected samples (three rows) and the center of Cluster #3. The numbers above the samples are the time indices (in sec).

Table 3 The Euclidean distances between each center

| Cluster \ Cluster | 1 | 2 | 3 |
|---|---|---|---|
| 1 | | 1.474 | 0.765 |
| 2 | 1.474 | | 0.895 |
| 3 | 0.765 | 0.895 | |

Table 4 The standard deviation of the distances of each sample to its center

| Cluster | Number of samples | Standard deviation of the distances |
|---|---|---|
| 1 | 266 | 0.250 |
| 2 | 246 | 0.232 |
| 3 | 197 | 0.242 |

*C. The representation of variations of alpha distribution*

Here we adopted color-bar to represent the variation of alpha distribution (see below). Here the color red, blue and green stands for the sample of cluster #1, #2 and #3 respectively. Black means the non-alpha dominant EEG.

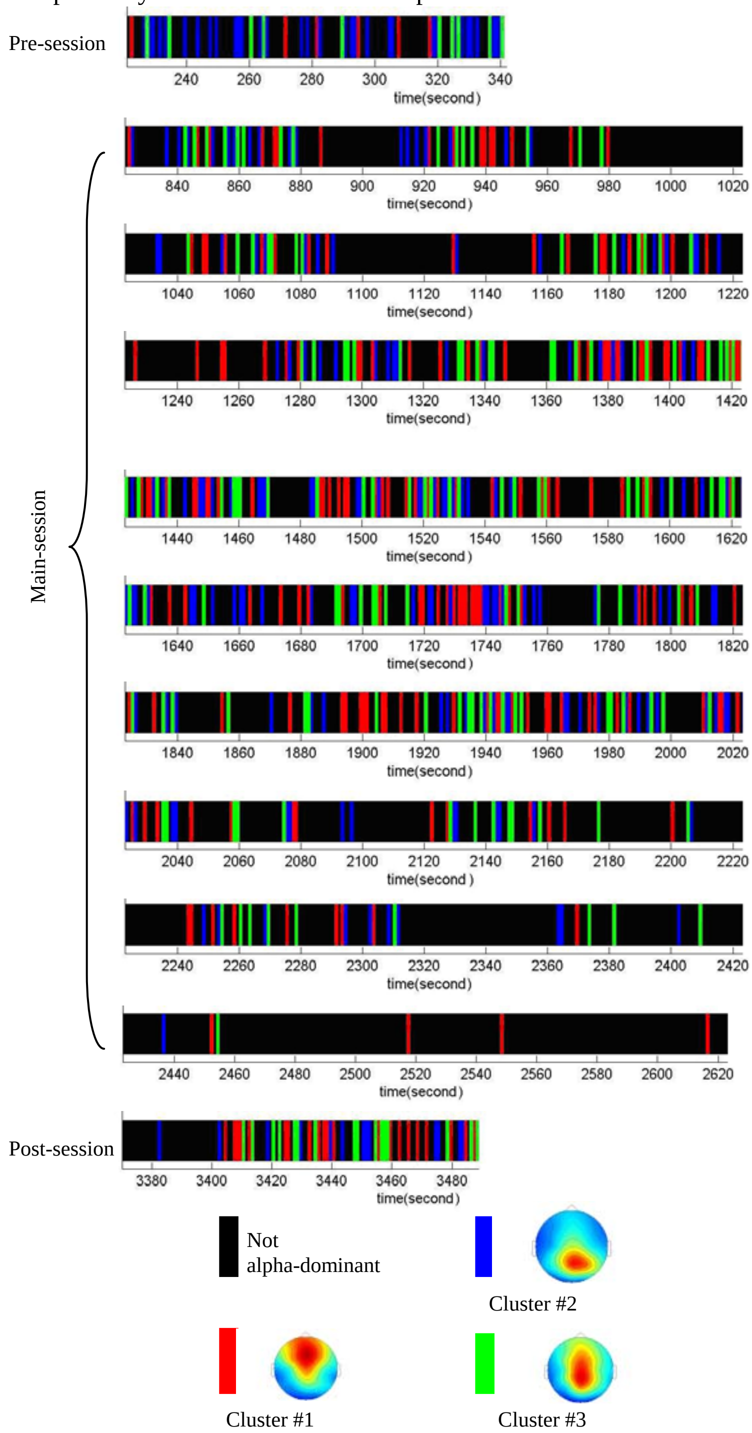


Fig. 8. The variation of alpha distribution

From the figure above we could obtain that alpha increased in the middle interval and decreased in the late interval of meditation. After meditation, the appearance of cluster #3 (centered on Cz) increased.

*D. Comparison of two groups*

Table 5 is the percentage of appearance on the frontal, central and parietal cortex in both groups. For example, there are 6 subjects in the experimental group that have the cluster locate on the frontal site. From this table we find that the probabilities of appearances on the central and frontal in the experimental group are higher that in the control group.

Table 5. The percentage of appearance on different locations (%)

| Category \ group | Experimental | Control |
|---|---|---|
| Frontal | 60 | 30 |
| Central | 70 | 50 |
| Parietal | 90 | 90 |

Table 6 shows the possessing percentage of alpha power on some important channels in the pre-session. We compared the difference of the two groups. Table 7 and 8 showed the difference in the main-session and the post-session respectively.

Table 6. The possessing percentage of alpha power on some important channels in the pre-session

| | PZ | P4 | P3 | CPZ | CZ | FCZ | FZ |
|---|---|---|---|---|---|---|---|
| Exp | 24.5 | 14.0 | 9.6 | 15.0 | 4.2 | 13.2 | 7.0 |
| Ctrl | 27.2 | 16.4 | 15.8 | 7.9 | 3.1 | 6.1 | 7.6 |
| Difference | -2.7 | -2.4 | -6.2 | 7.2 | 1.1 | 7.1 | -0.6 |

Table 7. The possessing percentage of alpha power on some important channels in the main-session

| | PZ | P4 | P3 | CPZ | CZ | FCZ | FZ |
|---|---|---|---|---|---|---|---|
| Exp | 20.4 | 13.1 | 6.1 | 16.1 | 5.6 | 12.5 | 9.1 |
| Ctrl | 29.7 | 15.2 | 16.0 | 6.3 | 3.5 | 6.3 | 6.4 |
| Difference | -9.4 | -2.1 | -9.9 | 9.8 | 2.1 | 6.2 | 2.7 |

Table 8. The possessing percentage of alpha power on some important channels in the post-session

| | PZ | P4 | P3 | CPZ | CZ | FCZ | FZ |
|---|---|---|---|---|---|---|---|
| Exp | 20.4 | 17.9 | 7.6 | 15.1 | 5.4 | 15.2 | 5.6 |
| Ctrl | 27.9 | 20.5 | 16.2 | 6.7 | 3.2 | 6.9 | 5.2 |
| Difference | -7.6 | -2.7 | -8.7 | 8.5 | 2.1 | 8.3 | 0.4 |

From the three tables we obtained that in the experimental group, the alpha on Cpz and FCz possess more than that in the control group. Besides, the alpha power on Fz was increased during meditation in the experimental group, but it was decreased in the control group during relaxation.

Figure 9 shows the changes of ratio of non-alpha dominant in both group.

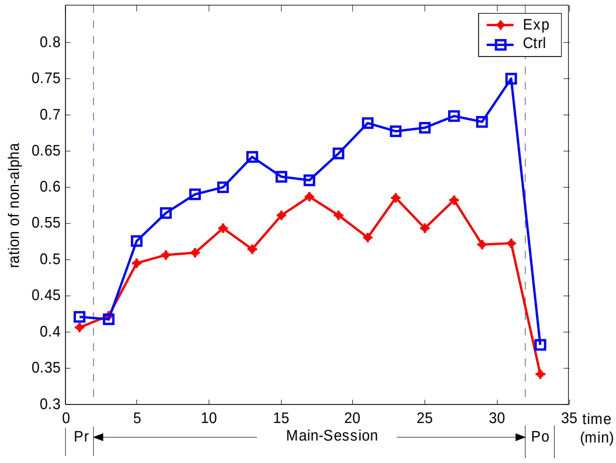


Fig. 9. Ratio of non-alpha dominant in both groups, where Pr means the Pre-session and Po is the Post-session.

From figure 9 we found that the ratio of non-alpha is getting higher while taking relaxation in the control group. Besides, the ratio of the control group is higher than it of the experimental group all the main session.

## IV. Conclusion and Discussion

In this study we developed a scheme to investigate the spatial distribution of alpha power, and we adopted this procedure to analysis this characteristics of meditators and control subjects. The results show that alpha waves in the central and frontal regions appear more frequently in the experimental group. From the previous study, the enhancement of frontal alpha during meditation may be related to the activation of the Anterior Cingulate Cortex (ACC) and medial Prefrontal Cortex (mPFC) [21]. The ACC has outflow to the autonomic, viscermotor and endocrine systems. Previous findings suggested that during meditation some changes of autonomic patterns and hormone are related to the ACC. Furthermore, the ACC and mPFC are considered to modulate internal emotional responses by controlling the neural activities of limbic system, that is, they may function via diffusing alpha waves. Besides, the trends of non-alpha are different in two groups. In control group the alpha wave was getting less during relaxation, and in the post-session it returned to the level which is the same in the pre-session. The reason of this trend may be drowsiness.

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