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Psychophysiological classification and experiment study for spontaneous EEG based on two novel mental tasks

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Abstract.
BACKGROUND: Study of imagination offers a perfect setting for study of a large variety of states of consciousness.
OBJECTIVE: Here, we studied the characteristics of two electroencephalographic (EEG) patterns evoked by two different imaginary tasks and evaluated the binary classification performance.
METHODS: Fifteen individuals (11 male and 4 female, age range of 22 to 33) participated in five sessions of 32-channel EEG recordings. Only by analyzing the subjects' output EEG signals from the central parieto-occipital region of P_Z electrode, under the circumstances of consciousness of relaxation-meditation or tension-imagination, we carried out the experiment of feature extraction for spontaneous EEG, as the subjects were blindfolded but asked to open their eyes all the same. The Hilbert-Huang Transform (HHT) was utilized to obtain the Hilbert time-frequency amplitude spectrum, and then with the feature vector set extracted, a two-class Fisher linear discriminant analysis classifier was trained for classification of data epochs of those two tasks.
RESULTS: The overall result was that about 90% ($\pm$ 5%) of the epochs could be correctly classified to their originating task.
CONCLUSION: This study not only brings new opportunities for consciousness studies, but also provides a new classification paradigm for achieving control of robots based on the brain-computer interface (BCI).

Keywords: EEG-based brain-computer interface (BCI), mental task of relaxation-meditation, mental task of tension-imagination, Hilbert-Huang transform, feature extraction, pattern classification

1. Introduction

Discovering the features and laws from the data of brain-activity is biologically significant and is becoming the hotspots and difficult points for neuroinformatics research on theory and practice of the time. As we know, when some kind of mental task is being carried out, the EEG signal generated in some specific region of brain will show certain obvious feature, and the rhythm will change along with mental state.

Based on that phenomenon, the brain-computer interface (BCI) has been provided as a channel for communication and control without muscle, for BCI can directly turn EEG signals of the user's into

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an output signal which describes the user's true intentions [1,2]. BCI technology not only can be used by severe motor disabled people in medical area, but also can be utilized in other areas [3,4].

In most studies of BCI control strategy, it is usually valid to ask subjects to imagine some specific parts of their bodies being moved [5,6]. Motor imaginary activates primary sensorimotor region of brain and leads to (de)synchronizes oscillatory components in the special frequency bands. And so, after analyzing or classification-processing the changes in the rhythmic activity of the brain's electrophysiological signals (event-related (de)synchronization, ERD/S) which were generated intentionally and recorded as nonlinear and non-stationary scalp electroencephalography (EEG) signals, BCI control could be realized [7,8]. It has been demonstrated by several studies that patients with motor dysfunction are still able to control BCI by means of motor imaginary [9,10].

BCI performance improvement can be realized by many approaches and most of the reasearches focused on aspects of signal processing and pattern classification. What is more, BCI performance improvement can also be realized by determining specific mental tasks appropriate for different subjects [11].

Motor imaginary perhaps are not the best choice as far as every people was concerned. Especially when the individuals have impairments in certain brain areas, it is valuable for them to make a choice among various mental tasks to realize BCI control. For instance, if the patient suffers a stroke in the motor area, the affected brain hemisphere or the size of the lesion maybe affect the motor imaginary task which might be substituted by a mental subtraction task [2]. In addition, for those patients who were with locked-in syndrome, their defects in selective motor imaginary were reported in contrast to their carrying out other mental tasks [12]. As the best strategy to result in brain activity for disabled or able-bodied subjects perhaps vary with each individual, a wider scope of feasible control policies of BCI and user's assessment and acceptance of various tasks are crucial [8,13].

Millán et al. and Galán et al. implemented asynchronous BCI protocols in which users achieved the control of a virtual keyboard, a wheelchair or a robot within certain time frames based on choosing different mental strategies such as: cube rotation, motor imaginary of left/right hand (or arm), relaxation, word association or subtraction [14,15]. That method stressed the necessity of choosing separate control policies for BCI.

Roberts et al. achieved the control of a cursor moving on a computer screen based on motor imaginary task together with mental subtraction task [16]. Keirn et al. realized discrimination among five mental tasks (relaxation and thinking of nothing, nontrivial multiplication problem solving, gometric figure rotation, mental letter composing and visual counting) but failed to find out significant differences [17]. And so they offered suggestions that some other mental tasks could be investigated as well and differences among various people might be focused on. Curran et al.compared two sets of mental tasks, one set was about acoustical imagery of a familiar tune and spatial imagery of navigating in a familiar region of space, and the other was about motor imaginary of left/right hand [18]. Results indicated not only that the accuracy of classification between the acoustical and spatial imagery was best, but also those two tasks were easier to perform and less concentration was needed, which could be indicated from the uses' evaluations. Cabrera et al. also implemented a BCI with acoustical imagery and spatial navigation imagery [19]. De et al. implemented a BCI with complete acoustical imagery [20]. The classification between stressed tones and unstressed tones within an imagined rhythm was realized.

Elisabeth et al. enlarged the above mentioned research findings and in different fields they explored a broader range of mental tasks such as mental figural rotation, word association of a verb, acoustical imagery of a melody, imagery of familiar faces [2]. They have carried on BCI control study in more aspects not only in respect of how to improve classification accuracy but also of how to obtain user's assesment and neurophysiologic correlative factors of those mental tasks.

It has been found out that nearly 20% of the subjects who would like to control a BCI, are not able to realize actually effective control [13,21]. Besides failures on the methodical issues, it is also possible that concentrations, distractions, fatigues, motivations, intentions and emotional states could exercise great influences on users' abilities to achieve and maintain voluntary control [22]. In addition, subject's acceptances, practices and thinking strategies could also affect BCI's usability, reliability and performance greatly. For example, a strategy of imaging familiar faces might be very easy and enjoyable for the users [23].

What is more, it was reported that different tasks could elicit various EEG-activation in different brain regions. Motor imagery of right hand would activate left central cortex [8]. Word association task would activate left frontal area and anterior cingulate gyrus [24]. Mental calculation is a fairly complex process and involves frontal as well as parietal processes [25]. There are controversial literatures about whether the task of mental rotation activates the left or right parietal area [26]. The task of spatial navigation is thought of as the right hemispheric task in general [27]. For the task of acoustical imagery, a cortical activation of the primary auditory cortex was proposed [28]. And the main center for imagery of familiar faces was reported to be localized in the regions of fusiform gyrus and prefrontal [29]. More comprehensively, Dyson et al. carried out research on different electrode positions relevant to different mental tasks [30].

Of course, there are other more possible mental tasks which have not been used for BCI control yet, and those tasks could elicit various EEG-activation in some other different brain regions [31–33].

From the 1990s on, because of the clinical efficacy of various meditation thoughts and practices, scientists have paid a lot of interest and attention to meditation. Herbert who is a professor at Harvard Medical School, describes the meditation experience as the "relaxation response". During meditation, a meditator might wander among states of open mindfulness, concentration, joyfulness, distraction, etc. [34]. Nowadays, the discussion of a variety of forms of meditation has been the hot point in the literatures of psychophysiological research [35]. All the meditation techniques can be categorized into two basically: concentrative meditation and mindfulness meditation. Concentrative meditation focuses on the attention to the breath, an image, or a sound (mantra), in order to still the mind and allow the awareness much clearer. At the same time, there are also imaginative methods that utilize a mental focus (e.g., an image of the Buddha). Mindfulness meditation, as Dr. Borysenko said, involves opening the attention to become aware of the continuously passing parade of sensations and feelings, images, thoughts, sounds, smells, and so on without becoming involved in thinking about them.

With the development of scientific instruments, a large number of experimental researches on brain science and neuroscience about meditation which mainly concentrates on attention, mood, and health effects have been carried out. During a prolonged meditation, muscle tension decreases, blood pressure drops, oxygen needs of the body reduces, and for some supernormal practitioners, even temperature and basal metabolism rates drop. It has also been found in meditators that when they are in highly relaxed states, their brain waves would change from busy beta-waves to blissful alpha-waves, which could be shown by EEG recordings that during meditative states of the mind there would be distinct patterns of increases in the power of alpha band [34].

So as an attempt, based on the turning of busy beta-waves to be blissful alpha-waves, two opposite types of mental imagery tasks – "high tension" and "high relaxation" might be selected as BCI-suitable tasks for classification.

In this paper, as an new exploration, we didn't asked the subjects to use the most commonly described tasks, instead, we explored the spontaneous EEG features of the subjects based on the consciousness of relaxation-meditation (a mental focus on imaginative vast sky) and tension-imagination (imaginative experience of being caught up by some kind of terrorist animal such as wolf, alligator, python, etc. Of course, which kind of animal is scary varies from person to person). The relaxation-meditation used in our experiments was imaginative method which belonged to concentrative meditation that utilized a mental focus on an image of the vast sky. It should be pointed out that, in this study, the subjects were all trained on that one type of meditation which was thinking of a vast sky. What is more, when the subjects are implementing those two different mental tasks, besides the blinks of the eyes, they are blindfolded but asked to open their eyes all the time to prevent eyes closed alpha from interfering with the alpha during relaxation-meditation. Moreover, it should be pointed out that, because data with the highest standard alpha band activity mainly appear in parieto-occipital areas [34], so we only used the subject's output EEG signal from the central parieto-occipital region of Pz electrode as the signal to be analyzed for classification.

In this study, we just want our contribution exactly to the current state of knowledge to be an attempt to new types of mental imagery tasks, or in other words, to be an addition to the existing available mental strategies, so that the subjects could have a choice in the mental tasks according to their preferences. The positive results of the experiments will supply a new method for realization of controlling the brain-computer interface (BCI), after the EEG signals are classified. In addition, the study of special consciousness phenomena which are brought by meditation, will not only can open up visual field of the scientific method fundamentally, but also can bring people the much deeper understand of the scientific method and consciousness.

2. Experimental subjects and methods

As we know, the brain wave rhythm of alpha and beta are usually described as follows:

Alpha wave means the 8 Hz–13 Hz rhythm of higher values of voltage appeared in the back of head or the central parieto-occipital region in the waking state. The alpha wave's frequency is fairly constant if there is no external stimulation, and the amplitude for normal adults is less than 50 μV. Alpha wave is usually sinusoidal, sometimes serrated or arc-shaped. Alpha wave can be observed most easily when the subject's body is relaxed with his or her eyes closed. The alpha wave may be also observed when the subject is under the circumstances of the consciousness of relaxation-meditation or in the process of hypnosis. When the subject's eyes are opened, with light stimulation or mental activities, alpha wave can be displayed with amplitude decreased or rhythm disappeared and being replaced by beta waves as well. This phenomenon is most apparent in the occipital region, clinically known as alpha wave's "block-phenomenon", which is the result of the desynchronization (ERD) of electrical activity of cerebral cortex.

When the previous subjects participated in the scientific experimental observation of alpha wave's generation or being blocked, their eyes were not covered, and when they opened their eyes, there existed visual stimulation to them from the surrounding environment more or less. Assuming that the subjects were blindfolded and couldn't see anything even when they opened their eyes but with the consciousness activity of relaxation-meditation, whether or not the alpha wave exists? What is the alpha wave amplitude? Those are yet to be discovered and proved scientific problems.

Beta wave appears mainly in frontal lobe and central region, and the beta wave in central region is usually associated with mu rhythm. The amplitude of beta wave is generally less than 30 μV, and the frequency value is between 14 Hz and 30 Hz. Beta wave appears under the circumstances of mental stress or emotional excitement, and it can be blocked by movement or tactile stimulation. There also existed a close relationship between Beta wave and ERD/ERS, and the amplitude can also be controlled

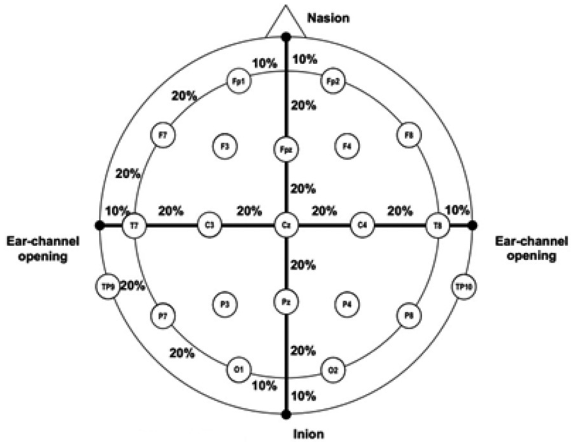

Fig. 1. Arrangement pattern for the electrodes satisfying international standards of 10–20 system.

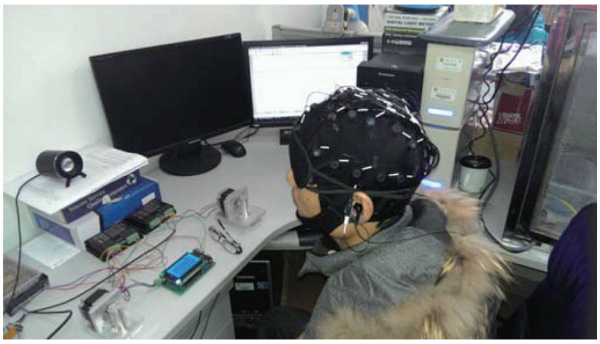

Fig. 2. The Subject was blindfolded while he (or she) was focusing his (or her) mind to perform the experiments of completing mental tasks of total relaxation-meditation or tension-imagination.

freely by trained subjects, so beta wave plays an important role in the study of BCI. Similarly, assuming that the subjects were blindfolded and couldn't see anything when they opened their eyes but with the consciousness activity of tension-imagination, whether or not the beta wave exists? What is the beta wave amplitude? Those are yet to be discovered and proved scientific problems too.

The main experimental researches in this paper are described in following subsections.

2.1. *EEG signal acquisition*

As for the experimental study carried out in this paper, the 64-channel EEG acquisition and analysis system made by American Neuroscan-company was adopted for experimental design and EEG signal acquisition. The system included a Quik-cap electrode cap for collection of scalp EEG signals, SynAmps2 preamplifier, software system equipped with Scan software for EEG signal acquisition, raw EEG re-reference (common average reference, CAR) module working as spatial filter, low-pass filter module with the cut-off frequency to be 30 Hz, time-frequency analysis module, pattern classification module and display interface. In this experiment, we adopted the 32-channel electrode cap, whose arrangement pattern for the electrodes satisfied international standards of 10–20 system (as shown in Fig. 1). As it has been introduced in the end of the introduction, although there were 32 electrode injected with conductive paste, we only used the output EEG signal from the central parieto-occipital region of Pz electrode. We might construct, though, some larger regions such as clusters covering frontal or central to test if classification rates turned to be much lower, but in fact we didn't do so in this study, because focusing on Pz would have been easily found out to be valid for classification by subsequent test.

2.2. *Experimental objects selection, laboratory setup and matters needing attention*

In this experiment, a total of 15 volunteers served as experimental objects, 11 male, 4 female. Their ages range from 22 to 33, averaged to 26.13 years old. Experimental objects were all healthy undergraduate or graduate students, without any mental illnesses or neurological diseases or family hereditary diseases, and they were all in good spirits without any medicines taken within one week before the test. Before recording data, laboratory technician should illustrate the matters need to be pay attention to in

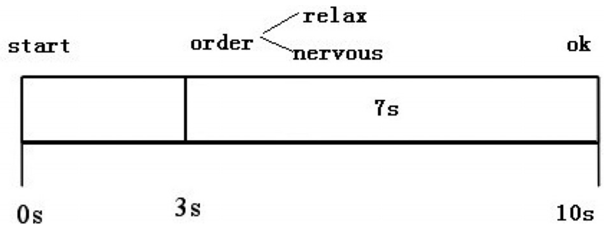

Fig. 3. A single experimental process.

the check to the subjects in detail, and the subjects were asked to prevent emotional tension as far as possible.

Subjects were blindfolded wearing earphone to avoid the impact of light and artifacts like line hum of machings, in order to facilitate focusing their minds to perform the experiments. (Note: the covered eyes were still needed to be open, as subsequent experiments would indicate that alpha wave still accounted for the major components of the EEG in the case of subjects being relaxed with their eyes open. The reason for we selected the eyes open condition and not eyes closed was just that eyes closed alpha would interfere with the alpha during relaxation-meditation, and we wanted to avoid that interferance). Subjects were listening to verbal instructions via earphone throughout the experiment and were unable to hear the environment noise. Subjects were seated in the comfortable chair with arms and a high back in front of the display of 70 centimeters away (see Fig. 2).

During EEG acquisition experiments, subjects were asked to be in the state with no movements and with muscles relaxed in addition to complete tasks of relaxation-meditation or tension-imagination. Pz electrode is located in the region that close to the parietal eye field area, in order to eliminate the possible effects induced by fast eye movements on the Pz activity, the eyes movements were asked to be minimized as far as possible during the experiments. What is more, some actions like swallowing slobber were also asked to be restrained. In order to make the offline analyzing data be applied to the online BCI system design, the artifacts such as the extra blink of eyes and unavoidable light eyes movement contained in EEG signals were not eliminated during analysis processing, and the vertical and horizontal electro-oculogram (EOG) signals were recorded together with EEG signals.

2.3. Experiment setup for EEG signal acquisition with tasks of different consciousness imaginary being implemented

The subjects were asked to perform tasks of relaxation-meditation or tension-imagination according to verbal instructions. Each session consisted of 20 trials (10 for each task) in random order. Each subject participated in 5 sessions, resulting in a total of 50 trials per task per subject. The subjects relaxed for 2 minutes–5 minutes with their eyes closed after the end of each session.

A single experimental process (as shown in Fig. 3) was as follows: ① After the experiment started, as soon as the subjects heard "start", they concentrated on the order which would appear 3 seconds later. ② At the 3rd second after the experiment began, the voice prompted "relax" or "nervous" to prompt the subjects to begin the task of relaxation-meditation or tension-imagination. Considering the consciousness pattern or imagination content of relaxation-meditation and tension-imagination varied from person to person in the habits, the imagination content of relaxation-meditation was unified to be vast sky, and the imagination content of tension-imagination was unified to be experience of being caught up by some kind of scary animal. ③ 7 seconds later, the voice prompted "ok", and the subject stopped imagination and blinked once. ④ At the end of a single test, the next experiment of "3 s + 7 s" was launched immediately, with no interval.

It should be pointed out that, within a session, the subject blinked only at the end of each trial, in other words, the subject blinked every 10 seconds, so the subject blinked totally 20 times within a session. During one session, besides 20 times blinks, the subject was asked to open his (or her) eyes at other times. And between the five sessions, the subject was asked to close his (or her) eyes to have a rest.

3. Data analysis

In this paper, spontaneous EEG features were extracted in time-frequency domain. Feature extraction is the key to EEG pattern recognition, and it affects the design and performance of classifiers directly. Because the EEG signal is nonlinear and nonstationary, the traditional analysis methods based on the linearity and stability are not suitable for the analysis of EEG data, so the time-frequency analysis algorithm is introduced into the EEG recognition. The wavelet packet decomposition uses the joint time- scale function to analyze the non-stationary signal, so that it can make up the shortcomings of the Fourier transform which can't describe the local time-frequency property. But the shortcomings of wavelet packet decomposition is that wavelet basis function should be set in advance of the wavelet transform, and the accuracy of pattern recognition has great relationship with the basis function which is needed to be tried and selected repeatedly.

In order to solve the problem, we utilized a new time-frequency analysis method named Hilbert-Huang transform (HHT) [36], which was based on empirical mode decomposition (EMD) and Hilbert transform (HT). The basis function of that HHT method doesn't need to be set in advance, and the transform method makes the basis function be selected automatically according to the local characteristic of the signal, and so that characteristic makes this method particularly suitable for analysis of nonlinear and non-stationary EEG signals. The HHT method can make the original high-dimensional signal space be changed into low-dimensional characteristic space, so the Hilbert amplitude spectral characteristics which aren't easy to be observed and tested in the original feature domain can be displayed in the transform domain, and the differences among different features of categories are brought larger, that make the optimal input provided for the classifier in order to improve the accuracy of pattern recognition.

3.1. EMD method

The EMD method breaks a time series into a small number of mono component oscillatory modes called intrinsic mode functions (IMFs). Once we calculate the first IMF, it is subtracted from the original signal to produce a residual. We consider the residual as a new signal, and the EMD is applied again. The process repeats until the residual no longer contains any oscillations. Thus, we can represent the original signal $s(t)$ as a sum of IMFs plus a residual $r_n(t)$:

$$s(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

3.2. HT

After obtaining the IMFs, we apply the HT on each IMF.

$$H[c_i(t)] = c_i(t) * \frac{1}{\pi t} = \frac{1}{\pi} p \int_{-\infty}^{\infty} \frac{c_i(\tau)}{t-\tau} d\tau \tag{2}$$

P denotes the principal Cauchy value.

By definition, the analytic signal corresponding to each IMF is

$$z_i(t) = c_i(t) + jH[c_i(t)] = a_i(t)e^{j\theta_i(t)} \tag{3}$$

where $a_i(t)$ and $\theta_i(t)$ are the instantaneous amplitude and the instantaneous phase of the signal at time t, respectively.

According to the analytic signal, $c_i(t)$ can be represented as:

$$c_i(t) = a_i(t)\cos\theta_i(t) \tag{4}$$

In the usual manner, we define the instantaneous amplitude and instantaneous phase of the analytic signal which can be represented respectively as:

$$a_i(t) = |z_i(t)| = \sqrt{c_i(t)^2 + H[c_i(t)]^2} \tag{5}$$

$$\theta_i(t) = \arg[z_i(t)] = \arctan(H[c_i(t)]/c_i(t)) \tag{6}$$

The analytic signal represents the time-series as a slowly varying amplitude envelope modulating a faster-varying phase function. The instantaneous frequency (IF) is then given by

$$f_i(t) = (1/2\pi)d[\theta_i(t)]/dt \tag{7}$$

The IF is a function of time, and it reveals a degree of signal energy at some time in frequency set, namely the instantaneous frequency of signal, the same as the definition of frequency in classical theory about waveform.

The following is the expression of $c_i(t)$:

$$c_i(t) = \mathrm{Re}\left[a_i(t)\exp\left(j2\pi\int f_i(t)dt\right)\right] \tag{8}$$

After $a_i(t)$ is indicated in the associated time-frequency plane, the Hilbert spectrum of $c_i(t)$ can be got as:

$$H_i(t,f) = \begin{cases} a_i(t), & f = f_i(t) \\ 0, & f \neq f_i(t) \end{cases} \tag{9}$$

Then, after the Hilbert spectrum analysis is carried on signal $x(t)$ entirely, according to formula Eq. (9), $x(t)$ can be expressed as:

$$x(t) = \mathrm{Re}\left[\sum\nolimits_{i=1}^{n} a_i(t)\exp\left(j2\pi\int f_i(t)dt\right)\right] \tag{10}$$

Similarly, by means of that formula, we can make the change of amplitude and instantaneous frequency with time indicated in one three-dimensional "map". We can define the time-frequency distribution of that amplitude as the Hilbert amplitude spectrum $H(t,f)$ of the original signal $x(t)$, or called as Hilbert spectrum for short. Then according to Eqs (9) and (10), Hilbert spectrum of the signal $x(t)$ can be expressed as:

$$H(t,f) = \sum\nolimits_{i=1}^{n} H_i(t,f) \tag{11}$$

That is the whole process of the Hilbert spectrum analysis.

The Hilbert spectrum is the three-dimensional distribution of a weighted associated time-frequency-amplitude, and the local amplitude is the weight given to each time-frequency unit. For the Hilbert spectrum, the co-ordinates of a point represent the local emergence of a wave in some moment of the entire time course, and at some frequency.

3.3. Feature extraction based on EMD and Hilbert transform

Research shows that, when human carries on different imagination tasks, there would be difference for EEG to a certain extent, in some time band or frequency band. Therefore, we chose the statistical properties of amplitudes in different time-frequency bands as features, such as the mean, the standard deviation, etc. In other words, a rectangle window was chosen in the Hilbert spectrum, and the statistical properties of the amplitudes in the window were selected as features. Because there was no prior knowledge of in which time band and frequency band the differences of Hilbert spectrum caused by different imagination tasks existing, the selected window should include all the time-frequency planes. In addition, in order to find the best position of the window, there should exist some overlaps among each time-frequency window.

Supposing that we divide the imagination process into M time quanta, the m^{th} time quantum can be expressed in the following vector quantity form $m = 1, 2, \ldots, i, \ldots, M$. Supposing that EEG signal is acquired by C channels, it should be paid attention to the channels should be selected according to mental tasks and the distribution positions of electrodes, not feature extraction of signal from each channel. In this paper, only one channel of P_Z was selected, and then the mean AVE_i and the standard deviation SD_i of amplitudes of the time-frequency window in the i^{th} time quantum were calculated to constitute the feature vector $T_i = \{AVE_i, SD_i\}$, in a similar way, the statistical properties in other time quanta were calculated to constitute the eigenvector set $X = \{T_1, T_2, \ldots T_i, \ldots T_M\}$ in ime quanta. The optimal feature subset was selected based on the Fisher distance criterion. We calculate the Fisher index values $F(W)$ of each component of the eigenvector set X at first. Then based on the principle of selecting the number of the elements of optimal eigenvector, the first few elements of larger $F(W)$ were selected respectively to constitute the multi-dimensional feature vector X^* which was then input to the Fisher linear discriminant analysis classifier for the follow-up processing.

4. Example of feature extraction

We can abbreviate tension-imagination to TI and relaxation-meditation to RM. Experimental instruction are TI, TI, RM, RM, TI, RM, TI, RM, RM, TI, TI, RM, TI, RM, RM, TI, RM, RM, TI and TI respectively.

With the sampling frequency to be 1000 Hz, the signal was collected. Then ideal low-pass filter based on FFT was carried on at first, with the cutoff frequency of 30 Hz. After signal filtering, we can draw the signal graph as Fig. 4.

The signal corresponding to two single thinking experiments of "relaxation-meditation" and "tension-imagination" were selected for analysis respectively. Figures 5 and 6 are the signal graphs for those two single thinking experiments respectively:

Figures 7 and 8 are the two single thinking experiments respectively. We can find that there existed mode mixing phenomena in the two fist IMFs obtained by EMD. Because of the intermittency signal mixed in the signal source, after we sifted the original signal, there would be some IMF containing different event scale components, namely some decomposed IMF maybe contain more than one mode.

The two associated time-frequency-amplitude Hilbert spectra corresponding to the two single thinking experiments were drawn as Figs 9 and 10 respectively.

Note: Normalized Frequency $\times$ sampling frequency $=$ Actual Frequency

The two above graphs were the Hilbert spectra of original EEG signals corresponding to two mental tasks on channel P_z. It could be seen from the graphs that the frequency components of Hilbert spectrum

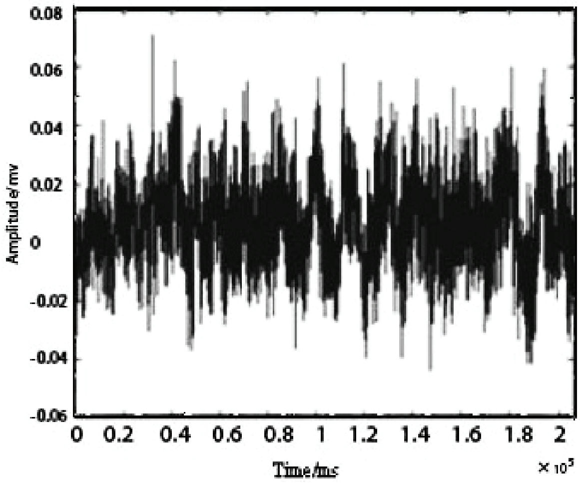

Fig. 4. The signal graph after the ideal low-pass.

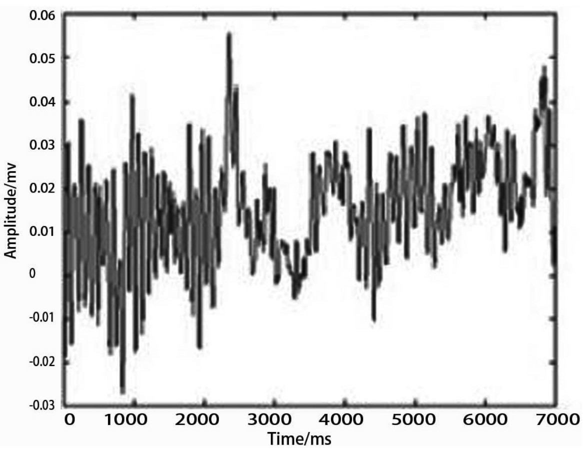

Fig. 5. The signal graph for the single thinking experiment of relaxation-meditation.

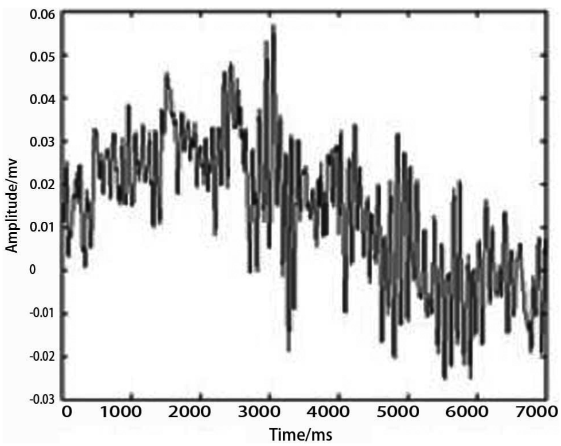

Fig. 6. The signal graph for the single thinking experiment of tension-imagination.

are located approximately in the frequency interval of alpha wave when the subject was performing relaxation-meditation task, and in the frequency interval of beta wave when the subject was performing tension-imagination task, the frequency components of Hilbert spectrum are located approximately in the frequency interval of beta wave. So, the experiment found an interesting phenomenon, that was when the subjects were blindfolded yet with their eyes opened and the conscious activity was relaxation-meditation state, the alpha wave still existed; but when in tension-imagination state, the alpha wave was replaced by the beta wave.

Thus, the difference of frequency interval of Hilbert spectra of main components of spontaneous EEG when the subject was performing different mental tasks could provide the basis of feature extraction and classification. According to data description, the imagination process could be divided into 10 time spans, so 10 rectangular windows could be selected within the Hilbert spectrum of EEG signal. In this paper, only one channel of P_z was selected for feature extraction, and so there was only one time-frequency window in specific location needed to be considered in the i^{th} time quantum. Then the mean AVE_i and

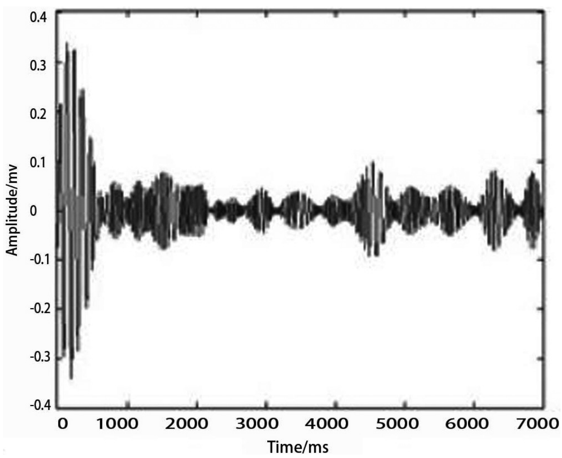

Fig. 7. The first IMF graph corresponding to the single thinking experiment of relaxation-meditation.

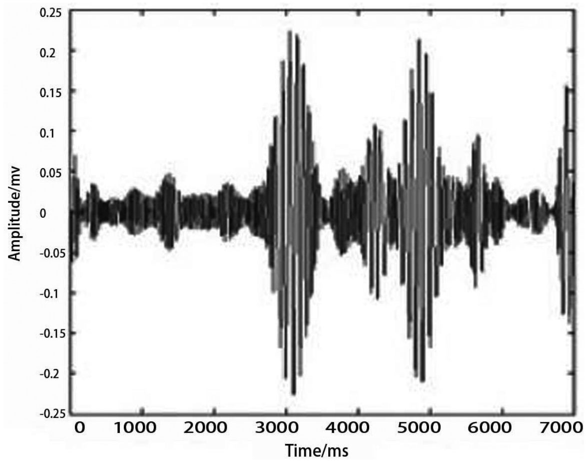

Fig. 8. The first IMF graph corresponding to the single thinking experiment of tension-imagination.

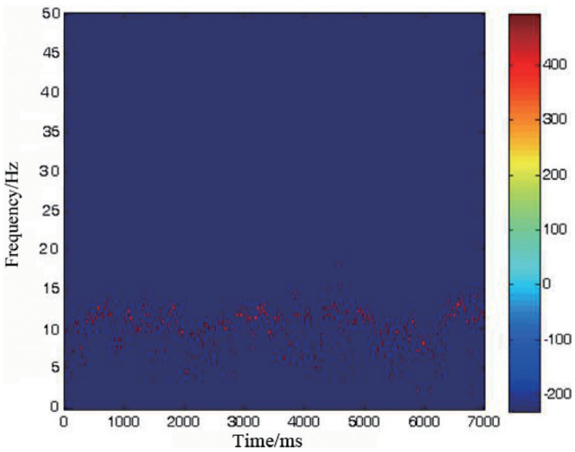

Fig. 9. The associated time-frequency-amplitude Hilbert spectra corresponding to the single thinking experiment of relaxation-meditation.

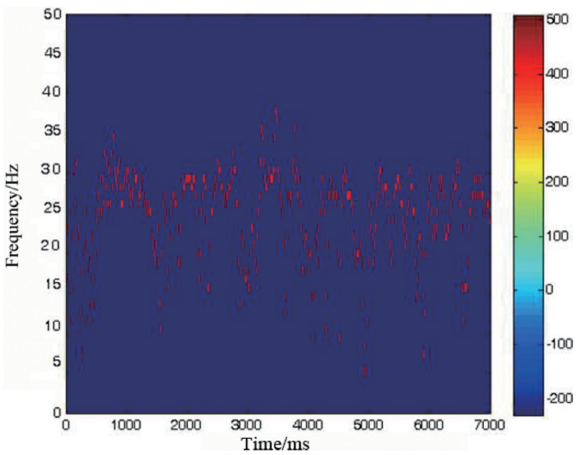

Fig. 10. The associated time-frequency-amplitude Hilbert spectra corresponding to the single thinking experiment of tension-imagination.

the standard deviation *SDi* of amplitudes of the time-frequency window in the i^{th} time quantum were calculated to constitute the feature vector $T_i = \{AVE_i, SD_i\}$, in a similar way, the statistical properties in other time quanta were calculated to constitute the eigenvector set $X = \{T_1, T_2, \ldots T_i, \ldots T_{10}\}$ in all time quanta.

Furthermore, according to the Fisher distance criterion, the feature selection was carried on about X. Then the Fisher index values $F(W)$ of each component of the eigenvector set X were calculated. Then based on the principle for selecting the number of the elements of optimal eigenvector, the first ten elements with larger $F(W)$ were selected to constitute the 10-dimensional feature vector X^*, after that X^* was input to the Fisher linear discriminant analysis classifier, and the correct rates of identifying the test samples could be calculated.

Thus, the difference of the frequency interval of Hilbert spectra of main components of spontaneous EEG, when the subject was performing different mental tasks could provide the basis for feature ex-

Table 1
The classification and recognition results for all of the fifteen subjects

Subject	Sex	Age	Correct	Miss	Fault	Correct rate
1	Male	23	90	5	5	0.9
2	Female	22	85	10	5	0.85
3	Male	25	95	5	–	0.95
4	Male	28	90	–	10	0.9
5	Female	25	90	10	–	0.9
6	Male	27	95	–	5	0.95
7	Male	26	90	5	5	0.9
8	Male	24	85	5	10	0.85
9	Female	26	95	5	–	0.95
10	Male	23	90	10	–	0.9
11	Male	33	85	5	10	0.85
12	Female	28	95	–	5	0.95
13	Male	27	90	10	–	0.9
14	Female	25	90	5	5	0.9
15	Male	30	90	–	10	0.9

traction and classification. Table 1 shows the classification and recognition results for all of the fifteen subjects participating in 5 sessions of mental tasks.

5. Discussion and conclusion

In this paper, under the circumstances of consciousness of relaxation-meditation or tension-imagination, the experiment of feature extraction and classification for spontaneous EEG signals collected from each subject's central parietooccipital region of P_Z electrode was carried out. We can obtain the Hilbert spectra in each time quantum by the EMD and Hilbert transform, then the classifications for the imaginations of two mental tasks were carried out better, with statistical properties within time-frequency windows, combined with the Fisher linear discriminant classification approach. Compared with the method based on wavelet packet decomposition, the advantage is that it does not need to set the basis function in advance, but it can select it automatically according to the local characteristics of the signal in the transform process. The shortcomings of that method lie in the fact that there aren't any rules of time division and channel combination-selection, and a large number of data analyses and tests are necessary.

From the upper table for classification and recognition results, it can be calculated out that, the correct rate of classification average is 90.3%. The calculation was done based on the EEG measures recorded during two random different mental tasks. In terms of classification results, it could be said that the mental task of relaxation-meditation versus tension-imagination investigated in the present study achieved much more considerable and positive mean accuracies comparable to the standard task of left versus right-hand motor imagery [37]. The classification stayed stable across the five sessions. Participants' evaluation of classification performance and in task evaluation showed that the choice of new types of mental imagery tasks, compared with the existing available mental strategies, could enhance BCI acceptance, user-friendliness and performance. So the mental tasks proposed in this study can be considered appropriate for BCI control. Based on the Hilbert time-frequency amplitude spectrum combined with the Fisher distance criterion, the processing, feature extraction and classification of EEG signals were finished. Compared with the traditional data analysis methods, HHT is totally adaptive. It can handle nonlinear and non-stationary data, not districted by the Heisenberg uncertainty principle. What is more, compared with wavelet transform, HHT avoids the trouble of selecting the wavelet basis. Of course, in all studies we use different mathematical methods for classification [38–40] and the subjects were also different, so this research work is only a try, as an addition to the existing work.

Though it is known that Beta wave appears mainly in frontal lobe and central region, it has been proved by our experiment that Beta wave might also appear in central parieto-occipital region. In addition, an interesting phenomenon has also been affirmed by the experiment, that was when the subject was blindfolded yet with his or her eyes opened and the conscious activity was in relaxation-meditation state, the alpha wave still existed; and when in tension-imagination state, the alpha wave was replaced by the beta wave.

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References

[1] Pfurtscheller G., Neuper C., Birbaumer N., Human brain-computer interface. In: Vaadia, E., Riehle, A. (Eds.), Motor Cortex in Voluntary Movements: A Distributed System for Distributed Functions. Series: Methods and New Frontiers in Neuroscience. CRC Press, Boca Raton, FL. 2005; 367–401.
[2] Elisabeth V.C.F., Reinhold S., Christa N., The effect of distinct mental strategies on classification performance for brain-computer interfaces. International Journal of Psychophysiology. 2012; 1–9.
[3] Venthur B., Blankertz B., Gugler M., Curio G., Novel applications of BCI technology: Psychophysiological optimization of working conditions in industry. Proc. Int. Conf. Systems, Man, and Cybernetics. 2010.
[4] Zander T.O., Kothe C., Towards passive BCI: Applying BCI technology for human-machine systems in general. Journal of Neural Engineering. 2011; 8: 1–5.
[5] Müller K.R., Tangermann M., Dornhege G., Krauledat M., Curio G., Blankertz B., Machine learning for real-time single-trial EEG-analysis: From brain-computer interfacing to mental state monitoring. Journal of Neuroscience Methods. 2008; 167: 82–90.
[6] Royer A.S., Doud A.J., Rose M.L., He B., EEG control of a virtual helicopter in a 3-dimensional space using intelligent control strategies. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2010; 18: 581–589.
[7] Halder S., Agorastos D., Veit R., Hammer E.M., Lee S., Varkuti B., Bogdan M., Rosenstiel W., Birbaumer N., Kübler A., Neural mechanisms of brain-computer interface control. NeuroImage. 2011; 55: 1779–1790.
[8] Neuper C., Scherer R., Reiner M., Pfurtscheller G., Imagery of motor actions: Differential effects of kinesthetic and visual-motor mode of imagery in single-trial EEG. Cognitive Brain Research. 2005; 25: 668–677.
[9] Kübler A., Nijboer F., Mellinger J., Vaughan T.M., Pawelzik H., Schalk G., McFarland D.J., Birbaumer N., Wolpaw J.R., Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface. Neurology. 2005; 64: 1775–1777.
[10] Neuper C., Müller G.R., Kübler A., Birbaumer N., Pfurtscheller G., Clinical application of an EEG-based brain-computer interface: A case study in a patient with severe motor impairment. Clinical Neurophysiology. 2003; 114: 399–409.
[11] Curran E., Stokes M., Learning to control brain activity: A review of the production and control of EEG components for driving brain-computer interface (BCI) systems. Brain and Cognition. 2003; 51: 326–336.
[12] Conson M., Sacco S., Sarà M., Pistoia F., Grossi D., Trojano L., Selective motor imagery defect in patients with locked-in syndrome. Neuropsychologia. 2008; 46: 2622–2628.
[13] Allison B.Z., Neuper C., Could anyone use a BCI? In: Tan D.S., Nijholt A. (Eds.), Applying our minds to human-computer interaction, brain-computer interfaces. human-computer interaction series. Springer Verlag, London. 2010.
[14] Millán J.D.R., Renkens F., Mouriño J., Gerstner W., Brain-actuated interaction. Artificial Intelligence. 2004; 159: 241–259.
[15] Galán F., Nuttin M., Lew E., Ferrez P.W., Vanacker G., Philips J., Millán J.D.R., A brain-actuated wheelchair: Asynchronous and non-invasive brain-computer interfaces for continuous control of robots. Clinical Neurophysiology. 2008; 119: 2159–2169.

[16] Roberts S.J., Penny W.D., Real-time brain-computer interfacing: A preliminary study using Bayesian learning. Medical and Biological Engineering and Computing. 2000; 38: 56–61.
[17] Keirn Z.A., Aunon J.I., A new mode of communication between man and his surroundings. IEEE Transactions on Biomedical Engineering. 1990; 37: 1209–1214.
[18] Curran E., Sykaceck P., Stokes M., Roberts S., Penny W., Johnsrude I., Owen A.M., Cognitive tasks for driving a brain-computer interfacing system: A pilot study. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2003; 12: 48–54.
[19] Cabrera A.F., Dremstrup K., Auditory and spatial navigation imagery in brain-computer interface using optimized wavelets. Journal of Neuroscience Methods. 2008; 174: 135–146.
[20] De Kruif, B.J., Schaefer, R., Desain, P., Classification of imagined beats for use in a brain computer interface. Conference Proceedings – IEEE Engineering in Medicine and Biology Society. 2007; 678–681.
[21] Blankertz B., Sannelli C., Halder S., Hammer E.V., Kübler A., Müller K.R., Curio G., Dickhaus T., Neurophysiological predictor of SMR-based BCI performance. NeuroImage. 2010; 51: 1303–1309.
[22] Curran E., Stokes M., Learning to control brain activity: A review of the production and control of EEG components for driving brain-computer interface (BCI) systems. Brain and Cognition. 2003; 51: 326–336.
[23] Başar E., Özgören M., Öniz A., Schmiedt C., Başar-Eroğlu, C., Brain oscillations differentiate the picture of one's own grandmother. International Journal of Psychophysiology. 2006; 64: 81–90.
[24] Petersen S.E., Fox P.T., Posner M.I., Mintun M., Raichle M.E., Positron emission tomographic studies of the cortical anatomy of single-word processing. Nature. 1988; 331: 585–598.
[25] Burbaud P., Camus O., Guehl D., Bioulac B., Caillé J.M., Allard M., Influence of cognitive strategies on the pattern of cortical activation during mental subtraction. A functional imaging study in human subjects. Neuroscience Letters. 2000; 287: 76–80.
[26] Papanicolaou A.C., Deutsch G., Bourbon W.T., Will K.W., Loring D.W., Eisenberg H.M., Convergent evoked potential and cerebral blood flow evidence of task-specific hemispheric differences. Electroencephalography and Clinical Neurophysiology. 1987; 66: 515–520.
[27] Cutmore T.R.H., Hine T.J., Maberly K.J., Langford N.M., Hawgood G., Cognitive and gender factors influencing navigation in a virtual environment. International Journal of Human-Computer Studies. 2000; 53: 223–249.
[28] Zatorre R.J., Halpern A.R., Mental concerts: Musical imagery and auditory cortex. Neuron. 2005; 47: 9–12.
[29] Boly M., Coleman M.R., Davis M.H., Hampshire A., Bor D., Moonen G., Maquet P.A., Pickard J.D., Laureys S., Owen A.M., When thoughts become action: an fMRI paradigm to study volitional brain activity in non-communicative brain injured patients. NeuroImage. 2007; 36: 979–992.
[30] Dyson M., Sepulveda F., Gan J.Q., Localisation of cognitive tasks used in EEG-based BCIs. Clinical Neurophysiology. 2010; 121: 1481–1493.
[31] Farid Y., Pradeep M., Sridhar S.*, Naive scoring of human sleep based on a hidden Markov model of the electroencephalogram. IEEE Engineering in Medicine and Biology. 2014; 5028–5031.
[32] Yaghouby F., Schildt C.J., Donohue K.D., O'Hara B. F, Sunderam S., Validation of a closed-loop sensory stimulation technique for selective sleep restriction in mice, IEEE Engineering in Medicine and Biology. 2014; 3771–3774.
[33] Yaghouby F., Sunderam S., Quasi-supervised scoring of human sleep in polysomnograms using augmented input variables. Computers in Biology and Medicine. 2015; 59: 54–63.
[34] Thilo H., Tsutomu K., Harald W., Psychophysiological classification and staging of mental states during meditative practice. Biomed Tech. 2011; 56: 341–350.
[35] Cahn B.R., Polich J., Meditation states and traits: EEG, ERP, and neuroimaging studies. Psychol Bull. 2006; 132: 180–211.
[36] Huang N.E., Shen Z., Long S.R., Wu M.C., Shin H.S., Zheng Q., Yuen Y., Tung C.C., Liu H.H., The empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time series analysis. Proc R Soc Lond. 1998; 454: 903–995.
[37] Allison B.Z., Brunner C., Kaiser V., Müller-Putz G., Neuper C., Pfurtscheller G., A hybrid brain-computer interface based on imagined movement and visual attention. Journal of Neural Engineering. 2010; 7: 1–9.
[38] Wen X. Z., Shao L., Fang W., Xue Y., Efficient Feature Selection and Classification for Vehicle Detection. IEEE Transactions on Circuits and Systems for Video Technology, 2015; DOI: 10.1109/TCSVT.2014.2358031.
[39] Gu B., Sheng V. S., Feasibility and Finite Convergence Analysis for Accurate On-line ν-Support Vector Learning. IEEE Transactions on Neural Networks and Learning Systems, 2013; 24: 1304-1315.
[40] Zhang H., Wu Q. M. J., Nguyen T. M., Sun X. M., Synthetic Aperture Radar Image Segmentation by Modified Student's t-Mixture Model. IEEE Transaction on Geoscience and Remote Sensing, 2014; 52: 4391-4403.