EEG signal representation of basic geometric bodies

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Abstract. In the field of intelligent design, much attention is paid to the generation of design knowledge and experience. Today, EEG signal is a direct method to explore the design idea and brain consciousness. The purpose of this paper is to establish a basic geometric representation pattern of EEG signals. Firstly, the basic geometry representation of EEG signal is given, EEG signal is collected and the preprocessing method of EEG signal is proposed. Then, the feature extraction and recognition method of EEG signal is described, and the recognition rate is improved by feature decision fusion. Finally, the correctness of the representation pattern is verified by experiments.

1. Introduction
At present, in the field of intelligent design, most geometric modeling methods require designers to click mouse and hit keyboard frequently, which costs more physical energy. It is easy to make design errors due to fatigue, and it also reduces the time for designers to carry out "innovative" work. In addition, this method also requires designers to be familiar with the design software, which also increases the learning cost and makes it difficult to improve the automation level of geometric modeling. According to above problems, this paper establishes EEG signal representation mode of basic geometric bodies, which provides an idea for the design of basic geometry through human brain imagination. Firstly, this paper designs the experimental paradigm of EEG signal of basic geometric bodies. Then, we collect EEG signal of geometric bodies and preprocess those signals. Finally, EEG signal characteristic of basic geometry bodies are established by using multi-feature decision fusion.

The brain is the most sophisticated organ of human beings and the source of thinking and consciousness. Human brain neurons can generate nerve impulses, namely EEG signals. By analyzing corresponding EEG signals, we can identify corresponding brain activity intention[1]. In this paper, the establishment of EEG signal representation pattern of basic geometric bodies is taken as the research target. The specific content is to find EEG signal characteristics of five kinds of geometric bodies, including triangular pyramid, cube, sphere, cylinder and cone. This paper mainly involves three parts, namely, signal acquisition and preprocessing, feature extraction and recognition and experimental research, as shown in figure 1. Difficulties are signal acquisition and preprocessing, feature extraction and recognition, which will be discussed in detail below.

Figure 1. Diagram of EEG signal representation pattern for basic geometric bodies.
2. EEG signal acquisition of basic geometric bodies

Experimental paradigm is the basis of signal acquisition. Based on different experimental requirements, experimental paradigm design needs to determine type and stimulus content. Stimulus type mainly include visual, auditory and somatosensory stimuli. Visual stimuli include text, pictures, lighting and video. Auditory stimuli include music, speech, short tones, long tones, artificial sound and natural sound. Somatosensory stimuli include pain, touch, electric stimulation and mechanical stimulation. Stimulus content arrangement include stimulus duration, interval time of stimulus and randomness of stimulus.

(1) Stimulus duration: duration of stimulus varies because basic geometric bodies are different. Short duration cannot inspire related signal, so more information detail can't be collected. Otherwise, long duration easily mixed noise into original signal, thus it increases the difficulty of signal processing[2]. In addition, longer duration may also lead to the difficulty of experimental operation and affect the accuracy of signal acquisition.

(2) Interval time of stimulus: interval time should be set according to specific experimental analysis. Also, buffer time between different trails should be set. It is generally set the same, so the interval setting should be randomized as far as possible[3].

(3) Randomness of stimulus: some researches indicated that randomness of stimulus had an impact on some ERP signals[4]. To avoid that effect, general experimental paradigms of stimulation are presented by random way.

![Figure 2. Five different basic geometry stimuli.](image)

As for stimulus type, studies shown that EEG signal representation of stimulus object is endogenous reactivated from long-term memory and maintained in visual memory space[5]. Cornoldi et al.[6] found that six basic characteristics affect the maintenance of visual mental images, which are specificity, rich detail, color, salience, shape contour and context. Although the intensity of perception of different features of visual stimuli varies from person to person, the shape profile is the most characteristic feature of visual stimuli. Therefore, shapes and contours of visual stimulus entities can be distinguished by analyzing EEG signals. This paper will select five basic geometric bodies as stimulus entities, including triangular pyramid, cube, sphere, cylinder and cone, as shown in figure 2. Where, five visual stimulus images are gray scale. Background is white, every image size is 200×200 (pixel). Both vertical and horizontal resolutions are 96dpi. To avoid effect from other factors, shadow, angle and light angle of five geometric images remain the same. Their geometry features, such as roundness, sharpness, symmetry and curvature, are obviously different from each other. They can be used as a visual stimulus material.

![Figure 3. Experimental paradigm of image stimulation.](image)

The experimental paradigm of image stimulation is shown in figure 3. For stimulus arrangement, both stimulus duration and interval were set to 3000ms because of visual delay of human eyes.
Considering that imagination process of human brain needs time, blank imagination time was set to 6000ms. To avoid human fatigue, 3000ms was left between different blocks. Meanwhile, a black cross is design to show for 3000ms befo re visual stimulus experiments. During visual stimulus experiment, subject needs to focus on watching stimulus image for 3000ms. Then, subject needs to visualize that geometry body in their minds. This experiment will be conducted repeatedly. There will be a rest time of 2 to 3 seconds after each experiment. Six seconds of imagery served as EEG data, followed by three seconds of fixation as baseline.

![Figure 4. Schematic diagram of the experimental platform.](image)

Experiment platform is shown in figure 4. Experiments were conducted in relatively quiet room, which can avoid external disturbance. 10 subjects were tested. All subjects were right-handed and had normal or corrected visual acuity. Electrodes Fp1, Fp2, AF3, AF4, F7, F3, F4, F8, FC5, FC6, T7, T8, P7, P3, P4, P8, O1, Oz, O2 are selected to acquire EEG signals. Electrode A1 is chose as reference signal and Fpz is used as ground electrode[7-8]. Sampling rate is 1000Hz and limited high frequency is 120 Hz. Time constant is 0.3s and trap power frequency is 50Hz. Stimulus images are projected for convenience of subject observation. All subjects are divided into 10 groups. For each group, five stimulus geometric objects appear in a random order. Each group has 5 trials and there is 5s rest time between different blocks. During experiments, it is important to observe EEG signal waveform. If noise is too obvious, it needs to adjust setup parameters in time. After experiments, each subject needs to validate signal acquisition results.

### 3. EEG preprocessing process

EEG signal preprocessing aims to remove noise from EEG signal. Now, signal preprocessing algorithm is faced with many problems, such as EEG signal artifacts, large noise and non-stationary. For the complexity of human thought, EEG signal denoising algorithm takes too long time. To solve the problem, this paper designs the related preprocessing process, as shown in figure 5.

![Figure 5. Block diagram of EEG signal preprocessing process.](image)

Firstly, FastICA algorithm is adopted to extract independent components and the miscibility matrix. Thus, noise component in independent components is removed by combining kurtosis and power spectrum. Secondly, electrical reference components in independent components can be removed by analyzing same symbol columns in mixed matrix. Finally, noise component of independent component matrix can be removed and EEG signal is restored by matrix calculation. Fast independent component analysis (FastICA) algorithm is adopted to solve slow convergence speed of ICA algorithm and general separation effect. After independent component analysis, independent components and miscibility matrix can be obtained, but those independent components still include noise component and electrical reference component. Generally, noise component is super-Gaussian noise and electrical reference component include bioelectrical and environmental electrical signals[9]. To get effective EEG signal, it is necessary to remove noise and electrical reference components after FastICA processing.

Since independent components have different gauss properties and EEG signals are sub-Gauss, we
can use Gauss properties to judge independent components and to remove the super-Gaussian noise signals. In this paper, Kurtosis method is used to identify and remove super-Gaussian noise in independent components. Kurtosis formula of discrete signal is shown as equation (1):

$$K = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{x_i - \bar{x}}{\sigma_i} \right)^4 - 3$$

Where, $x_i$ is signal amplitude and $\bar{x}$ is average amplitude. $N$ is sampling length and $\sigma_i$ is standard deviation. If kurtosis $K$ is zero, signal is gaussian. If kurtosis $K$ is greater than zero, signal is super-Gaussian. If kurtosis $K$ is less than zero, signal is sub-Gaussian. Since EEG signal is a sub-Gaussian, kurtosis $K$ should be less than zero. Therefore, super-Gaussian noise can be identified by calculating kurtosis $K$. After removing super-Gaussian noise, next step is to remove electrical reference component. Electrical reference component has two types. The first one is physiological electrical signal of human body. The other is environmental interference signal, which specifically refers to hardware interference signal and remote interference signal. All electrical reference signal almost has the same property. Their influence is always in positive or negative direction. They are uniformly distributed in all EEG signals. In this paper, vector angle calculation is adopted to evaluate independent component removal. Firstly, all positive columns and negative columns in mixed matrix $A$ are extracted. Generally, electrical reference components have all positive or negative effects on EEG signals. The vector angles of symbol consistent column and standard direction vector can be calculated respectively, where vector angles are suitable for all positive or negative columns. When two columns are very close, standard direction vector can be used as all positive and negative columns. Thus, independent components are represented by all positive columns. Electrical reference components are related to all negative columns, which need to be removed. After removing electrical reference signal, effective EEG signal is obtained.

4. EEG feature extraction and recognition

The traditional time-frequency signal analysis can study signal from time domain or frequency domain, which may lose the effective information of opposite analysis domain. Traditional spectral analysis methods can be used for stationary signals, but not for non-stationary EEG signal. In this paper, the dynamic characteristic approximate entropy and marginal spectrum are adopted to express geometric characteristics in EEG signals. Approximate entropy is used to quantify the complexity of EEG signals. Its physical significance is to reflect the possibility of generating new sequences in time series[10]. It does not require high quality of EEG signals and has a strong anti-noise capability[11]. Approximate entropy calculation is expressed as equations (2), (3) and (4).

$$C(i,m) = \frac{\sum_{j=1}^{N-m+1} k_j}{N-m+1}$$

$$k_j = \begin{cases} 1 & \text{if } |x(i,m) - x(j,m)| < r \\ 0 & \text{otherwise} \end{cases}$$

$$ApEn(m,r,N) = \frac{1}{N-m+1} \left[ \sum_{i=1}^{N-m+1} \ln \frac{C(i,m)}{C(i,m+1)} \right]$$

Where, $N$ is length of EEG signal, and $m$ is the number of data, and $r$ is tolerance threshold of similarity between sub-fragments, and $C(i,m)$ is the proportion of the number of other sub-sequences similar to the $i$th sub-sequence in all sequences, and $k_j$ represents whether the $i$th sub-sequence is similar to the $j$th sub-sequence, and ApEn is approximate entropy.

To extract marginal spectrum characteristics, Hilbert-Huang Transform (HHT) is used for the
independent components in previous section. That calculation method is divided into two steps: empirical mode decomposition (EMD) and Hilbert spectrum analysis. EMD method can be used to express time signal in the form of \( n \) intrinsic mode functions \( u_i(t) \) and residual wave \( r \). After obtaining intrinsic mode function IMF, we apply Hilbert transform to each intrinsic mode function to obtain instantaneous amplitude \( \alpha_i(t) \), phase \( \theta_i(t) \) and frequency \( \omega_i(t) \). The related calculation formulas are shown as follows.

\[
\alpha_i(t) = \sqrt{u_i^2(t) + H\left\{u_i(t)\right\}^2} \quad (5)
\]

\[
\theta_i(t) = \arctan \left( \frac{H\left\{u_i(t)\right\}}{u_i(t)} \right) \quad (6)
\]

\[
\omega_i(t) = \frac{d\theta_i(t)}{dt} \quad (7)
\]

Where, \( H\left\{u_i(t)\right\} \) is Hilbert transform. \( H(\omega,t) \) is Hilbert spectrum. The calculation formula of marginal spectrum is shown in equation (8).

\[
h(\omega) = \int_0^T H(\omega,t) \, dt \quad (8)
\]

By using Hilbert marginal spectrum, energy of five frequency bands for each independent component can be calculated, including Delta 0.5-4 Hz, Theta 4-8 Hz, Alpha 8-13 Hz, Beta 13-30 Hz and Gamma 30-64 Hz. Each sample provides 95 features. Since total energy varies, baseline characteristics of the same experiment should be normalized. Based on approximate entropy and marginal spectrum, the geometric features in EEG signals can be extracted respectively. Both methods can obtain geometric characteristics and classify geometric objects from EEG signals. To improve result, it is better to fuse above two characteristics, as shown in figure 6.

![Block diagram of EEG signal feature extraction from basic geometry based on multi-feature decision fusion.](image)

There are two multi-feature fusion methods. The first one is simple fusion and the other is decision fusion. Simple fusion refers to fuse different features into a feature vector. Decision fusion refers to
establish a single feature classifier based on each feature and use certain strategies to fuse different single features. As far as geometric representation in EEG signals is concerned, approximate entropy and marginal spectrum characteristics from 19 channels of EEG signals can be extracted. Thus, it is easy to establish basis classifiers respectively. Then, the weight values can be calculated based on prediction errors. Finally, the weight and outputs of single classifier are weighted and summed to obtain confidence of each class. The class with the highest confidence is taken as output result. After extracting information entropy and marginal spectrum characteristics, prediction error should be calculated for single classifier. The calculation formula is show as equation (9).

$$\text{error} = P(X_i \neq Y_i)$$

(9)

Where, X represents sample data and Y represents the true class of this sample. The weight of each single classifier is shown as equation (10).

$$w = \frac{1}{2} \log(1 - \frac{\text{error}}{\text{error}^*})$$

(10)

5. Experiments

Experiment includes two parts. The first part is to compare classification performance between approximate entropy and marginal spectrum, as shown in figure 7. The second is to compare classification performance between simple feature fusion and decision feature fusion, as shown in figure 8. In figure 7, classification results of two feature extraction methods are shown. Respectively, 10 experiments were conducted for two feature extraction methods. It can be seen that average accuracy is 45% for marginal spectral method and approximate entropy is 43%. Average classification accuracy of marginal spectral is higher than approximate entropy. In figure 8, average accuracy of simple fusion is 38.0%, and average accuracy of decision fusion is 47.0%. Since human brain is a complex system, it is hard to fuse two features into a feature vector. This method loses some essentially geometric characteristics of EEG signals. The decision fusion has advantages of different features and maintains nonlinear characteristics of EEG signals.

![Figure 7. Classification results of approximate entropy and marginal spectrum.](image)

![Figure 8. Classification results of simple feature fusion and decision feature fusion.](image)

6. Conclusion

Around geometric representation of EEG signals, this paper designed experimental paradigm of geometry imagination, and described the preprocessing process of EEG signals, and discussed feature
extraction based on approximate entropy and marginal spectrum, and explained two feature fusion methods of EEG signals. Some experiments were carried out to verify above methods. Experiments shown that decision feature fusion has higher classification accuracy. There is no obvious classification difference between approximate entropy and marginal spectrum. Probably, future work is to improve feature recognition rate and geometric feature refinement.

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