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Neural Markers of shootig performance: An explore of EEG frequency features during aiming

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Abstract. The frequency-domain characteristics of electroencephalogram (EEG) during shooting used to evaluate and improve shooting performance has become a research hotspot in recent years. However, neural markers that can be effectively and stably used to characterize various shooting performances remain unclear. In this study, a real shooting experiment was designed to study the effective EEG neural markers for different shooting performances. EEG data were obtained during the aiming period,the frequency domain characteristics such as spectrum, power spectrum, and differential entropy corresponding to Delta wave, Theta wave, Alpha wave, Beta wave, and Gamma wave were extracted respectively. Classical statistical analysis and machine learning methods were used to investigate the effectiveness of the characteristics. The results revealed that the overall energy of the EEG signals was low and stable for the participants with excellent shooting performance. The differential entropy feature of the gamma band as a effective neural marker had achieved the best classification accuracy of 74.91% throughout the aiming period. The results verified that the brain state of shooters is stable and their brains exhibit higher cognitive information processing efficiency during accurate shootings. The feasibility of using EEG neural markers to evaluate shooting performance is a novel avenue for the selection and performance evaluation of high-performance shooters.

Keywords: component; Electroencephalogram (EEG); Shooting performance; Neural markers; Feasibility

1. Introduction

Shooting is a fine-skill sport that is useful in military and other fields. Shooting requires an excellent regulation of the central nervous system to achieve the best performance. The relationship between shooting performance and neurophysiological parameters has attracted considerable research attention in kinematics [1]. However, neural markers that can be effectively and stably used to characterize various shooting performances remain unclear. Electroencephalogram (EEG) has been widely used in the field of fine motion as a measurement method of nervous system oscillations [2]. This method can be used to analyze the activity state of the cerebral cortex of the shooter and the cognitive process of the brain during the shooting task. The measurement method based on EEG signals can be used to objectively observe, analyze, and predict shooting performances. Therefore, the evaluation of the central function level of the shooter and quantitative index parameter analysis are the focus of the study for effective training.

Studies have revealed that the EEG frequency-domain characteristics of shooters are closely related to shooting performance. Gong et al. verified that rifle shooting performance was related to the connection network of the beta band in the brain of shooters during the aiming period [3]. Cheng et al. believed that the decrease in the cortical activity in the sensory motor area influenced shooting performance. They revealed that the power of the sensorimotor rhythm (SMR) during the aiming period of skilled shooting athletes was negatively correlated with shooting performance, but skilled airpistol shooters exhibited higher SMR power during the last second before best shots than before worst[4]. Lange et al. performed a dynamic performance test and revealed that shooting without hitting the target induced strong theta activity in the middle frontal lobe [5]. Janelle et al.

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confirmed that the alpha and beta power of the left hemisphere of expert shooters decreased during the preparation stage before shooting, which indicated that the neural structure needed for high-level shooting performance was highly optimized [6]. The correlation analysis between shooting and EEG frequency-domain characteristics provides a theoretical basis for the analysis of neural indicators of the shooting movement.

The use of effective neural indicators for the performance evaluation and training of shooting tasks can not only reduce the use of guns but also detect the adaptability of shooters during relevant neural processing at any time during shooting. EEG neural indicators have been widely used for training for shooting. Liu et al. verified that the neural feedback training effect using a single theta/beta ratio protocol was effective [7]. Gong et al. designed neurofeedback training experiments based on the SMR and alpha frequency band powers. A study revealed that after three weeks of training, the shooting performance of the SMR group was higher than that of the alpha group [8]. Studies have revealed that the shooting performance of shooters is closely related to the frequency-domain characteristics of brain signals. However, the effectiveness of neural indicators of frequency-domain is yet to be evaluated.

In this study, the neural mechanism of shooting of brain signals was analyzed to investigate the cognitive ability and psychological activities of shooters. The characteristics of various frequency bands were detailed to investigate the representation of shooting performance differences in the frequency domain. In this study, a shooting experiment was designed to evaluate the brain activity between various shooting performances and detail the quantitative index of brain signals that can be used to distinguish shooting performance. The EEG data of five college students during the aiming period of 200 shots were obtained. The linear discriminant analysis (LDA) method and P-test were used for feature selection and visual analysis after obtaining the frequency-domain features. Finally, the classification verification of various periods and frequency-domain features was performed, aims to assess and analyze the impact of the single feature on supporting the creation of models capable of discriminating shooting performance.

2. Materials and Methods

2.1 Subjects

Five shooting volunteers (two men and three women) were recruited for the study. All subjects were freshmen with more than 50 live ammunition shooting experience, aged 18 to 20 years (M = 19.4, SD = 0.8). All subjects had normal or corrected visual acuity, were righthanded, and exhibited no history of mental illness. This experiment was reviewed by China National Digital Switching System Engineering and Technological Research Center committee. Subjects did not consume any stimulating food such as alcohol or caffeine within 24 h before the experiment. The participants volunteered for the experiments but completed the written investigation of the Beck anxiety scale [9], TAS-20 questionnaire [10], and EEG shooting questionnaire. The experimental requirements were explained to the participants and written informed consent was obtained from the participants. Furthermore, the participants were compensated after the experiment.

2.2 Experiment Paradigm

A standard 100-m shooting training field was used as the testing field. All participants maintained a standard supine position while shooting. Actions unrelated to the shooting were minimized. Participants aimed to fire a type-95 rifle with 5.8-mm caliber bullets at the 52 × 52 cm chest ring target 100 m away with a maximum score of ten rings.

The shooting task included holding a gun, aiming, and firing in three stages. Each participant was required to shoot 40 bullets at a free speed in the shooting task with the aiming time not less than 6 s. EEG data acquisition was performed using a 64-Channel Neuracle wireless EEG instrument. The electrode of the instrument was placed according to the international 10-20 standard system. The reference electrode was placed in the bilateral mastoid, and the sampling

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frequency was 1000 Hz. The impedance of all electrodes was always less than 10 kΩ when collecting EEG data. Triggerbox was used to collect shooting sounds for synchronous marking. Four blocks were contained in this experiment, each containing 10 trials. The specific process is displayed in Figure 1.

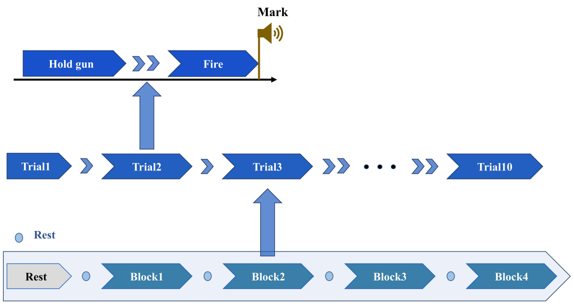

Figure 1. Experimental paradigm of live shooting.

2.3 Preprocessing

To reduce the interference of electrooculography (EOG), electromyogram (EMG), electromagnetic, and other noise in EEG signals, preprocessing the initial EEG data is critical for ensuring subsequent signal analysis. As triggerbox was used to collect shooting sounds for synchronous marking, To remove the interference between adjacent shooting samples, the public minimum time of 6s before shooting is taken as the aiming period, so the EEG data of the first 6 s before the shooting label were considered as the sample data of a single shooting, the score of a single shooting was used as the sample label. The marks with a shooting score higher than and equal to nine rings were excellent samples, and the marks with shooting score lower than nine rings were poor samples. A total of 200 trials of the sample data were obtained.The pretreatment process was Re-reference, Filter [11], Epoch truncation, Baseline correction [12], Artifact removal [13],Downsampling.

2.4 Feature Extraction

Studies have revealed that the closer to the shooting time, the greater of the difference in brain activity between different shooting performances. To investigate the changes of EEG signals in the aiming period intuitively, the aiming time of 6 s was categorized into six adjacent stages, and the sixth stage was nearest to the shooting time.

Feature extraction is performed for reliable quantitative index analysis to investigate the EEG characteristics of shooting performance. The oscillation components and rhythm features of brain activity are represented using frequency-domain features, which are used to observe the frequency components of various states. Studies have revealed that these features exhibit excellent effects on non-time-locked tasks. The EEG signals are categorized into five frequency components [14], namely delta wave (1–4 Hz), theta wave (4–8 Hz), alpha wave (8–12 Hz), beta wave (12–30 Hz), and gamma wave (30–80 HZ). In this study, the frequency-domain features including spectrum, power spectrum [15], differential entropy [16], and spectrum energy, were obtained.

Fourier transform is a conventional method to transform the brain signal from the time domain to the frequency domain. The technique is widely used to extract the frequency-domain characteristics of EEG signals. Furthermore, the Fourier transform is typically used for quantitatively analyzing the spectrum characteristics typically used in EEG [17]. Assuming the brain signal is $x[n]$, where n is the number of sampling points of the signal, $F(f)$ denotes the spectrum signal corresponding to various frequency bands, the expression of the corresponding spectrum is expressed as follows:

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$$F(f) = \sum_{n=1}^{N} x[n]\, e^{-j2\pi nf} \tag{1}$$

where N represents the number of single sampling points, and f represents the sampling frequency.

The energy of the random signal is infinite; however, its average power is limited. The power spectral density (PSD) is a critical frequency-domain feature, which describes a change in the signal power with frequency [18]. The corresponding expression is expressed as follows:

$$PSD(f)=\frac{1}{N}\,|F(f)|^2 \tag{2}$$

Differential entropy (DE) quantifies the population uncertainty in the probability distribution of random variables [19] . For a fixed length EEG sequence, the estimation of differential entropy is equivalent to the logarithm energy spectrum in a certain frequency band[20] and expressed as follows:

$$DE(f) = log_2(PSD(f)) \tag{3}$$

where PSD(f) represents the PSD corresponding to various frequency bands.

2.5 Feature Selection

Feature selection is performed to reduce the dimension of high-dimensional signal features, improve the operation efficiency and eliminate over-fitting, and improve model efficiency. In the BCI system, feature selection is used as a feature reduction technology to determine the linear combination of features that can separate two or more categories, and the classification error is small [21]. As a classical linear discriminant method, LDA exhibits high computational efficiency and fusion. Therefore, LDA was used as the basis for distinguishing feature separability to measure the effectiveness of various features for sample classification. In LDA, all features are projected onto a vector so that the distance between various categories of sample points after projection is maximized, and the distance between similar samples is minimized. The discriminant criterion expression of LDA is expressed as follows:Feature extraction

To analyze feature performance, the T-test method [8] was used to test the saliency of extracted features. The independent samples T-test was used to determine whether significant differences exist in various types of feature vectors.

2.6 Classifiers

The five-fold cross-validation method was used for training, and nonrepeated data were randomly selected from the total sample library to construct the training and test sets. A total of 84 training samples and 24 test samples were extracted, and the number of excellent samples is consistent with that of general samples, each sample correspond to the shooter's single shooting performance.

In this study, the conventional support vector machine (SVM) machine learning algorithm was used to verify the classification effect. In the model, the interval is maximized to obtain the optimal separating hyperplane linear classifier that can correctly separate the two types of data [22]. The SVM algorithm maps the feature vector of the instance to points in the space and segments the mapped samples through a hyperplane to maximize the interval. This model exhibits several advantages in solving small samples and high-dimensional pattern recognition.

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3. Results

3.1 Analysis of Shooting Performance

Table 1 displays a summary of various performances of all participants. The average number of excellent performances was 6.5 in a single block, and the average number of poor performances was 3.5; however, no significant difference was observed in the same participant (p > 0.05).

Subject number	Excellent / Poor (trials)			
	Block 1	Block 1	Block 1	Block 1
1	9/1	7/3	9/1	8/2
2	9/1	7/3	5/5	3/7
3	9/1	9/1	9/1	9/1
4	1/9	1/9	4/6	3/7
5	6/4	7/3	7/3	8/2
mean	6.8/3.2	6.2/3.8	6.8/3.2	6.3/3.8

Table 1. Summary of various test scores.

3.2 Analysis of Frequency-Domain Energy

Figure 2 displays the frequency-band energy distribution during the aiming period. The results revealed that the energy during the excellent shooting performance was the lowest compared with poor performance in the global and local frequency bands throughout the aiming period. Excellent and poor samples both revealed a downward trend during the aiming period and stabilized in 2 s.

3.3 Feature Selection

After a collection of a total of 885 frequency-domain features, the LDA method was used to project all features onto a vector for selection to maximize the distance after projection between various categories of sample points and minimize the distance between similar samples was minimized. The T-test test was performed to analyze the distinction between excellent and poor sample feature vectors.

Table 2 reveals the categories, lead locations, LDA results, and visibility results for the top 20 features in the separability ranking. The results revealed that the characteristics with excellent separability were concentrated in the DE of the gamma band at the positions of CP3, CP4, CP5, CP6, C4, P3, FC2, PO5, and PO7. The energy of the gamma band at the positions of CP3, CP4, CP5, CP6, and C4, the DE of the beta band at the positions of CP5, PO5, and PO7, the energy of beta band at the positions of CP5 and CP6, and the PSD of the gamma band at the positions of CP5.

In poor shooting performances cases, the top 20 features were high-frequency features, and the gamma band exhibited the highest contribution rate of the feature domain. This result is primarily concentrated in the parietal region. This result indicated that excellent performance and poor samples differed considerably in the high-frequency band. This result may be related to the processing of cognitive motion information during shooting.

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Order number	Feature name	Lead	P-Value
1	gamma-DE	cp5	***
2	gamma-AMP	cp5	***
3	gamma-DE	cp3	***
4	gamma-AMP	cp3	***
5	gamma-DE	cp6	***
6	beta-DE	cp5	***
7	gamma-DE	cp4	***
8	gamma-DE	c4	***
9	gamma-PSD	cp5	***
10	gamma-AMP	cp6	***
11	beta-DE	po5	***
12	beta-DE	po7	***
13	gamma-AMP	cp4	***
14	gamma-DE	p3	***
15	beta-AMP	cp5	***
17	gamma-DE	po5	***
18	gamma-DE	po7	***
19	gamma-AMP	c4	***
20	beta-AMP	cp6	***

Table2. Collection of top-20 of feature selection, in which DE represents differential entropy of different frequency bands, PSD represents power spectral density of different frequency bands, AMP repre-sents amplitude of different frequency bands.($P < 0.01$* $P < 0.001$** $p < 0.0001$***)

3.4 Classification Results of Neural Markers During Aiming Time

Figure 3 reveals that the classification results of 15 types of frequency-domain features during various aiming times The results revealed that the classification accuracy of the gamma and beta frequency features in the high-frequency band was considerably higher than that of the delta, theta, and alpha frequency features of the low-frequency band. The classification accuracy of the gamma frequency spectrum, PSD, and DE in each period was the highest, and the classification accuracy of the beta frequency spectrum, PSD, and DE is the second highest. The variance results in the figure revealed that the variance of gamma-band characteristics is the smallest within the aiming period of 2–6 s.

The results revealed that the classification effect of these 15 types of frequency-domain features in each aiming time was consistent, and the classification accuracy of the high-frequency band features was always in a dominant position. This result confirmed the stability of the high accuracy of the high-frequency band features. Gamma-band features achieved the best classification effect.

Figure 4 reveals the accurate classification of the frequency spectrum, PSD, and DE characteristics of the gamma band in the aiming period. The results revealed that the DE feature of the gamma band is always in a dominant position in the classification accuracy after 1 s of aiming. This result is considerably higher than the spectral feature and PSD feature.

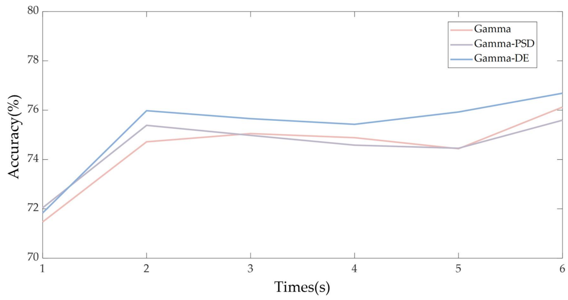

Figure. 4 Classification results of gamma band characteristics.

The average classification accuracy of DE features in the gamma band in the aiming period as 74.91%. The average classification accuracy of the PSD feature was 74.51%; and the average classification accuracy of the spectral feature was 74.45%. The variance of the DE feature is the smallest during the aiming period of 2–6 s. This result revealed that the DE features of the gamma band exhibited an obvious high accuracy in the performance distinction of shooters.

4. Discussion

4.1 Dynamic Change Analysis of Eeg Characteristics During the Aiming Period

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

Combined with the analysis of the frequency band energy change, the power values of the samples with excellent performance in each frequency band were always lower than those with poor shooting performance cases. The powers of delta, theta, alpha, and beta bands exhibited a rapid downward trend in the first 2 s of the aiming period, whereas the power of all bands exhibited a stable trend of slow decline after 2 s. This result is consistent with the conclusions of Gong [3] and Fronso et al [23], who confirmed that the fewer brain fluctuations of the excellent trials reveal a calm state when closer to the excitation time.

The difference between the average values of all frequency bands preliminarily verifies the separability of each frequency band feature between the excellent samples and the poor samples. The results revealed that significant differences ($p < 0.01$) were observed in the average power of all bands during the aiming period, and the gamma band exhibited the largest difference ($p < 0.001$) between the excellent samples and the poor samples. This result could be attributed to the limited state adjustment of the shooter during excellent performance [24]. Thus, shooter can perform rapid and stable adjustment to reach the best state.

4.2 Analysis of Effective Neural Markers

Feature selection improves the classification performance through dimensionality reduction, which includes feature domain and lead selection. This method is used to refine features and find appropriate fusion features. The lead selection can simplify the test process and improve efficiency. To evaluate the effectiveness of various EEG frequency-domain features, the frequency-domain features were sorted using LDA. Subsequently, 177 EEG features were then selected in the first 20%. From the perspective of the feature domain, the maximum proportion of DE features in the frequency domain was 47%, the PSD features was 36%, and the minimum proportion of frequency spectral features was only 17%. Thus, the DE feature exhibited the best discrimination effect.

From the classification effect diagram of frequency-domain features, the classification accuracy of gamma and beta features in a high-frequency band is considerably higher than that of delta, theta and alpha feature in a low-frequency band in each period, and the classification accuracy of the

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frequency spectrum, power spectrum density, and DE feature in the gamma band was the highest. Combined with the frequency band feature summary results of separability top 20 in Table 2, the strongest separability features were highly concentrated in the high-frequency features of the gamma and beta bands, which were consistent with the classification results. This phenomenon is consistent with the results of Gong et al. They revealed that beta1 bands at O1 and O2 electrodes of skilled shooters' brains during rifle shooting were positively correlated with shooting performance [3]. Because various frequency band characteristics of EEG signals correspond to various functional states of the brain, and frequency band characteristics are related to the degree of corresponding functional states. This study revealed that the excellent samples and the poor samples exhibited significant differences in the high-frequency band. This result indicated that the performance of the shooter was related to the advanced cognitive control during the aiming period.

Figure 4 showed the classification effect diagram of the gamma frequency-band characteristics. We Found that the DE feature classification effect of the gamma band was the best and always in a dominant position after 1 s of aiming. The results revealed that the gamma band DE feature can be used as a neural indicator for shooters with excellent and poor shooting performance, and also can used as a feedback indicator because of its high accuracy and high stability. This phenomenon was similar to the results of Cheng et al. The EEG of each participant in the best and worst five shots was analyzed, which revealed the lower gamma rhythm was related to shooting performance [25].

Table 2 reveals that the characteristics of the top 20 are highly concentrated in the channels CP3, CP4, CP5, CP6, PO5, and PO7. Combining these results with the location distribution of these channels revealed that the contribution rate of the leads in the parietal and left temporal lobe regions was higher. The excellent lateralization phenomenon of shooters in poor shooting could be related to motion information processing and visual space perception processing. This study expanded the relationship between brain signals and shooting performance and conducted difference analysis from the channel and feature domain to provide preliminary evidence for the realization of the difference in brain activity presented by shooters.

4.3 Limitation

Signal acquisition was performed in a nonlaboratory environment, which revealed that external interference resulted in poor signal quality. Although various methods were used to minimize the interference of electrocardiogram, electromyography, electromagnetic, and other noises in EEG signals, noise still existed in the data after preprocessing. Therefore, the subsequent EEG data preprocessing can be improved to ensure the authenticity and integrity of EEG data.

In this study, only the changes in brain signal during the aiming period of the shooter were considered. Related studies have revealed that the multimodal fusion effect was slightly better. In the future, multimodal analysis can be combined with physiological signals such as heart rate variability and body stability.

Because of the limitation of the shooting environment and time, the statistics are not conclusive. In the future, the universality of the conclusions can be ensured by increasing the sample size. Furthermore, the interactions in the brain function of the shooter during the aiming period should be investigated.

5. Conclusions

In this study, we investigated the neural markers that can used to characterize the changes in shooting performance. The results revealed that the brain signals of the shooter were stable when the performance was excellent, and the features of the gamma band exhibited a strong ability of characterize shooting performance. The best classification accuracy could be obtained by the gamma-band features, and this feature was always in a dominant position after 1 s of aiming. In this study, a preliminary exploration was realized to classify shooting performance using frequency-domain characteristics of EEG signals, found that the gamma band DE feature can be

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used as a neural indicator for shooter's shooting performance and a feedback indicator in daily training. This results of the study can promote the real-time monitoring of the state in daily training.

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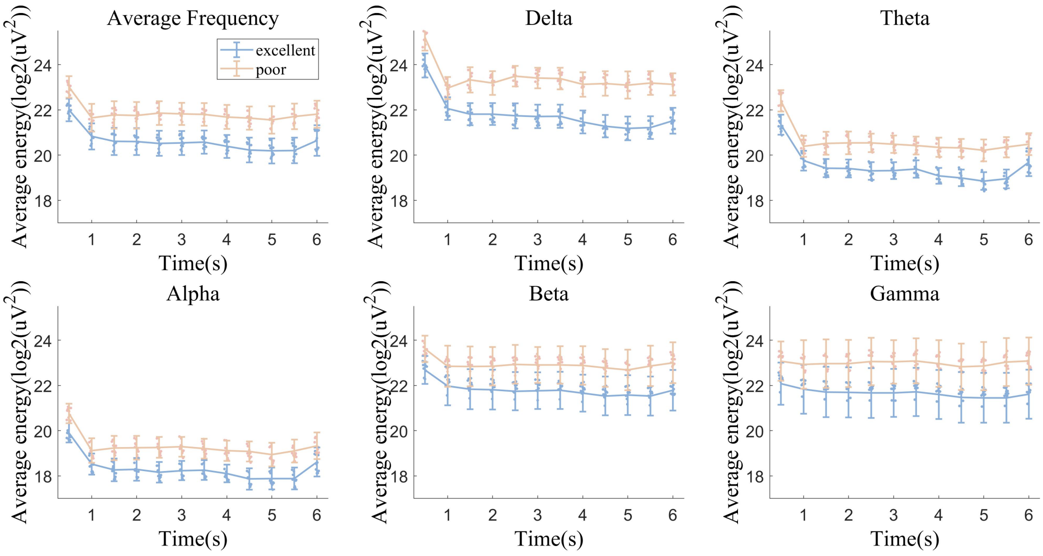

Figure. 2 Change of average frequency band energy during aiming period.

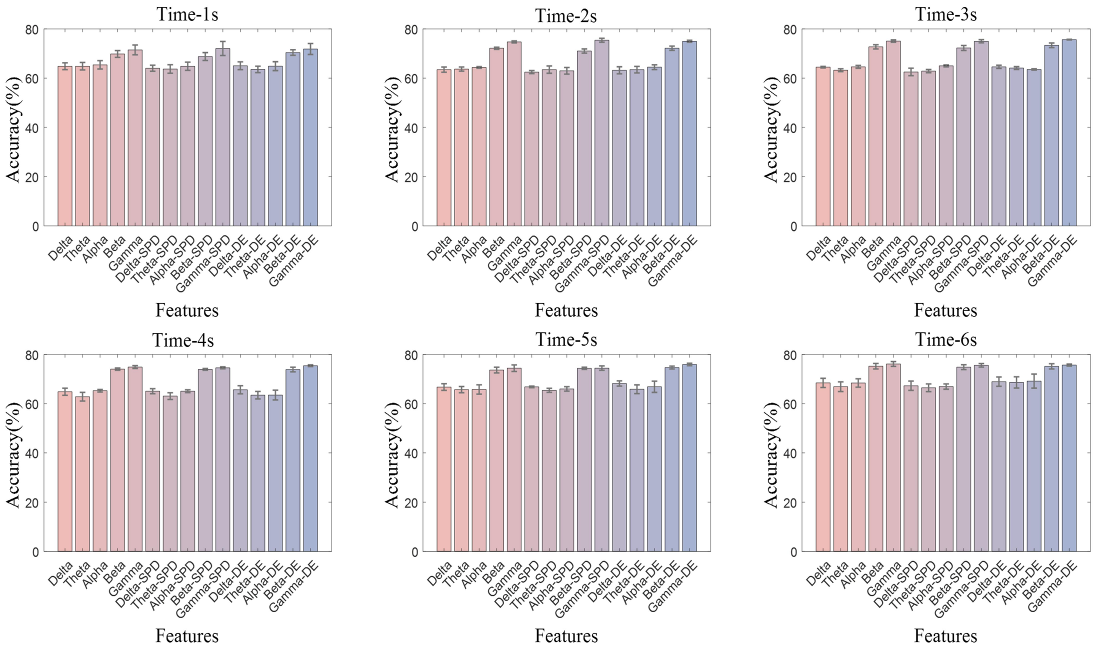

Figure. 3 Classification results of frequency-domain features during various aiming times.