Decoding Human Visual Colour EEG Information Using Machine Learning and Visual Evoked Potentials

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Abstract

With the rapid development of brain-computer interfaces (BCIs), human visual decoding, one of the important research directions of BCIs, has attracted a substantial amount of attention. However, most visual decoding studies have focused on graphic and image decoding. In this paper, we first demonstrate the possibility of building a new kind of task-irrelevant, simple and fast-stimulus BCI-based experimental paradigm that relies on visual evoked potentials (VEPs) during colour observation. Additionally, the features of visual colour information were found through reliable real-time decoding. We selected 9 subjects who did not have colour blindness to participate in our tests. These subjects were asked to observe red, green, and blue screens in turn with an interstimulus interval of 1 second. The machine learning results showed that the visual colour classification accuracy had a maximum of 93.73%. The latency evoked by visual colour stimuli was within the P300 range, i.e., 176.8 milliseconds for the red screen, 206.5 milliseconds for the green screen, and 225.3 milliseconds for the blue screen. The experimental results hereby show that the VEPs can be used for reliable colour real-time decoding.

Introduction

Visual brain-computer interfaces (BCIs) can benefit people with severe visual disabilities¹. In the early stages of investigation, visual BCI studies have focused on steady-state visual evoked potentials (SSVEPs)². An advantageous feature of SSVEP investigations is the use of fixed frequency flickering as visual stimuli that evoke brain responses. Notably, the accuracy of the typing performed by a visual spelling machine based on SSVEPs can reach up to 90%³. However, the main disadvantage of SSVEP experiments is that they do not allow the classification of nonflickering static observation targets⁴. If the observed target has different colours with the same flickering frequency, SSVEPs do not provide information that enable these colours to be effectively classified. Additionally, considering visual stimuli, long-term work with flickering images can cause eye fatigue, which may badly influence participants' interaction control⁵. With the development of image recognition technology, most visual BCI studies have focused on graphic decoding and hybrid BCIs (hBCIs)⁶. Graphic decoding can overcome the problem with SSVEPs; i.e., graphic decoding can be used to classify nonflickering static observations. However, graphic decoding cannot be used to classify objects of the same type with different colours⁷. An hBCI can help in the challenging task of classifying the same type of objects with different colours; however, the paradigm of an hBCI usually requires a combination of psychology, motor imagination, hearing, decision-making, etc⁸. The most common task used in visual hBCIs to ask a participant to find target colour graphics according to continuous prompts and to make decisions by tapping the keyboard at the same time⁹. The paradigm seems to be stable, but it often results in a series of interferences due psychological aspects and decision-making methods¹⁰. Moreover, there are too many interference factors, such as a lack of reliability and low classification accuracy, which are not ideal aspects^{11, 12}. Therefore, we urgently need a new visual colour decoding paradigm based on BCI techniques¹³.

In this paper, we proposed a new approach to visual colour decoding using machine learning and visual evoked potentials (VEPs) in a BCI-based interaction system. The purpose of such an approach is to combine the advantages of using VEP brain responses elicited by the quick presentation of stimuli and the stability of machine learning classification. This approach was employed when working with colour and visual stimuli only. Using adjusted red, green, and blue colours as stimuli to actively stimulate visual stimulation, the generated events and labels were used as methods to control supervised learning classification and VEP-extracted features on the time axis. This method of stimuli usage made the interface of the interaction system more scalable, intuitive, and applicable to daily needs than previous systems¹⁴.

Results

We selected 9 subjects to participate in our test. Through our newly designed task-irrelevant, simple and fast stimulus visual colour decoding paradigm, the random colours participants saw were classified by machine learning. Experimental results showed that the visual colour classification accuracy can reach 93.73%. This result indicated that the signal obtained by using visual perception to classify colours has good robustness. The fast stimulus-response time features extracted by VEPs on the time axis according to events and labels were 176.8 milliseconds, 206.5 milliseconds, and 225.3 milliseconds, which were shorter than the P300 component. This result revealed that the colour information elements had significant and strong features during their latency, and this feature can play an important role in visual colour information coding in the future.

Decoding Performance

We performed a detailed analysis of each channel's performance during the experiment. The results showed that under fast visual colour stimulation conditions, the 9 participants maintained a good classification accuracy rate in the cortical visual areas (Figure 1). In Figure 1, the horizontal axis shows the channel names, and the vertical axis shows accuracy. Each dot represents the average classification accuracy of 210 epochs generated by participants after the interaction of two colours with a 6:1 ratio of data training to testing by a support vector machine (SVM) or feedforward neural network (FNN) after 30 iterations. We can see that most of the channels with a classification accuracy of over 70% are gathered in the cortical visual areas (the dark grey area at the upper right of each diagram in Figure 1, channel Pz - O2), and the highest accuracy rate is nearly 93.73% (Table 1). Both SVM and FNN testing show the same classification accuracy characteristics results in Figure 1.

In Figure 1, SVM and FNN testing show similar classification accuracy distribution characteristics. However, to further verify the relevance of the two algorithms in the results, we averaged the classification accuracy results of all 9 participants, 59 channels, and 30 iterations. Then, we generated the two curves shown in Figure 2. The red curve represents the average result of SVM testing, and the green curve represents the average result of FNN testing. The two curves were fitted. To focus our decoding on visual processing, we restricted our main analyses to the 17 most posterior electrodes (P7, P5, P3, P1, Pz, P2, P4,

P6, P8, PO7, PO3, POz, PO4, PO8, O1, Oz and O2)¹⁵. At the same time, we averaged the classification accuracy results of channels POz-O2 in the cortical visual areas. We found that the classification accuracy results errors of two algorithms, SVM and FNN, with the three groups of red and green, red and blue, green and blue were 3.28%, 0.64%, and 0.14%, respectively. The results showed that the classification and decoding accuracy results obtained by the two algorithms are similar (Table 1). This classified decoding performance showed that the decoding of the task-irrelevant fast visual colour stimuli paradigm was highly robust.

Table 1
Accuracy classification with the channel of cortical visual areas under SVM and FNN. Average accuracy classification of all cortical visual areas channels under SVM and FNN. Errors of average accuracy classification between SVM and FNN.

Channel	Red and Green		Red and Blue		Green and Blue	
	SVM	FNN	SVM	FNN	SVM	FNN
POz	93.73%	90.48%	81.67%	88.10%	80.32%	78.57%
PO3	81.98%	85.71%	81.98%	85.71%	75.08%	78.57%
PO4	85.79%	85.71%	74.60%	76.19%	77.38%	80.95%
PO5	79.68%	73.81%	73.02%	69.05%	71.11%	71.43%
PO6	87.38%	73.81%	72.06%	71.43%	77.30%	78.57%
PO7	79.76%	76.19%	74.68%	69.05%	71.75%	66.67%
PO8	87.22%	78.57%	72.70%	73.81%	75.95%	76.19%
Oz	84.68%	85.71%	81.59%	78.57%	75.63%	69.05%
O1	83.02%	78.57%	81.27%	78.57%	75.00%	80.95%
O2	83.89%	85.71%	76.27%	85.71%	76.19%	76.19%
Average	84.71%	81.43%	76.98%	77.62%	75.57%	75.71%
Errors	3.28%		0.64%		0.14%	

Decoding characteristics

Although machine learning obtained perfect classification decoding accuracy, it is still unknown how the algorithm obtains these data features for classification. Second, we wanted to understand the visual colour properties that were preserved in VEPs. According to the previously reported classification decoding accuracy, the performance of the visual second-layer channel (POz - PO8) is better than that of the first-layer channel (Oz - O2), and the difference can reach 9.05% (Table 2). Consequently, we wanted to better understand the features of the visual colour detected in the visual second-layer channel (POz - PO8).

Table 2
Difference between cortical visual areas first-layer (POz - PO8) and second-layer (Oz - O2) under SVM and FNN.

Channel	Red and Green		Red and Blue		Green and Blue	
	SVM	FNN	SVM	FNN	SVM	FNN
POz - PO8	93.73%	90.48%	81.98%	88.10%	80.32%	80.95%
Oz - O2	84.68%	85.71%	81.59%	85.71%	76.19%	80.95%
Difference	9.05%	4.76%	0.40%	2.38%	4.13%	0%

VEP characteristics

We performed data visualization analysis of the EEG data of all 9 participants. Data were recorded using active tagging for related events in the epoch immediately before the current epoch, so the data recording was very complete. According to the synchronous label and events recorded during the data acquisition, epochs were classified into corresponding different colour labels. Each colour needed to be compared with the other two colours when performing binary classification. Therefore, each colour appears twice among the three groups overall but only appears once in a group. We reclassified these same colour epochs into new ones when the participants saw the same stimuli target. Figure 3 shows all 9 participants' 54 event-related potential (ERP) diagrams. In each ERP diagram, the vertical axis shows the potential discharge power (μV), and the horizontal axis shows the time windows. The width of the time window reflects the latency of a related event that occurred after 1 second. Each curve shows the average superimposed result of 1 participant on 1 channel over 105 epochs in 3 trials (data averaging). To determine whether the results met P300 criteria, we had to distinguish ERP components from time series data. From time-frequency analysis, we found that almost all the peaks of waves appeared within 300 ms after the visual colour stimuli interaction events occurred. This means that the latency of each ERP was less than that of the P300 component. This is theoretically in line with the law of P300. However, the components of ERPs are generally more complex. We usually think that the ERPs within P300 are endogenous components¹⁶. After analysing all 54 ERP diagrams, it was found that almost all the latency values were less than 300 ms (Table 3). All the waves had a peak energy of approximately 8 μV , and all the waves were forward (Figure 3). Therefore, we could prevent the interference of other external factors on visual colour stimuli during the experiment. This result also suggested that our stimuli target selection was effective, and VEPs only contain colour information.

As shown in Table 3, the average latency of red, green, and blue was extended regardless of the sequence. For example, in left column, the values for each colour potential group were 177.0 ms for the red potential latency, 225.2 ms for the green potential latency, and 238.5 ms for the blue potential latency. In the right column, the values for each colour potential group were 176.7 ms for the red potential latency, 187.7 ms for the green potential latency, and 212.0 ms for the blue potential latency. The final averages of the two same colours were red = 176.8 ms, green = 206.5 ms, and blue = 225.3 ms.

Table 3

Visual evoked potential which includes colour information of red, green, and blue based on ERP and P300

Subject	Red Potential Latency (ms)		Green Potential Latency (ms)		Blue Potential Latency (ms)	
	R _(g)	R _(b)	G _(r)	G _(b)	B _(r)	B _(g)
Sub-1	190.3	165.2	321.1	165.2	341.2	336.9
Sub-2	165.2	165.2	195.3	198.7	193.1	200.4
Sub-3	172.6	176.2	324.8	186.7	324.0	193.8
Sub-4	163.0	174.0	175.2	304.7	178.1	163.0
Sub-5	174.0	171.8	184.5	171.8	167.4	176.0
Sub-6	169.6	171.8	180.3	179.2	182.4	180.3
Sub-7	185.0	185.0	313.3	185.0	305.6	321.9
Sub-8	213.7	209.3	178.1	126.1	145.3	156.7
Sub-9	159.3	171.8	154.5	171.8	309.8	178.9
Average	177.0	176.7	225.2	187.7	238.5	212.0
Final Average	176.8		206.5		225.3	

The result showed that in the brain, when sensing the visual colour evoked stimuli potential latency, red had shortest, followed by green, and blue had the longest. This also showed that red evoked human visual attention the fastest, followed by green and then blue. This may also explain why red is used to alert others and to signify danger.

State-space decoding characteristics

Our findings suggest that the classify decoding accuracy is related not only to the spatial location distribution of the channel but also to the stimuli latency and the instantaneous discharge of brain nerve terminals. These three parameters form a state- space. In Figure 4, during the 300 ms latency period after the occurrence of each colour visual stimulus event, a 4-8 μ V high-energy region appeared in the location of the cortical visual areas (channel POz - O2). These high-energy regions indicate that the brain nerve cell terminal discharges a large amount of energy instantaneously. Interestingly, the channels with higher accuracy obtained through classifying decoding using machine learning were all the same as the channels that instantly discharged a large amount of energy within 300 ms (Figure 1, Figure 4). This result showed that the channel location of classifying decoding accuracy and brain nerve cell terminal energy discharge is the same in the P300 time series (Figure 1, Figure 4).

In addition, for the parameters of time, frequency, and energy, a three-dimensional data spectrogram composed of short-time Fourier transformation (STFT) also showed a strong correlation. We randomly

selected the EEG data from 3 participants and extracted the data from the channel with the highest classify decoding accuracy, POz, in the red and green, red and blue, green and blue groups for visual analysis. The 16 consecutive epochs in channel POz were randomly extracted from the EEG data of each group. These epochs were arranged in ordered intervals depending on time series and labels of different colours. After that, we found extremely high regularity: at a low frequency of approximately 10 Hz, the same high energy appeared within 300 ms of each epoch (approximately 0.6-0.8 μ V, Figure 5). This result also showed a potential correlation among classifying decoding accuracy, energy, and time.

Discussion

In this paper, we presented a completely task-irrelevant and fast visual colour stimuli interaction approach to classification decoding that combines VEPs with machine learning. We compared three P300-based conditions, namely, red and green, red and blue, green and blue. The first elicited ERP, P300, was used as a control condition to validate the accuracy of the classification model and to confirm the neurophysiological feature of visual colour evoked potentials. This visual-colour interface had the best results on 9 participants, with an accuracy of 93.73%. All 9 participants achieved more than 80% accuracy. Participants' feedback regarding the visual colour stimuli indicated that during the experiment, there was no other luminance source interference, and visual stimuli did not cause fatigue.

According to the research results, the distribution feature of classifying decoding accuracy, latency, and energy discharge on time series has a strong correlation. In this work, we obtained the eigenvalues of classification decoding accuracy and stimuli latency. However, for the third dimension parameter, energy, we only know the discharge range (0-8 μ V). If this parameter can be quantified in the next step, and then the above three features can be combined, visual colours can be efficiently coded and decoded online. Finally, the real-time information seen by the participants can be displayed through algorithms. In addition, regarding the choice of classifiers, this study chose a more stable support vector machine and feedforward neural network. If we want to perform fast, multiclassification tasks, we also need to choose better classification algorithms.

BCIs are rapidly becoming a solution to assist the evolution of human civilization, and there are many more explorations of brain-sensing decoding. One critical difference between this work and previously described studies is that we used an EEG setup rather than a magnetoencephalography (MEG) system, which typically contains a much larger number of sensors. MEG and EEG signals are sensitive to similar types of activity, demonstrating that MEG signals are also feasible to use to decode colour in scalp EEG, indicating an important advance. This is because EEG signals have a lower spatial resolution than MEG signals and because EEG techniques are more accessible to laboratories around the world¹⁷. Second, although Jasper E. Hajonides used EEG data to study visual colour decoding, the experimental paradigm was still based on traditional semitask-relevant classification. The results reflected fuzzy qualitative research without quantitative research on the features of EEG visual colour decoding¹⁸. Third, the SVM-, FNN-, and ERP-, P300-based machine learning and VEPs proposed here were validated as highly feasible to provide a stable and strong feature classification solution for decoding colour information. The VEP

with strong features exhibited a P300 signal corresponding to ERPs. Therefore, the visual colour interaction that we designed based on task-irrelevant fast active stimuli is effective. The classification decoding techniques, SVM and FNN, achieved high accuracy. Moreover, state-space decoding further revealed the relevance of VEP features and classification decoding features on channel location and time series. Further analysis of different properties of the discharge energy spike and time width of the nerve cell terminal can be conducted to better distinguish among red, green, and blue. Our results may be important for the next step in restoring visual coding for patients with visual disabilities.

Methods

Participants

Nine healthy participants took part in the study (5 males, 4 females, mean age 23.2 years). To protect personal privacy, all of them signed informed consent to participate in the study. All of them were renamed for Sub1 to Sub9. None of the participants had visual impairment, and all had normal or corrected-to-normal vision. None of them had previous experience with P300 BCIs. All experiments were approved by the Ethical Committee of the Academy for Engineering & Technology, Fudan University. We confirm that all methods were performed in accordance with the relevant guidelines and regulations under Declarations of Helsinki.

Environmental preparation

To prevent interference due to various external light sources and colours, the entire experimental process was completed in a dark room. Participants were asked to relax during the whole experiment. During the experiment, to control the variables as much as possible, all participants were required to rest their jaws on a shelf (15 cm) while maintaining a set viewing distance (36 cm) from the screen (Figure 6). Then, the EEG cap was placed on the participants' heads (Figure 6).

Channel location adjustment

Before the experiment began, we confirmed that all the channel locations were correct. In this study, we used the international standard Fpz-O2 system with 59 channels as leads¹⁹ (ECG, Heor, Heol, Veou and Veol are electromyography (EMG) signals that were not included in this experiment). Leather tape was used to ensure that the CZ channel was at the centre of the sagittal line. The spaces between the CZ channel and left/right ears, between the CZ channel and nasal tip of the forehead, and between the CZ channel and inion were adjusted so that they were equal. The CZ channel was accurately positioned, and the minimum error was controlled within 0.2 cm.

Stimuli targets

There are thousands of different colours in the natural environment. Red, green, and blue are known as the main and basic components of natural colour. All colours contain RGB elements. Primates, including

humans, are very sensitive to RGB elements, which exist in nature²⁰. Therefore, we selected red, green, and blue as stimuli targets in this work. To obtain more clear experimental results, we made deliberate adjustments to the colours red, green, and blue. For red, the R-value was adjusted to the extreme value of 255, and the G and B values were reduced to 0. For green, the G value was adjusted to the extreme value of 255, and the R and B values were reduced to 0. For blue, the B value was adjusted to the extreme value of 255, and the R and B values were reduced to 0. The values of hue, saturability and luminance were automatically adjusted by the system itself to fit the requirements, which did not affect the final results of the experiment. After adjustment, we finally obtained the purest red, green, and blue colours as the stimuli targets (Figure 7). At the same time, to prevent the stimulating computer screen luminance source from interfering with the outcome, we adjusted this source to 3/5 of the maximum to ensure that all participants saw the same background brightness.

Interaction design

In this work, we used task-irrelevant fast stimuli, active stimuli, and time series presented to elicit visual colour interaction. We used fast stimuli because visual rod nerve cells usually discharge in a short time after stimulation. This process usually occurs within a few milliseconds²¹. Therefore, it is difficult to document. In addition, although P300 can reflect external visual stimuli within a latency of 300 milliseconds, the latency period of the colour visual interaction is still unclear²². Therefore, we set the interaction time windows of each stimulus to 1 second during the experiment. At the same time, fast stimuli can reduce the interference of other elements in the process of visual interaction. Hence, we could have a highly pure signal. In addition to fast stimulation, we used the active stimulation method. Active stimuli use ERP to record related random events that can then be used during supervised learning to decode and classify colours. One visual colour stimuli interaction contained 1 random event and label. Such an interaction was defined as 1 epoch. On the time axis, we used time series. To decode the 3 colours through binary classification, we combined them in 3 groups of red and green, red and blue, green and blue. Each group was evaluated in 3 trials. In each trial, one colour underwent a random interaction 35 times on average. The two colours in each trial interacted 70 times in total. Each interaction was maintained for 1 second. One trial would generate 70 epochs. Before each trial, a “yellow triangle” image was displayed on the screen to tell the participants to prepare for the start of the trial. After that, the participants rested. A “white cross” image was displayed on the centre of the screen to encourage the participants to focus on the screen centre and prepare for the next interaction (Figure 8). The resting time after each trial was adjusted based on the participant's situation. However, the EEG data during this period were not recorded. Finally, the whole interaction time between two random colours in the 3 trials for each group was 210 seconds. The total interaction time for trials with red and green, red and blue, green and blue groups for one participant was 630 seconds.

Decoding procedures

After preparation, we began decoding visual colour EEG data. The whole process of visual colour decoding consisted of two parts. In the first part, participants viewed the stimuli target, resulting in active

signal transmission to the rod cell layer and then to the brain. When the brain sensed this stimuli information transmitted from the rod cell layer, nerve endings discharged after a short time. At the same time, we started recording EEG data by Start NeuSen W, which was manufactured by Neuracle Technology (Changzhou) Co., Ltd. In the second part, the EEG data saved in the NSW 64 system were transferred to the classify decoding model (Figure 9).

Data acquisition

To ensure the accuracy of the experiment, we applied a gelatinous medical coupling agent to each channel. During the recording of EEG data, we monitored the electrode channel impedance. Each channel's impedance was kept below 3 k Ω . High-level impedance produces more noise, which affects the accuracy of classification decoding. At the same time, we used the synchronizer to completely reduce the error between the simulation time and recording time during interaction.

Data preprocessing

Before classification decoding, it was necessary to process the raw data. Processing aimed to make the classified decoding results more accurate and precise. We used EEG data from 1 team and 1 participant as an example to practice the processing process.

First, 210 empty epochs (over 3 trials) were rejected. These empty epochs were generated during the resting period during which the "white cross" was shown; as these data were not significant to this work, we discarded them. Other epochs with colour information in 3 trials, divided into 210 epochs, were included. In these 210 epochs, two random colours accounted for 105 epochs each. Then, we downsampled the data. The raw data resampling frequency was reduced from 1000 Hz to 200 Hz. The purpose of resampling was to minimize the association between some uncorrelated sampling points. Since most of the noise above 50 Hz is power frequency noise, we performed notch filtering on the raw data. The effective frequency band of EEG signals was mostly in the low-frequency region below 30 Hz, so we used the basic finite impulse response (FIR) to filter out the high-frequency information above 30 Hz. Finally, we also processed the data to remove eye movement artefacts to ensure the purity of the signal (Figure 10).

Classification model and testing

In the classification model, this work used machine learning for binary classification. We trained the machine on all 59 channels of EEG data for all 9 participants. For a comprehensive analysis of the classification results, we used the SVM and the FNN techniques based on supervised learning. SVM use is equivalent to solving the problem of binary classification. At the same time, we tried to use neural networks innovatively to classify EEG data. The mutual verification of the two methods can better reflect whether the decoder we designed is stable.

When using the classification model, we constantly attempted and adjusted the ratio of the training datasets and testing datasets and finally determined that the fit ratio was 6:1. At the same time, we

adjusted the number of iterations. After several adjustments, we found that the system was overfitted when the number of iterations exceeded 30. Therefore, we decided that the result of 30 iterations was the best fit for the system. Finally, we used the average value after 30 iterations for classification decoding. We divided the 210 epochs of processed EEG datasets into a group of 180 epochs for training datasets and a group of 30 epochs for testing datasets. After 30 iterations, all training datasets comprised 5400 epochs, and the testing datasets comprised 900 epochs. Then, the data from these epochs were input to the SVM and FNN. The main functions of the SVM system include the linear function, kernel function, and Gaussian function. After repeated attempts, we found that the linear function was more suitable for handling EEG data binary classification in this work. For the FNN, the neural network mainly trained and classified data; then, the function layers.conv1d was used to extract features. After that, the features were input to the FNN that was fully connected for classification (Figure 10). After the system completed all the above processing, we obtained the final result of classification decoding.

These classification models can be run in MATLAB 2019A and Python. The SVM and FNN code used for classification accuracy analyses can be found in the Science Data Bank. This code can also be used for different configuration environments. All data presented in tables and figures in the manuscript can be reproduced using the provided code.

Declarations

Data Availability

The datasets used in this article are mostly in the form of matrices. The BDF format is stored in a text file and needs to be loaded through EEGLAB, an open source MATLAB toolkit for EEG data processing that can be loaded in a Python environment using another free package, MNE. The classification models are not limited to the SVM and FNN used in this paper. Other methods, such as deep learning, can also be used to achieve better results. All datasets can be obtained in the Science Data Bank.

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Author contributions statement

Y. Wu conceived the experiment and analysis the results. Y. Wu collaborated with K. Feng and collected all raw datasets. Y. Wu collaborated with K. Feng and D. Wei developed the SVM and FNN coding

methodology. L. Song and X. Zeng provided guidance on conceptual issues and coding queries. All authors reviewed the manuscript.

Additional information

Competing interests

The authors declare no competing interests.

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Figures

Figure 1

The accuracy distribution of all 59 channels of 9 participants under SVM and FNN (The light gray part is the cortical visual areas; The dark gray part is the cortical visual areas with an accuracy rate over 70%)

Figure 2

Comparison of the average classification accuracy of all channels of the 9 participants under SVM and FNN (the red line is SVM, the green line is FNN)

Figure 3

ERP temporal diagram of all 9 participants with red, green, and blue.

Figure 4

3-D Topographical maps for the stimuli target red, green, and blue of all 59 channels, for stimuli latency : 0 - 300 ms (obtained from the 9 participants).

Figure 5

16 epochs time-frequency of channel POz.

Figure 6

Schematic representation of the data acquisition and processing equipment (Since the entire experiment was carried out in a dark room, the schematic picture was taken after the experiment was over. At the same time, the stimuli screen is also just an example.)

Figure 7

RGB chromatography adjustments

Figure 8

Visual colour stimuli interaction paradigms based on ERP active stimuli, each team have 3 trials

Figure 9

Visual color stimuli presentation for brain sensing. All stimuli have a duration of 1 second. EEG data production and recording. How EEG data transmit and classified.

Figure 10

Overall procedure for data processed and data training, data testing, classification for conditions red and green. The classification procedure for conditions red and blue, green, and blue are the same.