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Enhancing Training Performance of Brain Computer Interface with Object-directed 3D Visual Guidance

Shuang Liang · Kup-Sze Choi · Jing Qin · Wai-Man Pang · Pheng-Ann Heng

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Abstract
Purpose
Effective and appropriate training of human brain activity could help us to improve the reliability of mind decision-making in brain computer interface (BCI). The brain activities adopted in a successful BCI need to be matched with the desired mind tasks and be easily detected. In this study, we aimed to investigate the effects of different visual guidance on the performance of user training and BCI setting.

Methods
In our BCI study, we trained and differentiated users motor imagery (MI) task with three kinds of scenarios in 3D virtual environment, as non-object-directed (NOD) scenario, static-opbject-directed (SOD) scenario and dynamic-object-directed (DOD) scenario respectively. Participants were required to imagine left or right hand movements with the aforementioned visual guidance.

Results
The results of EEG signal have significant differences by applying these three scenarios. Both SOD and DOD scenarios provide better classification accuracy, shorten single-trial period, and need smaller training samples comparing with the NOD case. We conclude that improving visual guidance may facilitate learning to use a BCI. Further comparing these results between single-subject and multiple-subject paradigm of BCI, we verify better classification and time performance could also be achieved by the multiple-subject paradigm.

Conclusions
We believed that our findings should have the potential for improving users BCI training and being applied in the medical applications.

Keywords Electroencephalogram (EEG) · Brain Computer Interface (BCI) · Motor Imagery · Visual Guidance · User Training · Single-subject Paradigm · Multi-subject Paradigm

Shuang Liang
Shenzhen Institutes of Advanced Integration Technology, Chinese Academy of Sciences
Tel.: +852-27666399
E-mail: shuang.liang.jsj@gmail.com

Kup-Sze Choi
School of Nursing, The Hong Kong Polytechnic University

Jing Qin
Shenzhen University

Wai-Man Pan
Department of Computer Science, Caritas Institute of Higher Education

Pheng-Ann Heng
Department of Computer Science and Engineering, The Chinese University of Hong Kong

1 Introduction

Brain computer interface (BCI) is a communication system, which enables users to directly send control commands to a computer or other systems only by using their specific brain activity without passing through peripheral nerves or muscle tissues [19]. The traditional objective of BCI applications mainly focuses on improving experiences of disabled people and helping them to recover abilities of interaction with external environments. In recent years, many researchers have paid attention to BCI applications for healthy people, such as in multimedia [5] or virtual reality [9].

Despite BCI has shown to be very promising in medicine, this technique still faces several challenges

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that prevent its widespread usage in real life. The current typical BCI research mostly relies on the non-invasive form of electroencephalography (EEG) to detect brain electrical signals [21,16]. This kind of BCI is cost-efficient, safe and portable. However, its technical obstacles [20], such as artifacts in EEG signals, a poor quality of signal acquisition and using large amounts of electrode, which produce the low reliability and less effective performance of mind recognition, may restrict the development of EEG-based BCI. In order to improve the accuracy in translating brain activities into required control signals, the BCI communities have been dedicated to explore powerful signal processing methods and machine learning techniques to solve these challenging problems [12,8,10].

However, considering unpredictable fluctuations of brain activities, the reliability of recognition performance depends to a great extent on how well a user performs the desired task [13]. The brain activities adopted in a successful BCI need to be matched with the desired mind tasks and be easily detected. It is important to consider different strategies in user training to induce high quality of EEG signals. Over the last decade, visual feedback, as a part of most BCI systems, has been considered as an effective approach for training users to successfully improving their abilities for controlling BCI [19].

Some researches has been conducted to explore on the roles different kinds of visual guidance take. For example, there is some evidence that the immersive visual presentations, such as a 3-dimensional (3D) video game, virtual reality (VR) environment or augmented reality (AR) environments, have the potential to vastly improve practicality and usability of BCI, especially for untrained users [4,6,7]. Thus, it seems plausible to expect that the improvement of visual guidance itself may be helpful for BCI training and controlling.

On the other hand, encouraging results from a study showed that multiple subjects' brain activities could be used to solve the problem of poor performance caused by low signal-to-noise ratio (SNR) of EEG signals in recent years [18]. A latest study proved that the multi-subject paradigm using BCI control can be introduced to video gaming applications [2]. The evidences from these studies seem to suggest that the multi-subject paradigm as an alternative way can improve the overall BCI performance and has the emerging application fields.

The protocols and approaches of user training have been promoted by the requirement for the usability of BCI. Nevertheless, to date, it is still relatively little attention paid to systematically explore on protocols of user training and the form of visual guidance for the improvement of BCI performance [13]. Therefore, in this study, we focus on seeking more efficient ways to design and evaluating the factors influenced by different visual guidance of BCI. The aim of our work is to investigate in detail on how different forms of visual guidance affect BCI training in both single-subject paradigm and multi-subject paradigm.

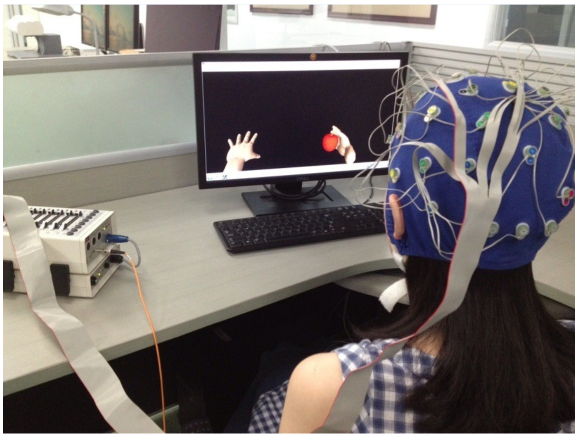


Fig. 1 A participant wearing the 32 channel electrode cap and performing an experiment of left and right hand motor imagery with the presentation of 3-dimensional scenarios.

Here we identify several questions that remain to be studied. The first is related to the design and evaluation of visual guidance based on motor imagery (MI) for user training. It has been noted that most previous studies only consider the classification accuracy of MI-based BCI [14,15]. While other factors, such as time needed for the user training, single-trial response time or user's experience, also have significant impacts on implementation and improvement of BCI. Accordingly, we mainly seek to answer the questions how different visual guidance may influence the classification performance, as well as whether it can also affect the time performance.

On the other hand, we focus on ensemble learning techniques to improve single-subject classification accuracy. In addition, we concern how multi-subject paradigm differs from single-subject paradigm in terms of user training based on the different visual guidance. This protocol may potentially benefit from extendedly utilizing various cognitive skill level of inter-user to obtain more robust results.

To address these challenge questions, we implement three different 3D visual guidances, such as non-object-directed (NOD) scenario, static-object-directed (SOD) scenario and dynamic-object-directed (DOD) scenario, and conduct users to perform the correlating MI-based training tasks.

In summary, the contribution of this paper are as follow:

– We demonstrate that the classification result and training time are significantly different in the aforementioned three visual guidances. Our findings suggest that a suitable design of visual guidances would help users to achieve the optimal performance of MI-based BCI.
– We compare the difference between single-subject and multiple-subject paradigm under the aforementioned three visual guidances. Our findings reveal that the multiple-subject paradigm could achieve better classification result and shorter training time.

2 Materials and Methods

2.1 Participants and Experiment

Five participants, including 3 males and 2 females, aged between 25 and 30 years old, were recruited for the experiments. All participants were right-handed, with normal or corrected-to-normal vision and without any neurological disorders. The participants were introduced to the entire experimental procedure in detail before the experiments. None of the subjects have prior background knowledge or experience of EEG-based BCI. Fig. 1 shows a participant performing the motor training in an experiment.

In this study, EEG signals were recorded using a Biosemi ActiveTwo system (www.biosemi.com) from 32 Ag/AgCl electrodes referenced to the CMS-DRL ground. The electrodes distributed over the entire scalp based on the international 10-20 system. All channel signals were amplified and digitized at the sampling rate of 256Hz. During the process of data acquisition, participants were asked to sit in a quiet and dimmed room, and looked at the screen of a 17 LCD monitor from a distance of about 75 cm. They also needed to observe and perform various MI training tasks presented on the screen, while synchronizing trigger signals used for data analysis were sent to the EEG acquisition computer.

2.2 Experimental design

In this study, we were interested in exploring how different visual guidance affect the performance of the user's motor training in MI-based BCI. For this reason, a 3D environment used to simulate different movements was firstly designed. During our experiments, participants were required to imagine left or right hand movements under the 3D environment displayed on the computer screen from first-person perspective, while keeping their arms and hands relaxed and avoiding any physical movements.

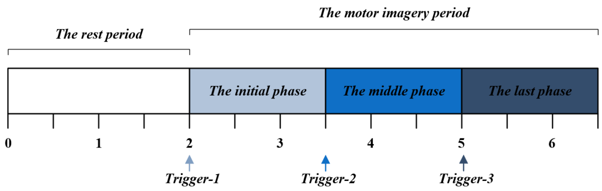


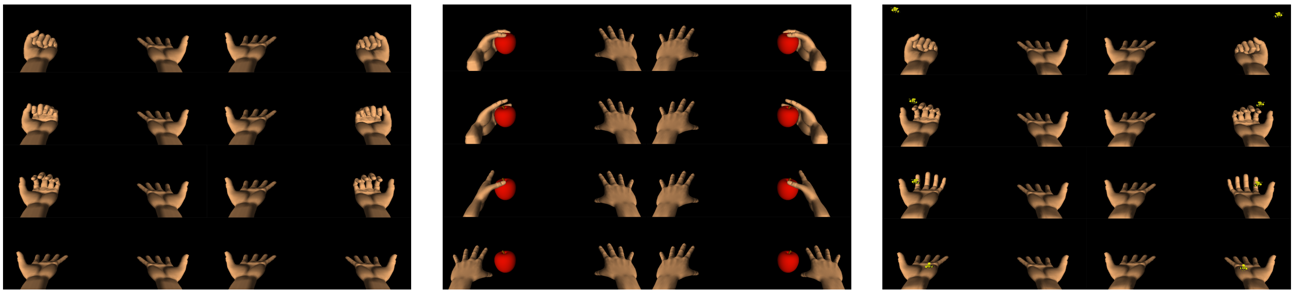
Fig. 3 The time distribution of a single-trial of left or right hand MI.

This 3D environment consisted of three scenarios: (a)The display of non-object-directed (NOD) hand movements, (b)display of static object-directed (SOD) hand movements, and (c)display of dynamic object-directed (DOD) hand movements. Snapshots of movements in these three scenarios are illustrated in Fig. 2. Under the NOD scenario, participants were asked to perform MI with the visual guidance only simulating hand movements from full open to full grasp. The second form SOD presented a moving hand to grasp the static object on one side, i.e., an apple or mug, while participants imagined their ipsilateral hand movements. In last scenario DOD, participants observed the simulation of open/grasp hand movements with an ipsilateral moving object, here using a flying insect.

2.3 Experimental procedure

For a single-trial MI, it consisted of *a rest period* of 2 seconds and *a motor imagery period* of 4.5 seconds. In particular, we typically divided *the motor imagery period* into three phases, as *the initial phase*, *the middle phase* and *the last phase*, each phase corresponding to a complete hand opening/grasping MI therefore maintained 1.5-second duration. The time distribution of a single-trial MI is illustrated in Fig. 3.

The whole experimental procedure was divided into two sessions: *training session* and *testing session*. In the training session, an auditory cue was initially played to signify the "*onset*" time in one run of MI training tasks, while a black screen displayed for 5 seconds, as *the preparation stage*. Then, participants performed a continuous MI task presented on the computer screen. For each scenario (NOD, SOD, or DOD), respectively, there were a total of 40 single-trail MI with 20 trails per class (left hand MI/right hand MI). At the end of the experimental process, another auditory cue would prompt the "*offset*" time in this run. The other run in our experiments would be performed following the same process. A short break was allowed for relieving



(a) (b) (c)

Fig. 2 Snapshots of left or right hand movements under (a) NOD, (b) SOD and (c) DOD scenario.

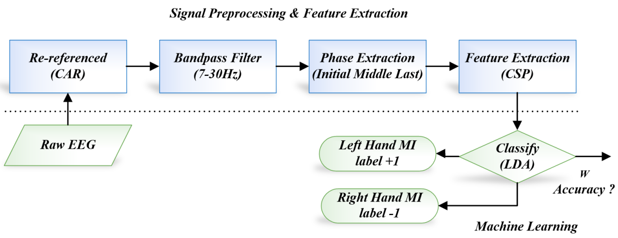


Fig. 4 Illustration of the signal processing and analysis procedure.

fatigue between two runs. All participants were asked to go through the experimental process, including 4 runs for each scenario.

In the testing session, the time arrangement of the single-trial MI was the same as in the training session. Altogether, participants performed a continuous left or right hand MI with the total of 120 trials evenly arranged into three scenarios.

3 EEG Signal Processing

As illustrated in Fig. 4, the scheme of pattern recognition of EEG signals consists of three typical components: signal preprocessing, feature extraction, and machine learning. After EEG data acquisition, we firstly performed preprocessing to filter raw EEG signals and extract MI periods. Subsequently, we applied common spatial pattern (CSP) algorithm [17] to make signal feature extraction. Finally, linear discriminant analysis (L-DA) [3] as a classifier was employed for performing classification. We precisely describe each of these phases in the following paragraphs.

3.1 Preprocessing and Feature Extraction

In the signal preprocessing, for each participate, raw EEG signals were at first re-referenced using common average reference (CAR) [11] to reduce sensitivity to noise, and resampled at 100 Hz. Additionally, in this study, we focused on discrimination of left and right hand MI tasks, which have a clear correlation between EEG feature and the underlying neurophysiological mechanism. Thus, the re-referenced EEG signals were then bandpass filtered within 7-30Hz, including mu and beta bands, which have been shown to do with hand MI. Next, we extracted the three phase from each single-trial MI with the aid of time markers obtained from the trigger signals.

CSP algorithm was used to filter and segment EEG signals to extract features for classification. The algorithm is suitably applied in BCI for two-class discrimination of left and right MI. The purpose of this method is to decompose original EEG signals into new time series with spatial filters, and then to maximize the variance of signals of one class and simultaneously minimize the variance of signals of the other.

Given a matrix E of size $N \times T$ representing preprocessed EEG signals from a single trial, where N is the number of channels and T is the number of samples, the spatially filtered signal Z can be expressed as

$$Z = WE, \tag{1}$$

where the rows of the projection matrix W are the constructed spatial filters by simultaneous diagonalization of the covariance matrices from two classes. The first m and last m rows of spatial filters W were selected as recommendation in [1], which associate to the maximal 3 and minimal 3 eigenvalues of the Generalized Eigen Value Decomposition. Finally, the extracted feature vector F_n can be expressed as

$$F_n = \log[\frac{var(Z_n)}{\sum_{i=1}^{2m} var(Z_n)}], n = (1 \cdots 2m). \tag{2}$$

3.2 Training and Testing Sessions

During the process of classifier training, we applied L-DA for classifying the EEG signals into one of the two classed (left or right hand MI). The log-variance of

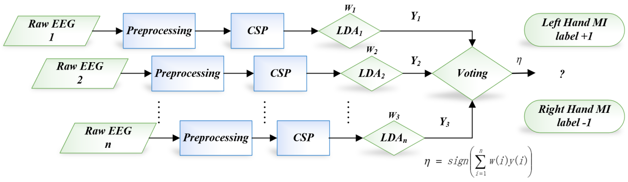


Fig. 5 Diagram of feature extraction and classification in a distributed multiple-subject paradigm.

the spatially filtered signals F_n were used as input feature for Linear discriminant analysis (LDA) [3], one of the most efficient classifiers for BCI. A 10×10 cross-validation procedure applied to test classifier performance may avoid over fitting and enhance the generalization of classification results.

The scheme of EEG signal processing was applied to each participant ending with specific spatial filters and an LDA classifier. Taking the NOD as an example, in the training session, we extracted three phases from a single-trial MI by a 1.5-second time window. A total of 480 training data, including 240 segments for MI tasks for each hand, were acquired from each participant. In this way, the 480×6 feature vectors eventually were obtained and used as the training data for the LDA classifier building. As 10×10 cross-validation was adopted, this means that the resulting feature vectors were randomly partitioned into 10 groups where a partition was used as the testing data for a classifier trained on the remaining 9 partitions. The procedure was repeated 10 times and the average classification accuracy was obtained.

In the testing session, we used the spatial filters and LDA classifier to continuously classify 120 segments of 1.5-second signals obtained from a new run of EEG data acquisition. The classification result provided an indication of the feasibility using visual presentation to facilitate MI training.

On the other hand, the multiple participants' signals relating to the same condition were combined to further improve the classification accuracy and the robustness of single-subject BCI. In this study, we can see from Fig. 5, by mean of ensemble LDA classifiers of each subject and the voting method [18], we applied the distributed paradigm of multi-subject BCI and analyzed the resulting performance due to different forms of visual guidance. For implementing the multi-subject paradigm, we selected single-subject data from combination subset of the number of participants as the input to these classifiers, which were trained separately for each participant in the training session before. The output results of these classifiers were then combined voting mechanism [18]. We finally averaged classification results of these subsets with the same number of participant for our further analyses. The procedure for a weighted voting can be described,

$$\eta = sign(\sum_{i=1}^{n} w(i)y(i)) \tag{3}$$

where n is the number of subjects, $w(i)$ is the subject weight by using the training accuracy, and $y(i)$ is the output of a sub-classifier in testing session.

4 Results

4.1 Classification Accuracy in Different Scenarios

Here, we first describe the classification accuracy of left and right hand MI in the three scenarios. As can be seen Fig. 6 (i), for the NOD scenario, the mean classification accuracy of subjects is 78.3% with standard deviations 2.9%, comparing with 85.1±2.6% in the SOD scenario and 82.3±5.1% in the DOD scenario, respectively. In addition, the accuracy of each subject is found in the range of about 75% and 80% in NOD scenario, while almost of the results in both SOD and DOD scenarios are between 80% and 90%. Altogether, there are no significant differences between the SOD and DOD scenarios, and either the average accuracy of them is much higher than the NOD scenario. However, the result from a subject (S1) has a drop in DOD scenario 73.4% comparing with NOD case 80.0%. After analysis of post-hoc survey, the undesired result might come from the poor subject state during the experiment. From these findings, we suggest that both SOD and DOD scenarios would be considered to design the form of visual display used in BCI application.

To further investigate classification performance of different scenarios, we combine the single-subject data to obtain more robust results by the multiple-subject paradigm. The mean classification results of all possible combinations with varying number of subjects are displayed in Fig. 6 (ii). The results are significantly enhanced by increasing the number of subjects and can eventually reach up to 96.2% in NOD, 98.2% in SOD, and 98.5% in DOD. To the end, it seems that we simply fuse single-subject EEG data and not perform online synchronous analysis among multiple subjects. However, our system can perform the reproducible and standard process, and thus guarantee subjects in the same experimental condition. In future work, the online system of the multiple-subject paradigm would be implemented based on this study.

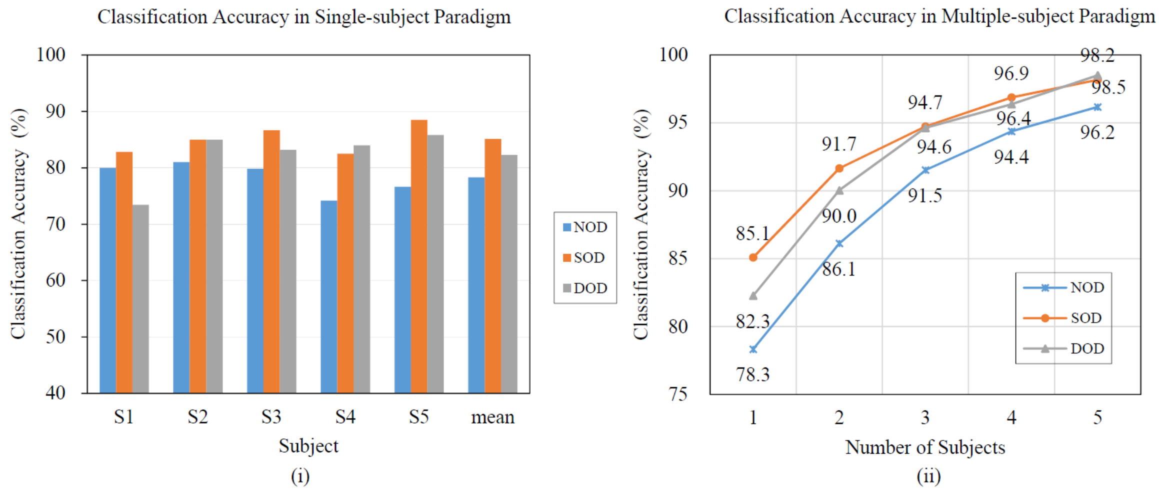


Fig. 6 (i) The classification accuracy of left and right hand MI for each subject in three kinds of scenarios. (ii) The changes of average classification accuracy in the multiple-subject paradigm with the number of subjects increases.

4.2 Classification Performance in Different Single-trial Phases

Based on the three different phases that are corresponding to 1.5s time window respectively, as shown in Table 1, we provide the classification accuracy of MI tasks in single-subject paradigm. From the row M1 to M5, we also show five group of the average classification accuracy in Table 1. The M1 present the mean classification accuracy from all subjects, and the other four group denotes the number of subjects used in multiple-subject (2, 3, 4 and 5) paradigm.

From the aforementioned table, the gray shaded areas reflect the best classification results and mainly appear in the middle phase. Thus it should be identified that suitable selection of the single-trial phase is significant to improve classification performance. Furthermore, comparing with the NOD case, the classification results of both SOD and DOD are more stable over the whole single-trial period, while the better classification performance may be achieved in relatively earlier phase. We therefore expect that more motivated visual display could shorten the single-trial period.

4.3 Classification Performance in Different Training Time

In the end, we investigate the effect of training data amount on classification accuracy in the three kinds of scenarios. As seen in Table 2, the classification performance is improved by the increase of the percentage of training data amount. Furthermore, classification results of SOD and DOD scenarios can reach 75% above by using 70p% and even 50% of total amount of training data and have better performances than of NOD by using relatively smaller amount of training data. In addition, the shaded gray areas show that better classification results of each training dataset can be obtained from either SOD or DOD scenario comparing with the NOD case.

On the other side, as shown in Table 2, we can get the comparable classification results by only using 50% of total amount of training data and even 30% for the SOD and DOD cases in the multiple-subject paradigm, while using more training data amount in the single-subject paradigm. Therefore, the results prove the multiple-subject paradigm can enhance classification performance in cases of small training samples.

Table 1 Classification accuracy of three different phases in the single-subject paradigm and the multiple-subject paradigm

Type	Initial Phase			Middle Phase			Last Phase		
	NOD	SOD	DOD	NOD	SOD	DOD	NOD	SOD	DOD
S1	77.5	82.5	74.0	83.0	83.5	72.5	79.5	82.5	74.0
S2	80.0	84.5	84.0	82.5	84.0	87.5	81.0	86.5	83.5
S3	77.5	86.0	82.5	80.5	87.5	85.0	81.5	86.5	82.0
S4	75.0	80.5	85.5	74.5	85.0	83.5	73.0	82.0	83.0
S5	76.5	87.0	87.5	80.5	88.5	86.0	73.0	90.0	84.0
M1	77.3	84.1	82.7	80.2	85.7	82.9	77.6	85.5	81.3
M2	85.2	91.1	91.7	88.6	91.7	91.6	84.6	92.3	86.9
M3	90.3	94.3	94.9	93.9	94.7	95.6	90.5	95.3	93.4
M4	95.5	96.4	96.8	95.8	96.7	98.2	93.6	97.5	94.1
M5	93.5	98.0	98.5	99.0	98.5	99.5	96.0	98.0	97.5

5 Discussion

We have presented the effects of different forms of visual guidance on the performance of MI training. This study mainly investigated on both single-subject and

Table 2 Effect of training data amount on classification accuracy in the single-subject paradigm and the multiple-subject paradigm

Type	Dataset 1 (30%)			Dataset 2 (50%)			Dataset 3 (70%)			Dataset 4 (100%)		
	NOD	SOD	DOD	NOD	SOD	DOD	NOD	SOD	DOD	NOD	SOD	DOD
S1	65.7	81.5	73.9	72.5	82.2	76.3	77.3	82.2	84.3	80.0	82.8	73.4
S2	73.6	58.9	80.3	62.5	76.5	75.1	80.5	80.0	94.3	81.0	85.0	85.0
S3	61.3	85.3	63.7	73.0	85.8	69.2	75.5	8p9.8	68.8	79.8	86.7	83.2
S4	63.7	73.8	77.2	68.3	65.8	76.2	67.5	80.3	76.0	74.2	82.5	84.0
S5	70.5	72.5	69.9	76.6	77.2	80.8	83.5	87.0	84.0	76.6	88.5	85.8
M1	66.9	74.4	73.0	70.6	77.5	75.5	76.9	83.9	81.5	78.3	85.1	82.3
M2	67.2	77.3	73.4	72.6	85.4	79.1	81.3	90.9	84.9	86.1	91.7	90
M3	68	84.1	75.2	77.1	88.8	81.7	84.4	94.6	87.6	91.5	94.7	94.6
M4	65.9	85.8	75.3	78.7	91.9	82.1	85	96.4	87.9	94.4	96.9	96.4
M5	64.3	89	77.5	80.2	92	83	85.2	97.7	88.2	96.2	98.2	98.5

multi-subject paradigm. The results demonstrated that our methodology as well as experiment design have the potential for improving MI training.

5.1 Classification Performance of Three Scenarios

We have demonstrated that the performances of user training have significant differences under the visual guidance of NOD, SOD, and DOD hand movements. The results further indicated that the SOD and DOD scenario had better performance of classification than the NOD scenario. Thus, the character of the SOD or DOD scenario could be considered to help us design the form of visual guidance used in BCI. In addition, there was no significant differences between the SOD and DOD scenarios. Therefore, we reject our initial assumption that we would have the best training performance with the help of DOD, which we initially considered involving more concentration or motivation. For these findings, we suggest that a suitable design of visual guidance would achieve the optimal performance of user training.

From analyzing accuracy results of each subject, we unfortunately discovered that the accuracy from one participant (S1) failed to satisfy the our findings. After analysis of post-hoc survey on participants, the undesired accuracy result might come from the poor state of mind during the experiment. It therefore suggested that the user's experience or the state of mind should be considered for evaluating on the performance of user training.

5.2 Classification Performance of Two Paradigms

The classification accuracy were significantly improved with the number of participants increasing. In our study, the DOD scenario could perform the most classification accuracy up to 98.5% by involving EEG signals of 5 participants, comparing 82.3% by one participant. Our investigation on multi-subject paradigm did simply fuse single-subject EEG singles and then analyze these. It seems that we did not collect EEG signals and perform online analysis from multiple participants at the same time. However, notice that our training system could guide reproducible process of the user training, while synchronous trigger signals were sent to the EEG acquisition software. It could simulate and guarantee that different participants performed at the same condition, with regard to training task and the synchronization of time.

5.3 Different Single-trial Phases and the Amount of Training Data

Besides the investigation of the classification accuracy, we also conducted studies on other factors, such as the phase of single-trial and the amount of training data, which as well could influence on user training and BCI setting. These results highlighted the process of user training and the adaptability of brain activities. For the single-subject paradigm, this study indicated that better response performances were achieved in the SOD and DOD scenarios. It suggested that more motivated scenarios could provide the possibility for speeding up mind processing. The results from multi-subject paradigm showed that increasing the number of participants could influence the training time. Therefore, based on the analysis and evaluation of the training results, it would help us to select the proper number of participants for multi-subject paradigm.

In summary, from the analysis of the results, these factors, such as visual guidance, the phase of single-trial, and the amount of training data, could affect user training and should be considered in BCI setting. However, in our current study, we ignored subject specific characteristics, such as frequency or time band of the brain rhythm differing from individuals, could also take an influence in MI-based BCI. Therefore, this study was mostly based on the average performance, we had reason to assume that the results were not satisfy in all stances. In future work, we will explore subject specific characteristics and utilize them to get better performance on the user's training.

6 Conclusion

In this study, we mainly focused on exploring strategies on the enhancement of desirable brain activities to improve the performance of user training. The results in this study showed that these factors, such as visual display, training phase, and training data amount, could influence user training and should be fully considered. We identified both SOD and DOD scenarios might provide better classification accuracy, shorten single-trial period, and need smaller training samples comparing with the NOD case. We further integrated single-subject brain singles and made analyses between single-subject paradigm and multi-subject paradigm in detail. These results constituted evidence that multi-subject paradigm might affect classification performance and time performance, and still needed to take further investigation. We believed that these findings should have the potential for improving user's BCI training and can be applied in the medical applications.

Conflicts of Interest: Shuang Liang, Kup-Sze Choi, Jing Qin, Wai-Man Pang, Pheng-Ann Heng declare that they have no conflicts of interest.

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Figure6

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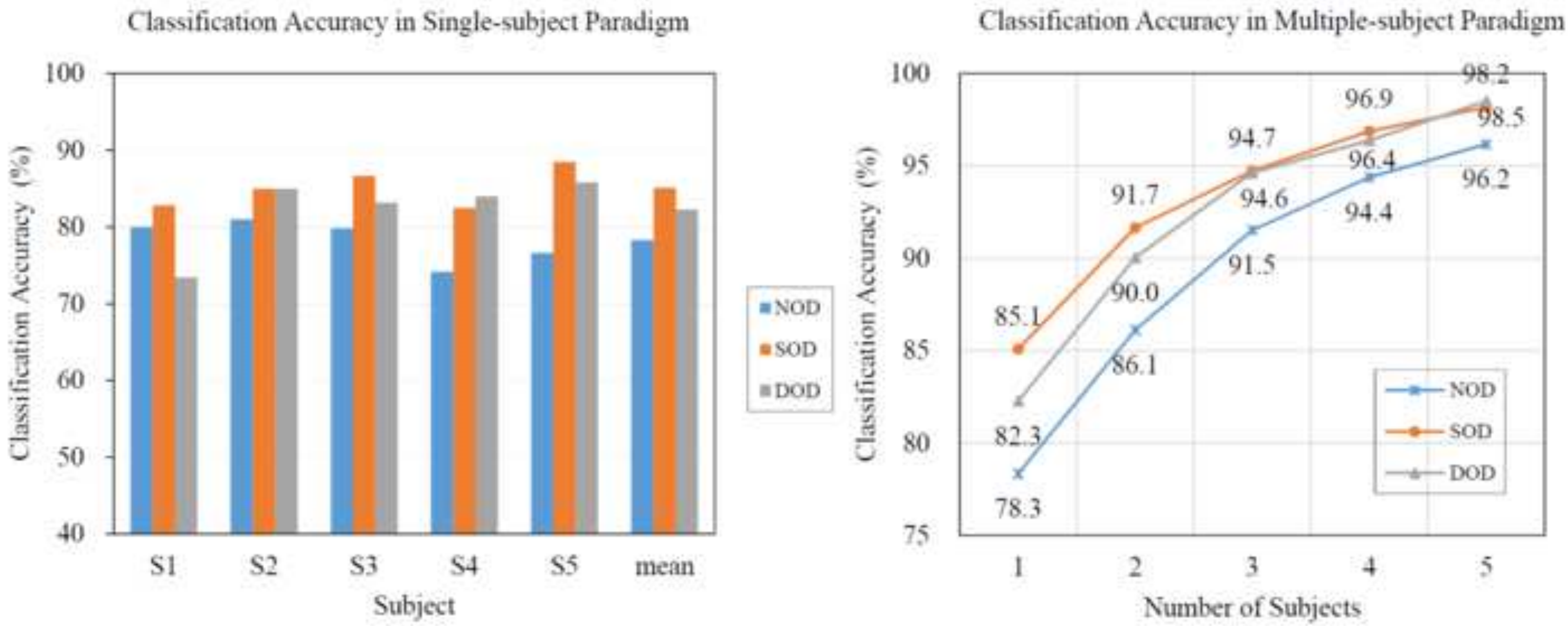

(i)

(ii)

Figure1
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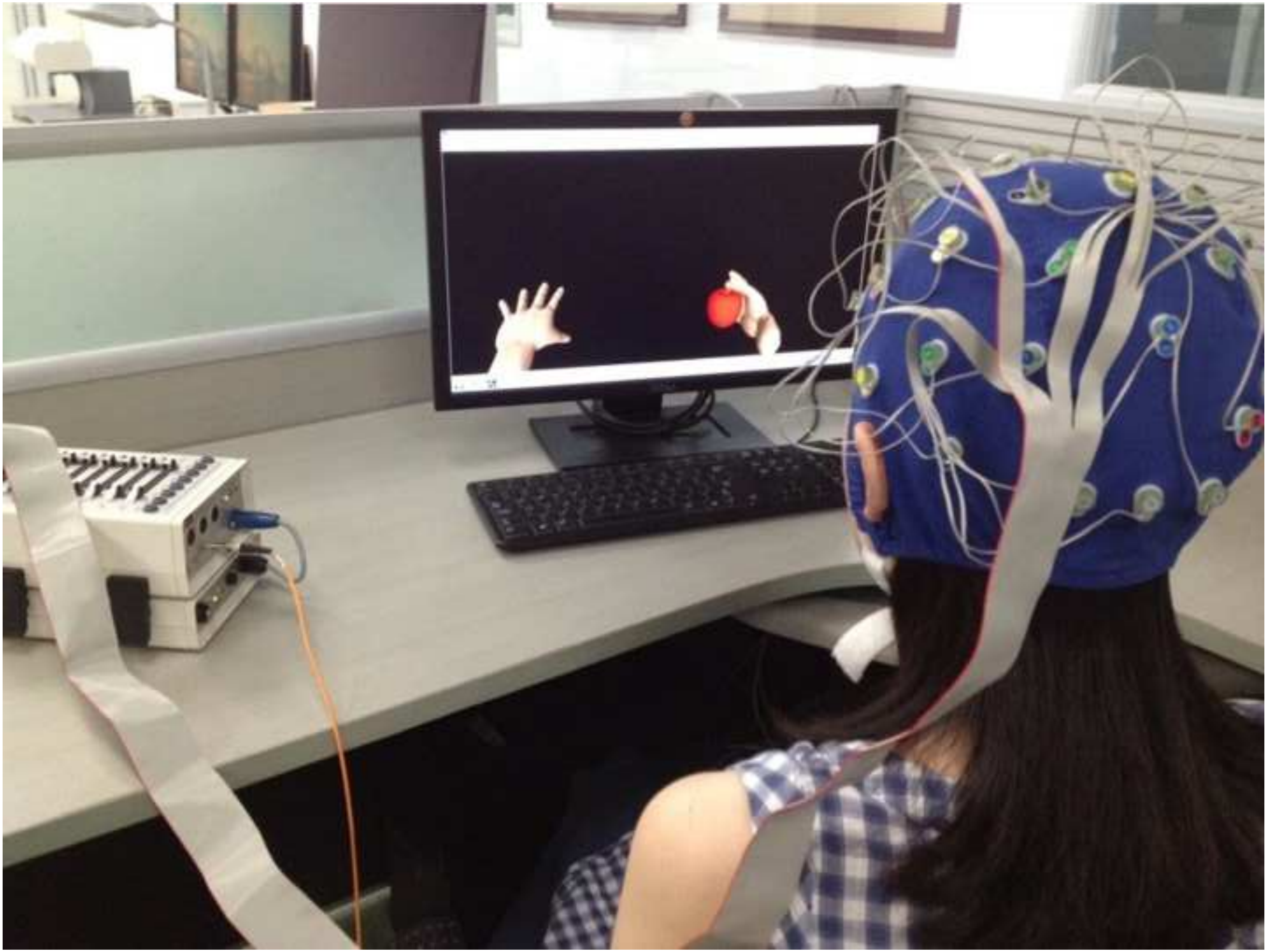

Figure3

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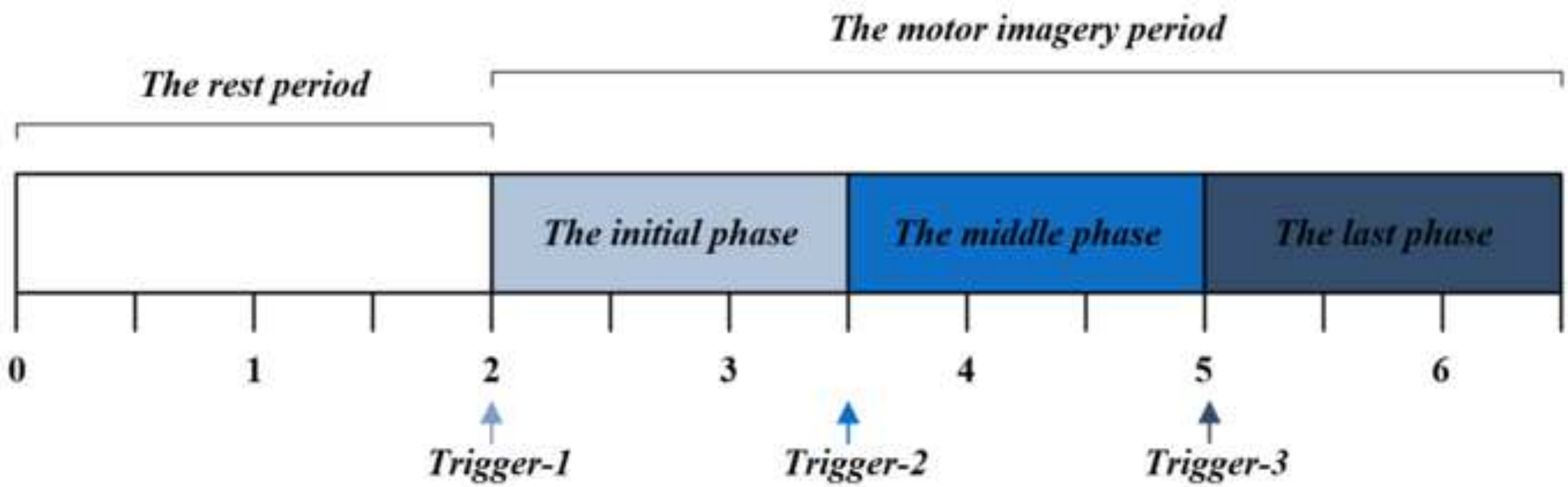

Figure5

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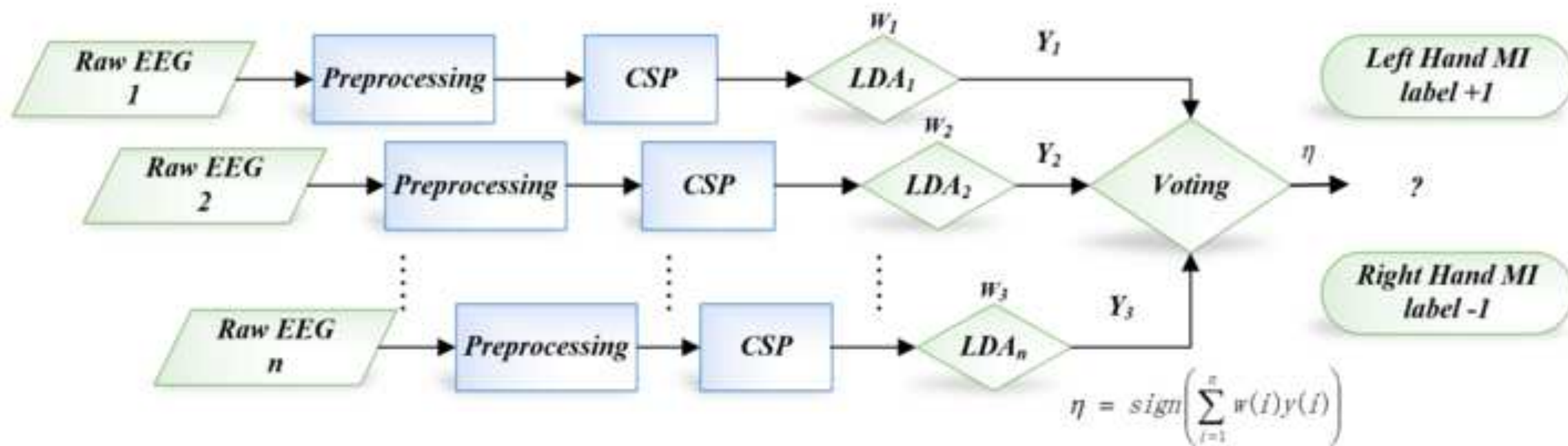

Figure4

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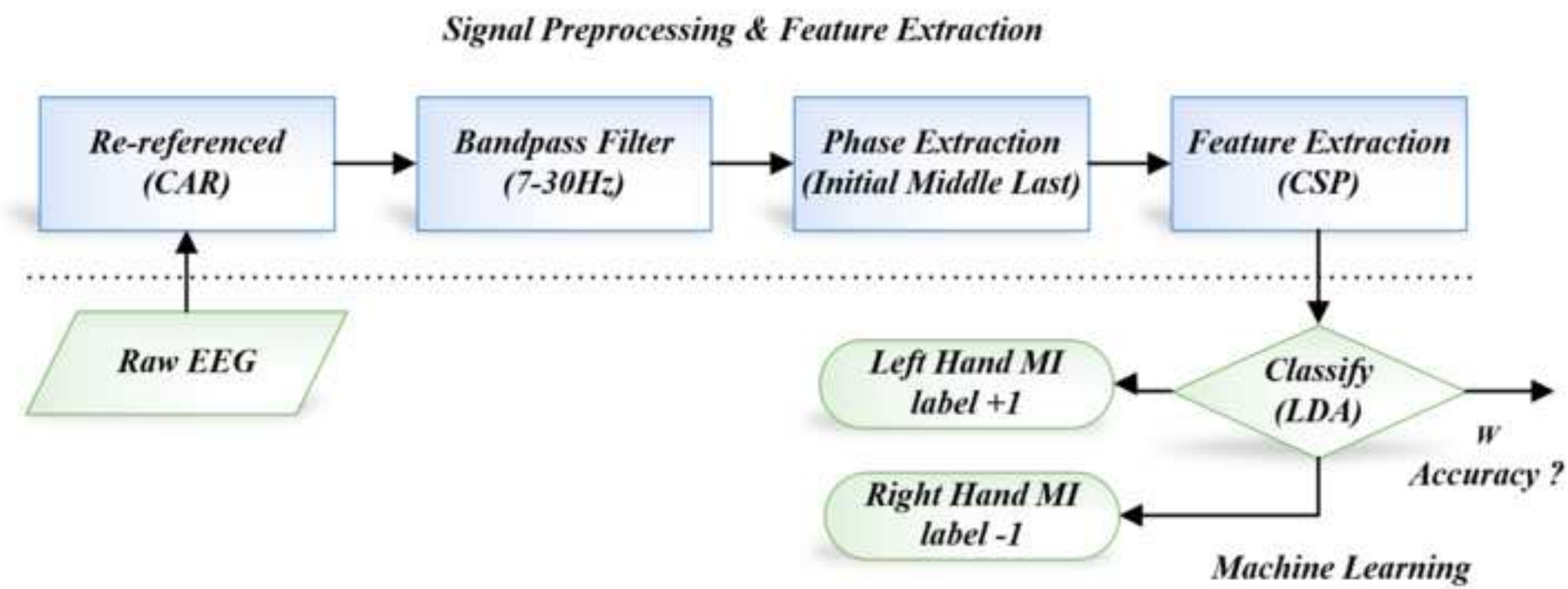

Figure2 (a)

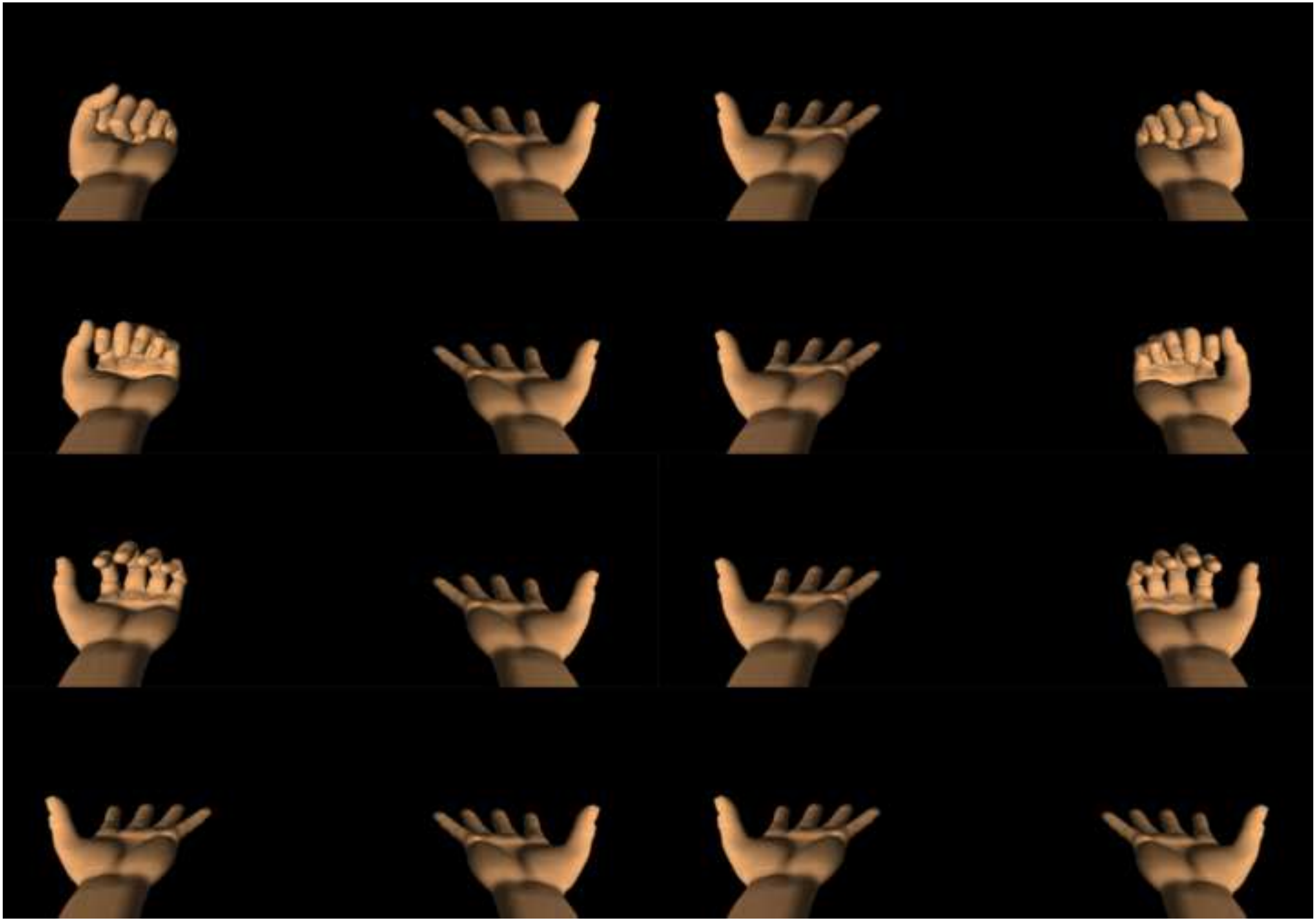

Figure2 (c)
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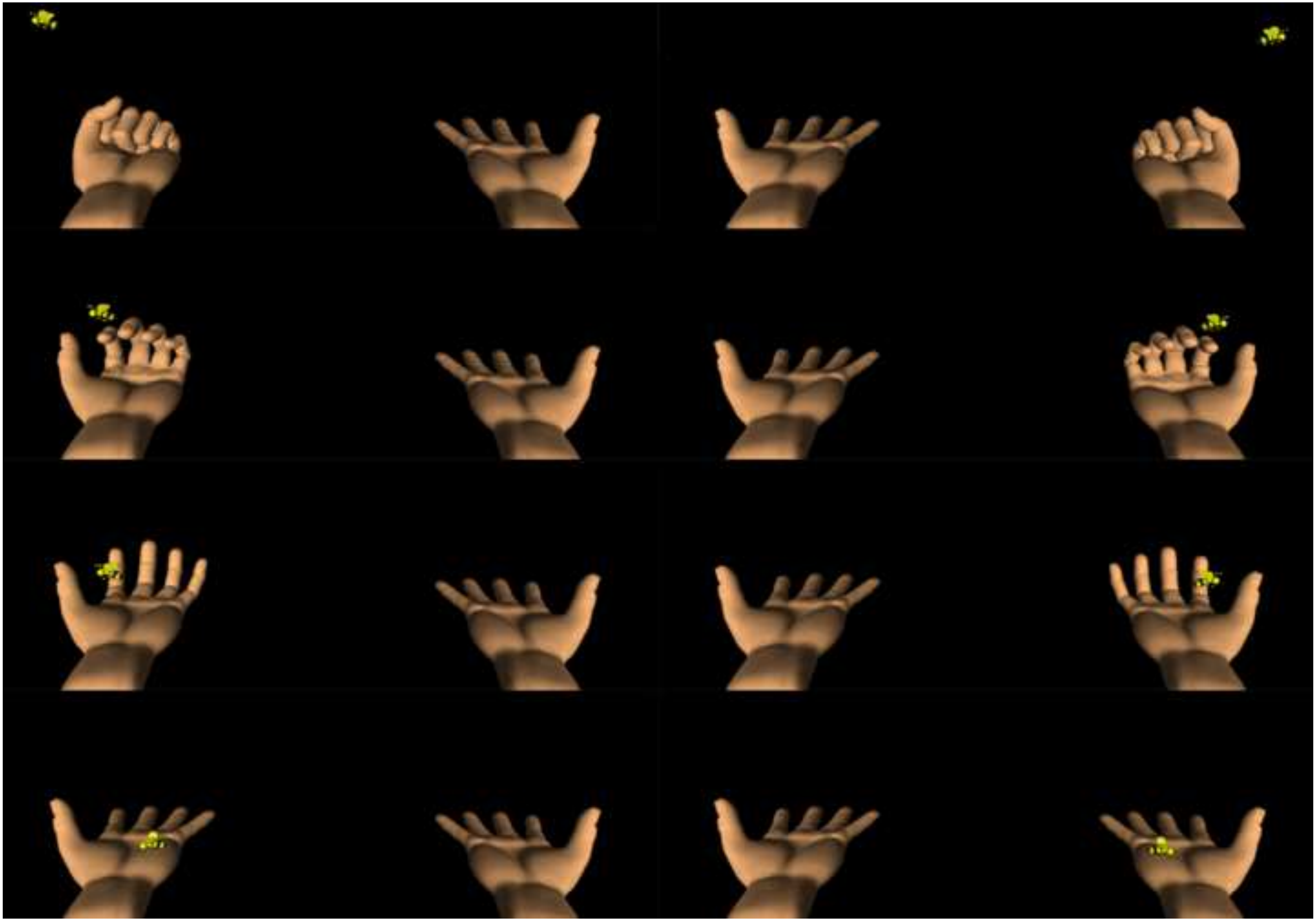
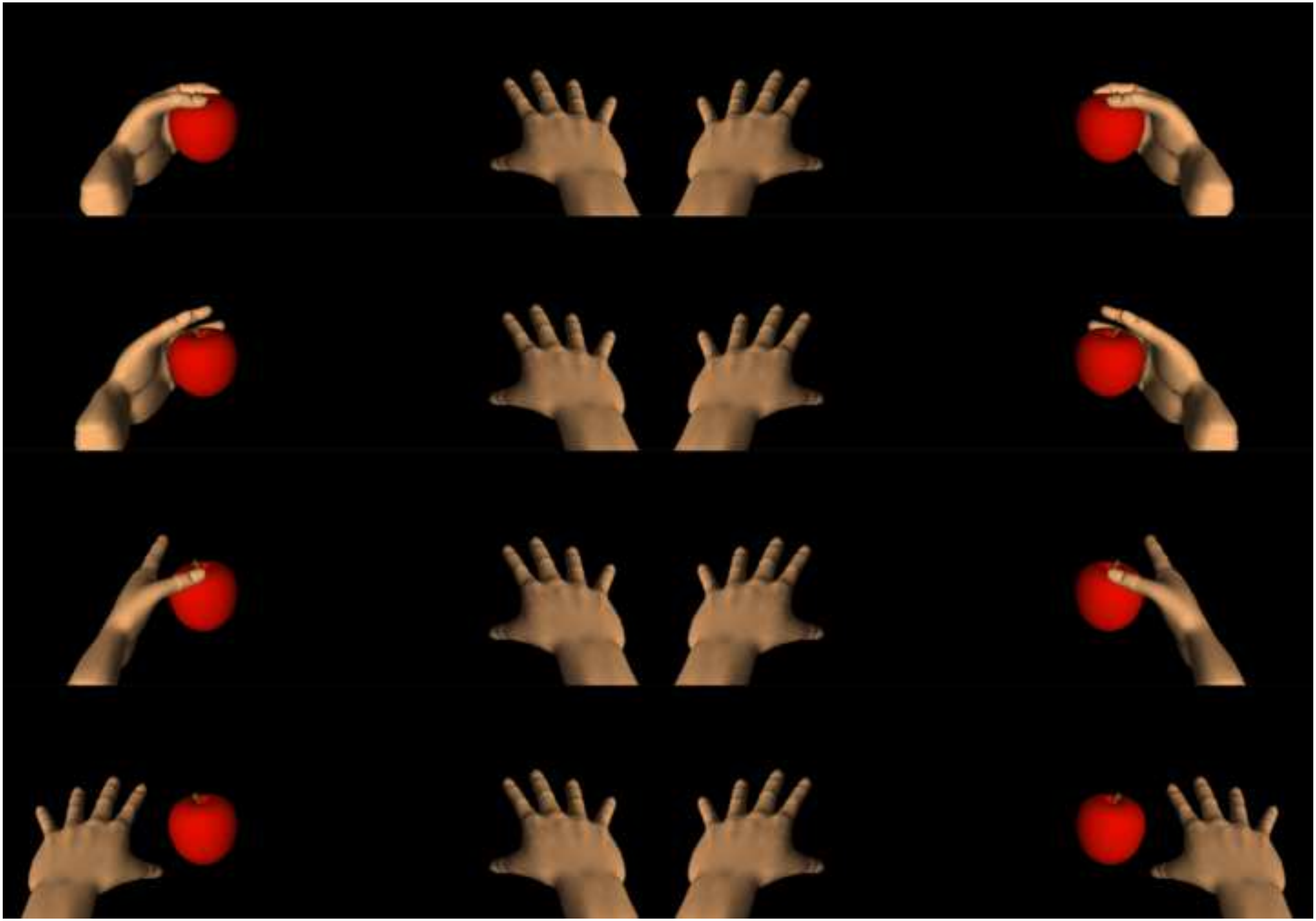


Figure2 (b)



including table 1 and table 2

Table 1. Classification accuracy of three different phases in the single-subject paradigm and the multiple-subject paradigm

Sub.	Initial Phase			Middle Phase			Last Phase		
	NOD	SOD	DOD	NOD	SOD	DOD	NOD	SOD	DOD
S1	77.5	82.5	74.0	83.0	83.5	72.5	79.5	82.5	74.0
S2	80.0	84.5	84.0	82.5	84.0	87.5	81.0	86.5	83.5
S3	77.5	86.0	82.5	80.5	87.5	85.0	81.5	86.5	82.0
S4	75.0	80.5	85.5	74.5	85.0	83.5	73.0	82.0	83.0
S5	76.5	87.0	87.5	80.5	88.5	86.0	73.0	90.0	84.0
M1	77.3	84.1	82.7	80.2	85.7	82.9	77.6	85.5	81.3
M2	85.2	91.1	91.7	88.6	91.7	91.6	84.6	92.3	86.9
M3	90.3	94.3	94.9	93.9	94.7	95.6	90.5	95.3	93.4
M4	95.5	96.4	96.8	95.8	96.7	98.2	93.6	97.5	94.1
M5	93.5	98.0	98.5	99.0	98.5	99.5	96.0	98.0	97.5

Table 2. Effect of training data amount on classification accuracy in the single-subject paradigm and the multiple-subject paradigm

Sub.	Dataset 1 (30%)			Dataset 2 (50%)			Dataset 3 (70%)			Dataset 4 (100%)		
	NOD	SOD	DOD	NOD	SOD	DOD	NOD	SOD	DOD	NOD	SOD	DOD
S1	65.7	81.5	73.9	72.5	82.2	76.3	77.3	82.2	84.3	80.0	82.8	73.4
S2	73.6	58.9	80.3	62.5	76.5	75.1	80.5	80.0	94.3	81.0	85.0	85.0
S3	61.3	85.3	63.7	73.0	85.8	69.2	75.5	89.8	68.8	79.8	86.7	83.2
S4	63.7	73.8	77.2	68.3	65.8	76.2	67.5	80.3	76.0	74.2	82.5	84.0
S5	70.5	72.5	69.9	76.6	77.2	80.8	83.5	87.0	84.0	76.6	88.5	85.8
M1	66.9	74.4	73.0	70.6	77.5	75.5	76.9	83.9	81.5	78.3	85.1	82.3
M2	67.2	77.3	73.4	72.6	85.4	79.1	81.3	90.9	84.9	86.1	91.7	90.0
M3	68.0	84.1	75.2	77.1	88.8	81.7	84.4	94.6	87.6	91.5	94.7	94.6
M4	65.9	85.8	75.3	78.7	91.9	82.1	85.0	96.4	87.9	94.4	96.9	96.4
M5	64.3	89.0	77.5	80.2	92.0	83.0	85.2	97.7	88.2	96.2	98.2	98.5