Proceeding of the IEEE
International Conference on Robotics and Biomimetics
Dali, China, December 2019

Haptic and Visual Enhance-based Motor Imagery BCI for Rehabilitation Lower-Limb Exoskeleton

Shengcai Duan[1,2,3], Can Wang[1,2,*], Mengyao Li[1,2,3], Xingguo Long[1,2,3] and Xinyu Wu[1,2,4]

***Abstract*— The motor imagery (MI) based on electroencephalogram (EEG) via non-invasive Brain Computer Interface (BCI) is a promising interactive method to provide effective communication between the disabled and rehabilitation robotic device. Interactive efficiency of MI-based BCI largely relies on the performance of subject's motor imagery. In this work, we proposed a simple and effective paradigm based on visual and haptic modalities for a high-quality initialized and calibrated MI-BCI model. Five healthy male subjects participated in motor imagery experiments with two paradigms. The proposed paradigm utilized mixed cues based on the visual and haptic modalities where the haptic cues were provided by the mini vibration motors, and a traditional paradigm utilized the ordinary arrow visual cues. The analysis of the topographic maps was conducted to illustrate the differences of the EEG in both paradigms. The average classification accuracy of motor imagery in the proposed paradigm improved about 14% compared to the traditional paradigm. Furthermore, a subject completed the qualitative verification experiment of the trained model on a rehabilitation lower-limb exoskeleton which proved the feasibility of the proposed paradigm.**

***Index Terms*— motor imagery, visual, haptic, lower-limb exoskeleton, rehabilitation**

I. INTRODUCTION

The lower-limb exoskeleton demonstrates a promising prospect which offers a valuable chance for lower-limb disabled people to stand up and walk normally [1]. Efficient and natural interaction methods between the users and exoskeletons are eagerly pursued by an increasing number of investigators [2][3]. Brain-computer-interface (BCI) provides a precious communication channel between a person and an artificial, external device, including the lower-limb exoskeleton, thus constructing a natural and efficient interactive way.

Motor imagery (MI) based on electroencephalogram (EEG) via non-invasive BCI, which is the mixed imagination of proprioceptive, visual and tactile feelings, has been widely investigated for rehabilitation in many BCI studies [4][5]. Most MI-BCI systems utilize transient event-related potentials (ERPs)[6], event-related (de)synchronization (ERD/ERS)[7], and steady-state visual evoked potentials (VEPs) as features in the EEG. It has been well established that imagining limb moving could result in ERS/ERD, which directly relates to motor intention of paretic limbs [7]. Consequently, for people with disabled limb, taking advantage of robotic rehabilitation device equipped with MI-BCI has a positive influence on motor recovery. As a result, the property of MI-BCI becomes a vital factor as it directly correlates with motor intentions of users and control signals in rehabilitation robotic device.

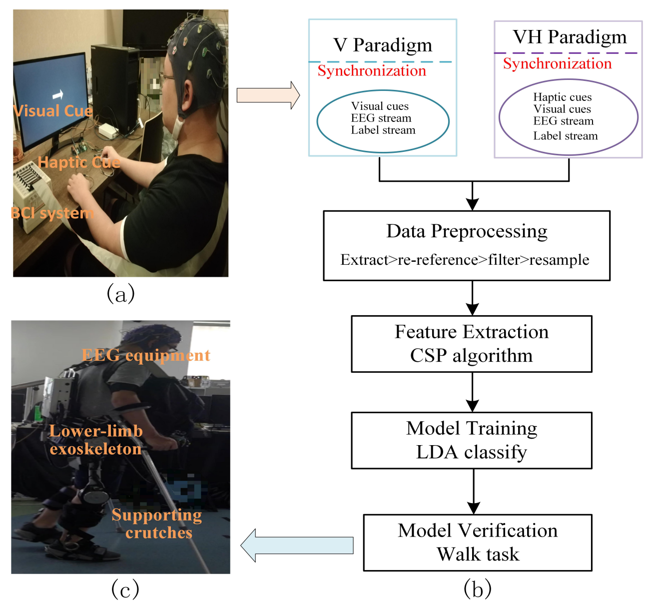


Fig. 1. Experimental system and the research's flowchart. (a)A subject is participating the motor imagery experiment with haptic and visual mixed cues in a shield room. (b)The flowchart: Two paradigms of motor imagery experiments are elaborated and a verification experiment is completed. (c)A subject is participating the verification experiment wearing the lower-limb exoskeleton controlled by MI-BCI.

Many researchers have endeavored to develop feature extraction methods [8] and classification algorithms [9] for the high-quality performance of MI-BCI. However, no matter how good the process algorithms are, MI-BCI cannot achieve the desired performance if subjects fail to efficiently regulate brain activity as required. To facilitate subjects to proficiently regulating motor imagery, feedbacks involving imaginary effects are returned to subjects to improve the performance of MI-BCI [10]. G.Pfurtscheller *et al.*[11] compared realistic feedback and abstract feedback for the same task whose results showed that there was not much difference in training performance. In [12], an auditory feedback was introduced

[1]Guangdong Provincial Key Lab of Robotics and Intelligent System, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen 518055, China.(sc.duan, can.wang, my.li, xg.long, xy.wu)@siat.ac.cn
[2]CAS Key Laboratory of Human-Machine Intelligence-Synergy Systems, Shenzhen Institutes of Advanced Technology.
[3]University of Chinese Academy of Sciences.
[4]Department of Mechanical and Automation Engineering, The Chinese University of Hong Kong.
*Correspending author.

to subjects, and the authors concluded that the auditory feedback was a suitable substitute for the visual equivalent. However, the view that feedbacks have both promotion and inhibition on EEG control was proposed in [13]. It is evident that the training session with feedback should base on precise calibration trained model without feedback. Hence, the feedback performance heavily depends on the calibration of the initial model.

To obtain a high-quality of MI-BCI, considerable researches with Visual modal cues about MI training have been investigated. In [14], virtual reality (VR) techniques was used to construct a virtual arm while participants had motor imagery and the results showed that VR could result in better intention detection due to amplified ERD caused by MI. Unfortunately, MI training with the ordinary visual cue fails to achieve satisfied classification accuracy to control application. Participants were asked to always keep an eye on the screen in [14], which indicates the disadvantage, poor anti-interference, of visual modal cue. Visual cue may be invalid for users with eye diseases. Furthermore, eyes fatigue and frequent distraction are also severe problems affecting the the performance in MI training procession. More modal cues seem necessary for MI-BCI training phase. Human touch is a common and practical sense which is attracting attention. In addition, we note that most researches with respect to MI-BCI lack online verifications on specific application, especially multimodal MI-BCI verification on the lower extremity exoskeleton robot.

The focus of this work is the application of haptic and visual mixed modalities in training of MI-BCI in order to acquire a high-quality MI, thus providing a natural and efficient human-robot interaction for disabled with rehabilitation robotic device, including lower-limb exoskeleton. Experimental system is shown in Fig. 1(a)(c). We investigate whether the rich haptic stimulations mixed with the traditional visual during MI training phase enhances the property of MI-BCI in this paper. The flowchart of this research is shown in Fig. 1(b). A simple and effective paradigm based on haptic and visual modalities of MI-BCI was proposed in this paper, which is compared with the traditional visual arrow paradigm. Five healthy male subjects participated in two paradigms experiments (traditional visual arrow cues, visual arrow and haptic stimulations mixed cues) to complete two classes motor imagery tasks involving the right hand and left hand respectively. Experimental results quantitatively approved the effectiveness of the proposed experimental paradigm. The average classification accuracy of motor imagery improved about 14% in the visual and haptic mixed paradigm than in the traditional visual paradigm. Moreover, we successfully verified the trained model for a walking task with a lower-limb exoskeleton.

The rest of this paper is organized as follows. In section II, the proposed method is elaborated, including the equipment and paradigm. Section III exhibits the quantitative results of our designed experiments and the qualitative verification of the trained model. Section IV makes a conclusion of this work and discusses the future work.

II. Method

A. Subjects

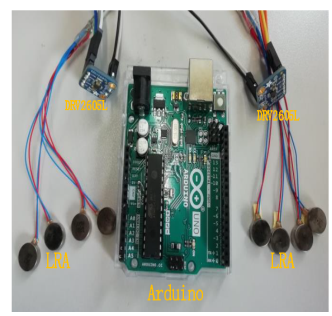
Five healthy male subjects (aged 22-26 years, mean 23.8$\pm$1.48) participate in the motor imagery experiment. Only one subject participate in the train model verification experiment due to the wearable size and operational safety problems of the lower-limb exoskeleton. All subjects are right-handed and had no clinical neurological diseases. All of them have the experience with MI based on BCI before this study except for subject 1 and 5. All subjects are informed prior to this experiment and are paid to complete the experiments. The local ethics committee approve the experimental procedure before all subjects participated.

B. Equipment

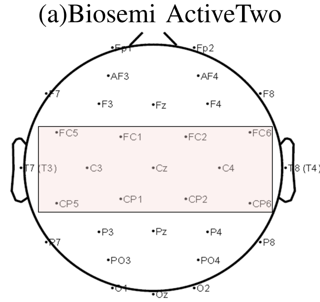
The principal experimental equipment consists of an EEG acquisition system, visual and haptic device utilized for guidance of MI-BCI, and a lower-limb exoskeleton for verifying the trained model. The experimental system is shown in Fig. 1.

1) EEG acquisition system: In order to quantitatively evaluate the MI performance, an EEG acquisition system, BioSemi ActiveTwo, with 32 Ag/AgCl electrodes following the 10-20 international system is used to collect the EEG signals, showed in Fig. 2. The EEG is sampled at 2048 Hz through the BioSemi amplifier (high-pass 2 Hz and the low-pass 50 Hz).

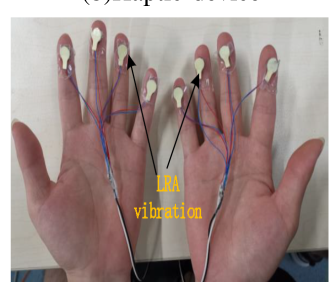
(a)Biosemi ActiveTwo



(b)Haptic device



(c)Electrodes distribution



(d)Hands with LRA

Fig. 2. EEG equipment and Haptic device.

2) Haptic and visual device: For the sake of providing a rich haptic effect, the linear resonance actuator (LRA) Coin Vibration is chosen. The LRA is driven by haptic motor driver (DRV2605L, Texas instruments) which is controlled by Arduino Uno, showed in Fig. 3. The LRA has lower start-stop time and more energy efficient compared to traditional Eccentric Rotating Mass actuator (ERM). Particularly, the DRA2605L module is compatible with adafruit haptic effects library which provides more 100 types licensed haptic effects. DRV2605L also supports custom haptic effects which is useful for haptic research. More details can be seen in [15]. The desktop computer (professional windows 10, CPU E5-1650 V3, 1920x1080 DELL screen, 60 Hz refresh rate) is used to provide a visual platform. In this research, visual arrow cues and haptic stimulations are synchronized with eeg acquisition streams in time series. We should note that the haptic effects provided in this paper are cutaneous haptic perception which are mediated by the responses of low threshold mechanoreceptors under the fingerpad skin within the contact area, other than the kinesthetic haptics referring to the sense of position and motion of the hand with the associated forces [15].

3) Lower-limb exoskeleton: The fourth SIAT Lower-limb exoskeleton is utilized to verify the trained model for completing the walk and step closing task controlled by MI-BCIs. The SIAT lightweight rehabilitation lower exoskeleton [16] includes active hip joints and knee joints, a control backpack, two supporting crutches and the Mechanical body.

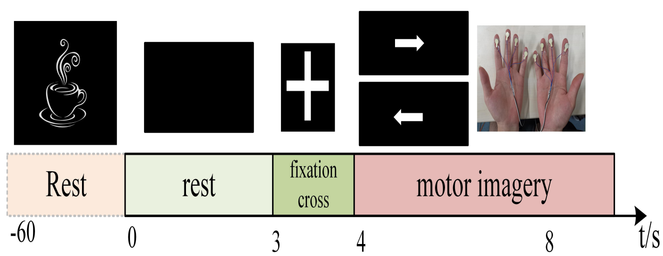


Fig. 3. Timing of a trial of the experimental paradigm. Before starting each experiment, the subjects would have a rest for one minute while the screen showed a relaxing picture. The haptic actuation are placed on the fingers except for thumb and these actuation work in VH paradigm, but cannot work in V paradigm.

C. Experimental Paradigms

Firstly, it approximately takes 30 mins to prepare EEG recording on each subject. Then, the subjects are seated in a comfortable chair about 75cm from a standard 23.8 inches LED monitor in a shield room accompanied by an experiment organizer. The visual cues are presented in the centre of the window. During the process of EEG recording, the subjects are asked to avoid unnecessary movements and keep relaxing. The entire EEG collection procession takes about 1.5 hours for each subject.

This research compares two paradigms: (1) the traditional visual arrow paradigm (V Paradigm), (2) the visual arrow mixed with haptic stimulations paradigm (VH Paradigm).

The subjects are focused on motor imagery without feedback during the experiment. For each subject, two types of motor imagery tasks are performed: involving left hand and right hand respectively. Each paradigm experiment consists of four sessions, and each session includes 20 trials. The two tasks are pseudo randomly presented throughout the session and each task is repeated 10 times in every trail. Hence, 80 trails with EEG recording are executed. All subjects firstly perform the V paradigm and then VH paradigm.

1) V Paradigm: The traditional visual arrow paradigm shows an arrow point to right or left on the screen indicating imagining movements of right or left hand, which is a common paradigm [4][5]. As illustrated in Fig. 3, at the beginning of EEG recording for each experiment, the subjects will have a rest for one minute while the screen showed a relaxing picture. Before starting of a trial (t=0s), a black screen is presented to remind the subject having a rest between every trial. After three seconds (t=3s), a white fixation cross appears on the central of a black screen for 1s to remind the subject to prepare to motor imagery. Then (t=4s), an arrow cue is exhibited to the subject that pointed to either the right or the left, which means the subject needs to complete a motor imagery task related to the movement of the right hand or left hand. The subject have 4s to imagine the corresponding movement as indicats by the cue arrow. Considering that every subject has varied preferences of hand movements, each subject is asked to imagine a hand movement that they feel the easiest and comfortable, therefore the specific imaginary hand movements are different probably. The first subject imagines playing basketball with the right hand or left hand. The second subject imagines turning the steering wheel with hands. The third subjects imagines the same movements with the first subject. The fourth imagines hitting the sandbag with the right or left fist. The fifth imagines the extention of right hand or rotation of the left hand. Then the trial is repeated 20 times for each session. Between two sessions, the subject has to rest for a while, then decides to start the next session by saying “Start” to the experiment organizer and the latter continues the experiment.

2) VH Paradigm: The visual arrow mixed with haptic stimulations paradigm is different to the V paradigm, which not only utilizes visual arrow cues, but also combines with rich haptic stimulations. The haptic sense is common and practical, which is considered to contribute to providing an immersive atmosphere and fixing on imagination attention. In this paradigm, in order to provide a more immersive sensory, four linear resonance actuators (LRAs) are respectively placed on the four fingers fingerpad of each hand except for the thumb, because of the fingerpads have perfect sensitivity over other parts of the body [17]. The haptic effects chosen from the Adafruit DRV2605L Library is different between left hand and right hand. The haptic effect on right hand is faster and more powerful, instead of slower and lighter on the left hand, which is more similar to the hand touch of the right-handed crowd. The haptic stimulations which are continuously synchronized with visual cues during the imagination process. In both paradigms, the haptic actuation are placed on fingerpads. The difference between two paradigms is that these haptic actuation work in VH paradigm, but can not work in V paradigm. Other setup is same for two paradigms, including the setup of time and imagined content.

D. Feature extraction and Classification Algorithm

When the data stream of the EEG signal is being collected, the label stream is also synchronously acquired. All 32 channels are used for signal recording and the channels associated with left and right hand movements, channel FC1, FC5, C3, CP1, CP5, CP6, CP2, C4, FC6, FC2, Cz, see in Fig. 2(c), are used to analysis. In addition, the trained model utilizing the selected channels data achieved almost the same performance of all channels data. Data of 4.5s to 7.5s during every trial are extracted to feature extraction and classification. The EEG data were processed on Matlab 2016a platform and the preprocessing procedures included re-reference, filter and resample. The data are average re-referenced firstly, then are band-pass filtered using a second Butterworth band pass from 5 to 35 Hz since this frequency contains the range of motor imagerys frequencies. In order to prevent spectral aliasing and get more data features, a 180 Hz resampling is performed.

Two types of motor imagery status (involving right hand or left hand) are decoded utilizing the Common Spatial Filter (CSP) algorithm, which has been widely used in MI based BCI systems [8]. Firstly, find the EEG covariance matrix (1):

$$C_{\mathrm{ij}} = \frac{W_{i,j}{W_{i,j}}^T}{tr(W_{i,j}{W_{i,j}}^T)} \tag{1}$$

where the $W_{i,j}$ represents the normalized EEG, $i \in \{1,2\}$ is the classification, j is the trials. Next, the mixed space covariance matrix of EEG is acquired:

$$C = \sum_i \sum_j \frac{1}{N_i} C_{i,j} \tag{2}$$

After C is decomposed into eigenvalues $C = M\lambda M^T$, a whitening matrix is obtained:

$$H = \sqrt{\lambda^{-1}} M^T \tag{3}$$

where λ is the eigenvalues of C. Then a whitening covariance matrix is acquired:

$$\widetilde{C_i} = HC_iH^T \tag{4}$$

The eigenvectors of $\widetilde{C_i}$ are arranged in descending order of eigenvalues to form $\widetilde{M}$. A CSP matrix P is calculated:

$$P = \widetilde{M}H \tag{5}$$

After calculating the CSP matrices, one pair of CSP filters, the first column and the last column constitute the actual projection matrix for feature extraction in this research.

The Linear Discriminate Analysis (LDA) is utilized in this work and get a better performance than support vector machine (SVM), which is also used for EEG signal classification [18]. The LDA algorithm for the two classifications can be transformed into an optimization problem for finding the projection w so that the objective function is maximized.

$$J(w) = \arg\max_w \frac{|w^T S_B w|}{|w^T S_W w|} \tag{6}$$

where w is the samples vector, S_{W} is an intra-class divergence matrix, and S_{B} is an inter-class divergence. In this paper, a sliding window method is utilized to search an optimal model during the 4s imagined procession. The window length is 1s, and the step length is 0.5s. The average 10*10-fold cross validations accuracy of the data are used for each subject.

E. Subjective Report

After completing the experiments in two paradigms, each participant is asked to finish a questionnaire. The participants are needed to quantify the hardiness of motor imagery in these two paradigms with a 1 to 5 Likert scales indicating quite easy, easy, neutrality, hard and quite hard on the questionnaire.

TABLE I: The subjects' responses to the hardness about two paradigms

	S1	S2	S3	S4	S5	**Average**
V Paradigm	5	4	4	2	4	3.8 ±1.09
VH Paradigm	2	3	2	2	3	2.4 ±0.55

III. RESULTS

Five subjects participate in both paradigms of motor imagery experiments and the third subject takes part in the verification experiment for walking task with trained model. The EEG results, classification accuracy comparison, trained model verification and subjective report will be presented in the results.

1) EEG Results: In order to illustrate the differences of EEG about the imagery of the left hand and the right hand movement between V Paradigm and VH paradigm, the EEGLAB v2019.0 is utilized for data processing. Subjects' topographic maps are calculated for each subject from averaged data in both paradigms, showed in Fig. 5. Each topographic map is based on 40 averaged trials (40 right hand motor imagery trials at C3 channel or 40 left hand motor imagery trials at C4 channel) after being filtered by 2-30 Hz band pass filter.

In Fig. 4, the topographic maps present the power density calculated with event related potential (2-30 Hz). The small bar chart with varied shades of color indicates the scale of the power density. The maps of each row came from the same subject. The maps on the left side of the dotted line represent the power density at C3 channel involving the imagery of right hand movement in both paradigm from five subjects respectively, and the maps on the right side of the dotted line represent the power density at C4 channel involving the imagery of left hand movement. As can be seen from the figure, the power density in VH Paradigm is higher and with wider area than in V Paradigm, whether it is the imagery of left or right hand movement, which

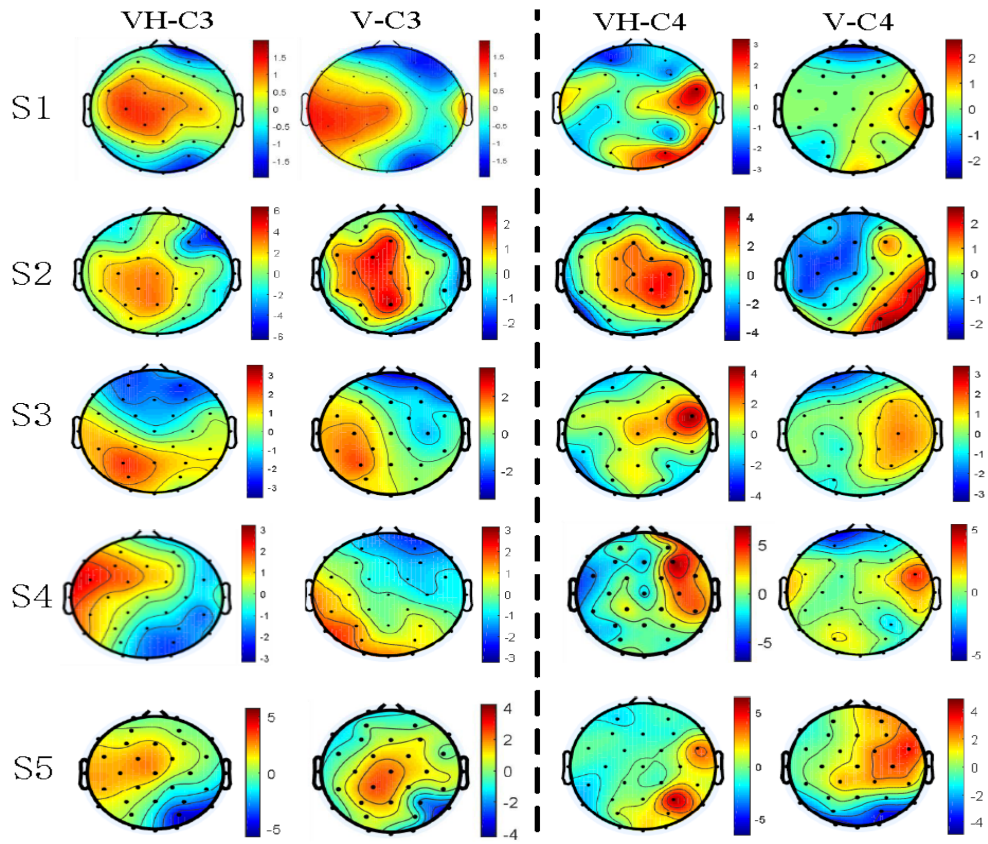


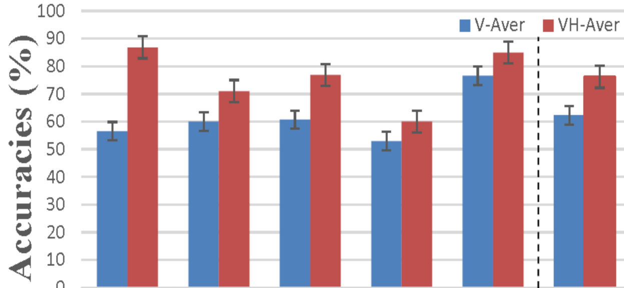
Fig. 4. This picture displays the subjects' topographic maps of all trials recorded at C3 channel) and C4 channel for the imagery of left or right hand movements in both paradigms (VH-C3: the motor imagery of the right hand in VH Paradigm, V-C3: the motor imagery of the right hand in V Paradigm. VH-C4: the motor imagery of the left hand in VH Paradigm, V-C4: the motor imagery of the left hand in V Paradigm). Each row of topographic maps comes from the same subject. The color scale of each map may be different.

indicates the effect of imagination is more intense in VH Paradigm. For most subjects, power density is higher in C4 channel than in C3 channel which indicates that the left hand is more sensitive to haptic sensory than right hand for the right handed person. The power density of subject 5 reaches a notably high level in both two paradigms, which is consistent his higher classification accuracy in two paradigms.

2) Classification Accuracy Comparison: For every subject, five times 10*10-fold cross validation accuracies (sliding window width is 1s, step length is 0.5s, for 4.5s to 7.5s in every trial) are acquired to quantify the performance of each paradigms. Fig. 5 presents the average accuracy of the five cross validation accuracies of each subject in both paradigms. The maximum accuracy of each subject is demonstrated in Fig. 6. Classification accuracy in VH Paradigm is evidently higher than in V Paradigm for the average accuracy and the maximum accuracy. The average accuracy in the new paradigm improves about 14% to the traditional paradigm. The highest classification accuracy is 88.75% from the first subject. The author analysis that the improvement results from the combination of haptic cues and visual cues and the haptic cues provide a more immersive atmosphere to the subjects, which facilitate the motor imagery of subjects. In order to demonstrate the differences between the VH Paradigm and V Paradigm, a paired samples T-Test in the average accuracy is completed ($P<0.05$). It indicates that the classification accuracy is significantly improved by utilizing the proposed VH Paradigm compared to the traditional V Paradigm.

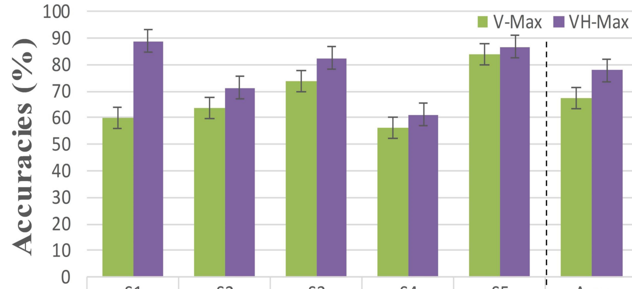
3) Verification Experiment : For further qualitatively validating the feasibility of the trained model, the third subject who is proficient in the exoskeleton completes the walk task utilizing his trained model in both paradigms. The healthy subject wears the SIAT exoskeleton to step by imagining right hand movement and take a step by imagining the left hand movement. The model with higher classification presents a robust performance. In addition, the author find that the delay time between two steps will be reduced when the wearer continuously receives feedback about the motor imagery classification results.

4) Subjective Report: The Table 1 shows the subjects' responses to the hardness of motor imagery in both two paradigms. The responses of subjects also exhibits the significant difference between the two paradigms ($P<0.05$). This P value is obtained from the permutation test method [19], which is suitable for a small number of samples verification.



	S1	S2	S3	S4	S5	Aver
V-Aver	56.56	60.00	60.75	53.00	76.56	62.27
VH-Aver	86.87	71.00	76.87	60.00	85.00	76.20

Fig. 5. The average accuracy of cross validation accuracies for each subject in the both paradigms. (Blue: the data of the V Paradigm, Red: the data of the VH Paradigm.) The right side of the dotted line is the average of the five subjects' accuracy.



	S1	S2	S3	S4	S5	Aver
V-Max	60.00	63.75	73.75	56.25	83.75	67.50
VH-Max	88.75	71.25	82.50	61.25	86.75	77.85

Fig. 6. The maximum accuracy of cross validation accuracies for each subject in the both paradigms. (Green: the data of the V Paradigm, Purple: the data of the VH Paradigm.) The right side of the dotted line is the average of the five subjects' accuracy.

IV. Conclusions

In this paper, we propose a novel paradigm based on motor imagery BCI combining the haptic and visual sensory in training phase. The multi-modalities trained model is applied to control a lower-limb exoskeleton. The experimental results based on five healthy male subjects demonstrate the visual and haptic mixed cues evidently improving the classification accuracy compared with the only visual cues ($P<0.05$). The apparent improvement can also be seen from the subjects topographic maps. In addition, most subjects feel the visual and haptic mixed cues facilitating motor imagery. A walk task is completed to validate the feasibility of our trained model from the proposed paradigm. Future work will focus on other haptic methods with more information and quantify the online test with more sensory feedbacks.

V. Acknowledgments

This work in the paper is partially supported by the National Key Research and Development Program of China (2017YFB1302303) and the NSFC-Shenzhen Robotics Research Center Project (U1613219). The authors would also like to thank all subjects who participate in experiments, and the members of SIAT exoskeleton team from the Center for Intelligent and Biomimetic Systems.

References

[1] Y. He, *et al.*, "BrainCmachine interfaces for controlling lower-limb powered robotic systems," *Journal of Neural Engineering*, 15(2), 021004, 2018.

[2] A. Sarasola-Sanz, *et al.*, "Design and effectiveness evaluation of mirror myoelectric interfaces: a novel method to restore movement in hemiplegic patients," *Scientific Reports*, 8(1), 16688, 2018.

[3] S. Crea, *et al.*, "Feasibility and safety of shared EEG/EOG and vision-guided autonomous whole-arm exoskeleton control to perform activities of daily living," *Scientific Reports*, 8(1), 10823, 2018.

[4] M. Song, J. Kim, "A paradigm to enhance motor imagery using rubber hand illusion induced by visuo-tactile stimulus," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 27(3), 477-486, 2019.

[5] M. Barsotti, D. Leonardis, N. Vanello, M. Bergamasco and A. Frisoli, "Effects of continuous kinaesthetic feedback based on tendon vibration on motor imagery BCI performance," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 26(1), 105-114, 2017.

[6] J. Jin, E. Sellers, S. Zhou, Y. Zhang, X. Wang, A. Cichocki, "A P300 brainCcomputer interface based on a modification of the mismatch negativity paradigm," *International Journal of Neural Systems*, 25(03), 1550011, 2015.

[7] O. Bai, D. Huang, D. Fei and R. Kunz, "Effect of real-time cortical feedback in motor imagery-based mental practice training," *NeuroRehabilitation*, 34(2), 355-363, 2014.

[8] J. Kevric and A. Subasi, "Comparison of signal decomposition methods in classification of EEG signals for motor-imagery BCI system," *Biomedical Signal Processing and Control*, 31, 398-406, 2017.

[9] F. Lotte, *et al.*, "A review of classification algorithms for EEG-based brainCcomputer interfaces: a 10 year update," *Journal of Neural Engineering*, 15.3, 031005, 2018.

[10] K. Ang and C. Guan, "EEG-based strategies to detect motor imagery for control and rehabilitation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(4), 392-401, 2016.

[11] C. Neuper, R. Scherer, S. Wriessnegger and G. Pfurtscheller, "Motor imagery and action observation: Modulation of sensorimotor brain rhythms during mental control of a brain-computer interface", *Clinical Neurophysiol*, vol. 120, no. 2, pp. 239C247, Feb. 2009.

[12] K. McCreadie, D. Coyle and G. Prasad, "Is sensorimotor BCI performance influenced differently by mono, stereo, or 3-D auditory feedback?" *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 22(3): 431-440, 2014.

[13] D. McFarland, L. McCane, and J. Wolpaw, "EEG-based communication and control: Short-term role of feedback," *IEEE Transactions on Rehabilitation Engineering*, vol. 6, no. 1, pp. 7C11, Mar. 1998.

[14] D. Achanccaray, *et al.*, "A virtual reality and brain computer interface system for upper limb rehabilitation of post stroke patients," *IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, IEEE, pp. 1-5, 2017.

[15] A. Maereg, A. Nagar, D. Reid and E.S ecco, "Wearable vibrotactile haptic device for stiffness discrimination during virtual interactions," *Frontiers in Robotics and AI*, 4, 42, 2017.

[16] X. Wu, D. Liu, M. Liu, *et al.*, "Individualized gait pattern generation for sharing lower limb exoskeleton robot," *IEEE Transactions on Automation Science and Engineering*, 15(4): 1459-1470, 2018.

[17] S. Ahn, M. Ahn, H. Cho and S. Jun, "Achieving a hybrid brainC-computer interface with tactile selective attention and motor imagery," *Journal of Neural Engineering*, vol. 11, no. 6, pp. 066004, 2014.

[18] A. Subasi and M. Gursoy, "EEG signal classification using PCA, ICA, LDA and support vector machines," *Expert Systems with Applications*, 37(12): 8659-8666, 2017.

[19] P. Legendre and L. Legendre, "Numerical ecology," *Elsevier*, Vol.24, 2012.