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microFE-BCI: An Asynchronous Practical EEG-based Control Paradigm Assisted by Micro-facial-expressions

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Abstract—In this study, an EEG-based control paradigm assisted by micro-facial-expressions (microFE-BCI) was developed, focusing on the mainstream defect as the insufficiency of real-time capability, asynchronous logic, and robustness. The core algorithm in microFE-BCI contained two stages (*asynchronous 'ON' detection & microFE-BCI based real-time control*) with four steps (*obvious non-microFE-EEGs exclusion, interface 'ON' detection, microFE-EEGs real-time decoding, and validity judgment*). It provided the asynchronous function, decoded 8 instructions from the latest 100 ms EEGs, and greatly reduced the frequent misoperation. In the offline assessment, microFE-BCI achieved $96.46\% \pm 1.07$ accuracy for *interface 'ON' detection* and $92.68\% \pm 1.21$ for *microFE-EEGs real-time decoding*, with the theoretical output timespan less than 200 ms. This microFE-BCI was implemented into a software, and applied to two online manipulations for evaluating the stability and agility. In *object-moving with a robotic arm*, the averaged IoU was $60.03 \pm 11.53\%$. In *water-pouring with a prosthetic Hand*, the averaged water volume was 202.5 ± 7.0 ml. During online, microFE-BCI performed no significant difference ($P = 0.6521$ & $P = 0.7931$) with commercial control methods (i.e., FlexPendant and Joystick), indicating a similar level of controllability and agility. This study demonstrated the capability of microFE-BCI, enabling a novel solution to the noninvasive BCIs in real-world challenges.

Index Terms— asynchronous, BCI, EEG, EEG-based control, microexpression

1 INTRODUCTION

ELECTROENCEPHALOGRAPH (EEG), ever since it was first proposed by Berger-H in 1929 [1], has been studied for nearly a hundred years. The EEG's unique character of representing human intention spontaneously and unconsciously has been used to regulate human-machine interaction in a natural way. Much research efforts has poured into operating peripherals with EEGs, namely EEG-based Control, also well-known as a typical noninvasive branch of brain-computer interface (BCI) [2]. Non-invasive EEGs are considered to have lower cost and higher universal application potentials [3]. Several paradigms have been developed to arouse typical responses of the brain activity and enhance the salient features under certain events or stimulus [4]. The basic form of EEG-based Control could be brought into reality at the current level of technology. Encouraged by the significant potential of EEG-based Control [5], research areas related to paradigm development and EEG interaction have attracted increasing attentions

To realize the EEG-based Control with a low signal-to-noise ratio (SNR) non-invasive surface EEGs, several mainstream paradigms have been developed, such as Steady State Visual Evoked Potential (SSVEP), Motor Imagery (MI) and so on [6]. SSVEP-BCIs realize the conversion from human intentions into machine instructions by decoding the

oscillatory components in EEGs within the primary visual cortex which match the frequency or harmonics of the repetitive visual stimulus, and establishing the correspondence between command sets and visual stimuli [7]. Early in 2008, Muller-Putz proposed an SSVEP-based 2-DoFs neuro-prosthesis with the ability to perform 4 types of hand movements [8]. In 2020, Han Jin developed an innovative BCI-controlled robot arm for both ideogram and phonogram writing, with an improved hybrid SSVEP paradigm, containing 108 commands [9]. Besides the usage in device control [10-12], SSVEP-BCIs and its variants were typically adopted in screen spellers for its characteristic in receiving visual stimulations [13]. MI-BCIs establish the correspondence between peripheral actions and imaginary movement by dealing with the event-related (de)synchronization (ERD/ERS) within the motor cortex under specific mental imagination [14]. MI-BCIs are widely used in the motor recovery after stroke and the control of alternative prostheses, considering the natural mapping relationship between MI and the motor cortex [15]. The first MI-based prosthesis including two classes operated by a patient with tetraplegia was reported by Pfurtscheller in 2000 [16]. The decoding of 4 complex right-hand MI tasks was reported by Edelman B J in 2016 including flexion, extension, supination, and pronation, which led to the development of naturalistic and intuitive MIs [17]. In addition, hybrid BCIs, as an improvement of unitary paradigm are developed rapidly [18], such as integrated MI and SSVEP [19], integrated P300 and SSVEP [20], and so on.

The mainstream paradigms, such as SSVEP and MI, face

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challenges to be transformed to peripheral operations with daily practicability. Specifically, SSVEP requires additional visual stimulator and period for steady-state visual evocation. The MI requires extra adaption to paradigm-self and highly concentration. The EEG-based control was considered as a promising control method, besides its primary function as a translator from human intention to machine instructions. Moreover, it needs to satisfy the basic requirements of real-time, precision, user-friendliness, and easiness, similar to the traditional control approaches. An EEG-based control paradigm assisted by facial-expression (FE-BCI) proposed by our research group [21-25] provides the capability for real-time decoding and control (each output generated from the latest 100 ms EEGs) [21], and has the characteristics of no additional user adaption, no stimulators, and no nerve adaptability [23].

In this work, an EEG-based control paradigm assisted by micro-facial-expressions (microFE-BCI) is proposed to improve its practical performance for comprehensive and complex daily situations. Both offline and online experiments were conducted. The effective connectivity analysis of microFE-EEGs was demonstrated to delineate the interaction among EEGs under microFE-BCI. The methodology of microFE-BCI, including computation logic, asynchronous strategy, and detailed steps, was illustrated. The offline performance and online controllability were assessed. The novel aspects of this new paradigm are: 1) An integral asynchronous BCI strategy is developed to enable users to switch on/off the paradigm in their will; 2) The microexpressions provides the possibility to distinguish the facial expressions in daily communication during EEG-based-control, and also increases the aesthetics, which ensures the suitability for patients who can hardly complete exaggerated facial expressions; 3) The instruction sets are expanded with the support of an improved core algorithm, combining the deep-learning framework; 4) A validity judgment step is added to decrease the frequent misoperations exposed in the traditional literal translation mode.

2 MATERIALS

2.1 EEG Recording

The commercial EEG acquisition system (Neuracle Technology Co., Ltd.) has 34 electrodes (including 30 EEG

channels, 1 reference, 1 ground, and 2 EOG channels, following the international 10-20 electrode location system) with 1000Hz sampling rate and WiFi (5G) wireless communication (Fig. 1). The reference was placed at CPz, and the ground was placed at AFz [26]. During the experiment, impedances were kept below 5 k Ω .

Fig. 1. The Neuracle device and its electrode placement. By system default, Afz is the ground, CPz is the reference, and A1, A2 are EOGs.

2.2 Subjects

Sixteen healthy subjects (25–38 years of age, 13 males and 3 females) participated in the experiments, without any known cognitive deficits and prior experience. Written informed consent was signed ahead, and all experiments were conducted in accordance with the Declaration of Helsinki [27]. These sixteen subjects were divided into two groups, where six subjects (S1-S6) participated only in the offline experiment for offline algorithm assessment and software development, while other ten subjects (S7-S16) participated directly in the online experiment to verify the practicability of the microFE-BCI.

2.3 Offline Experimental Procedure

To develop an asynchronous EEG-based control method, EEGs under resting-state, aroused by microexpressions and under relaxing-state were collected. To expand the instruction set, a total of 8 easy-to-execute microexpressions (microFEs) were adopted. In addition, experiments with the same facial expressions but in regular amplitude were also conducted as case comparison. An instruction video was displayed in beginning to illustrate the difference between microexpression and facial expression in regular amplitude. Fig. 2 illustrates the 8 microFEs and their comparison with the regular amplitude.

Fig. 2. The 8 microFEs adopted in this research and their comparison with the regular amplitude.

• Section one: Microexpression

8 microFEs were performed by each subject following the on-screen prompts. Each microFE was conducted for 5 sessions consisted of 8 trials. A total of 40 trials were completed by each subject for one single microFE.

In each trial, 3 s countdown, 4 s resting-state, 4 s

microexpression-state and 4 s relaxing-state were contained in turn. The switch among states was accompanied by different beepers and screen prompts. At the resting-state, subjects were asked to avoid extra movements. At the microexpression-state, subjects followed the on-screen prompts to make the designated microFE and hold it for 4

s. At the relaxing-state, subjects were free for any volunteered movement, including but not limited to talking, drinking, reading, writing, physical activity, and so on. The timing diagram for one trial is demonstrated in Fig. 3.

Fig. 3. The timing diagram of one trial, where IC represents 'in-control' and NC represents 'non-control', for details please refer to **ALGORITHM**.

• Section two: Facial expression (regular amplitude)

In the regular amplitude section, the same session settings as the microFE phase were adopted. For comparison, each facial expression was conducted for only 2 sessions, in other words a total 16 trials.

• Section three: Supplemental EEGs at Relaxing-state

Noticing that some subjects tended not to perform any volunteered movements at the relaxing-state, 3 additional

trials of EEGs under relaxing were collected, including 1 trial for reading & talking, 1 trial for drinking & eating, and 1 trial for physical moving. Each trial lasted for 96 seconds.

2.4 Online Experimental Procedure

After the offline experiment and its assessment, a software for microFE-BCI was developed. To verify the feasibility and the practicality of microFE-BCI for peripheral application, subjects S7-S16 participated in the online experiment directly without any prior experience with the offline.

Two specific external device manipulation tasks, atypical versus daily, focused on stability and agility respectively, were conducted. In both tasks, EEGs were sent wirelessly by WiFi to the computer (Windows 10, i5-6500 CPU, 3.20GHz, GTX 960 GPU). The stepping control were adopted by both devices. Before manipulation, training data for calculating the individual parameters and classifiers were collected first, of which the acquisition process is consistent with the offline experiment but with fewer trials and being more casual.

• Task one: Object-moving with a Robotic Arm

In this task, subjects were required to use this proposed microFE-BCI to first switch on the system, then operate the robotic arm to move a wooden block (4 cm * 4 cm * 4 cm) from its initial position A (bottom left corner of the desk) to the position B (as illustrated in Fig. 4(a)), and then switch off the system. The robotic arm used was the assembly of an AUBO-i5 collaborative industrial robot (6 DoFs, provided by AUBO Robotics China Co., Ltd.) equipped with an AG-95 servo-electric gripper (provided by DH-Robotics Technology Co. Ltd), as shown in Fig. 4(a).

(a) The initial state of the assembled robotic arm system in **Task one** (object-moving), and the plan view of the position A & B.

(b) Experiment scene layout and the 2-DoFs prosthetic hand of **Task two** (water-pouring).

(c) Experimental scene graph for **Task one** (object-moving).

(d) Experimental scene graph for **Task two** (water-pouring).

Fig. 4. The illustration for online experiment.

Before each trial, the robotic arm restored its initial state, with the block grabbed (Fig. 4(a)). To move the block, subjects need to first lift it, then adjust its position, and finally lower it and open the electric gripper to ensure a stable placement. For operation details please refer to **RESULTS**. The experimental scene is graphed in Fig. 4(c).

Before starting, subjects first had 5 mins to get familiar with the operation for microFE-BCI based robotic arm, then this task was repeated for 5 trials. In each trial, subjects began to complete the task after pressing the 'Start' button on the GUI by themselves. If the task was not finished within 5 mins or the block was fell halfway, this trial would be deemed as a failure. The deviation for the same task but using FlexPendant was recorded as a reference.

• Task two: Water-pouring with a Prosthetic Hand

In this task, subjects were required to use the microFE-BCI to first switch on the system, then operate the prosthetic hand to pour 200 ml water from cup C to beaker D, and then switch off the system. The prosthetic hand used was customized by Danyang Artificial Limb Co., Ltd. with 2 DoFs (wrist and finger joints) and Bluetooth module, as shown in Fig. 4(b).

Before each trial, the prosthetic hand was kept in front of the cup C with the hand opened to the maximum (95 mm), and the water initially stored in the cup C was nearly 250 ml, as in Fig. 4(b). To pour the water, subjects need to grasp the cup C first, then lift and whirl it to transfer demanded amount of water, and finally slightly lower it and open the palm. Fig. 4(d) shows the experimental scene.

Similarly, subjects had 5 mins first to get familiar with the, then this task was repeated for 5 trials. Each trial started with the 'Start' button being pressed, and would be viewed as a failure if not be completed within 3 mins or cup was dropped halfway. The deviation to perform water-pouring with this prosthetic hand but controlled by Joystick was also recorded as reference.

3 BRAIN CONNECTIVITY UNDER MICROFE-EEGS

Brain connectivity assesses the integration of cerebral areas by identifying variations in activation within and interactions between brain areas [28, 29]. As one major aspect, effective connectivity is defined as the direct or indirect influence that one neural system exerts over another [30]. To obtain a better insight into this microFE-BCI, Orthogonalized Partial Directed Coherence (OPDC) was used to measure the dynamic directional interactions among brain regions under microFEs.

3.1 Orthogonalized Partial Directed Coherence

OPDC, as an orthogonalized version of the classical Partial Directed Coherence (PDC) [31], focuses on reducing the spurious co-variability resulted from the similarity in several EEGs affected by volume conduction [32], which may be falsely perceived as connectivity [33]. OPDC developed out of the concept of Granger-causality [34], investigating the information flow within coupled dynamical networks based on multivariate autoregressive (MVAR) models [35], detecting not only direct but also indirect pathways linking interacting brain regions [36]. Based on the dual extended

Kalman filter-based time-varying PDC analysis [37], by orthogonalizing the imaginary part of the coherence [32], OPDC mitigates the common result of volume conduction effects. The estimating process of OPDC is as follows [38]:

1) MVAR model

For time series $y(n) \in \mathbb{R}^{ch}$ with L samples (where $n = 1, \dots, L$), the MVAR model is defined as [39]:

$$\begin{bmatrix} y_1(n) \\ \vdots \\ y_{ch}(n) \end{bmatrix} = \sum_{r=1}^m \begin{bmatrix} a_{1,1}^r & \cdots & a_{1,ch}^r \\ \vdots & \ddots & \vdots \\ a_{ch,1}^r & \cdots & a_{ch,ch}^r \end{bmatrix} \begin{bmatrix} y_1(n-r) \\ \vdots \\ y_{ch}(n-r) \end{bmatrix} + \begin{bmatrix} w_1(n) \\ \vdots \\ w_{ch}(n) \end{bmatrix} \quad (1)$$

where $[y_1(n) \cdots y_{ch}(n)]^T$ is the current value of each time series, ch denotes the number of channels, the real-valued parameter $a_{p,q}^r$ ($p=1, \dots, ch$; $q=1, \dots, ch$) in matrices A_r represents the predictor coefficient between the current value of channel p and the past information of channel q at the delay r , m is the model order indicating the number of previous data points used for modeling, and $[w_1(n) \cdots w_{ch}(n)]^T = w(n)$ is a normally distributed real-valued zero-mean white noise vector representing one-step prediction error.

The instantaneous effect among channels is explained by correlations among the off-diagonal element within the covariance of $w(n)$ [40]. The optimum order m was estimated using Akaike information criterion (AIC) [41].

2) Time-varying generalized OPDC (gOPDC)

To detect the coherence between channels in discrete frequency, A_r in the time-varying MVAR model is transformed into frequency domain:

$$A(n, f) = \mathbf{I} - \sum_{r=1}^m A_r(n) z^{-r} \Big|_{z=e^{j2\pi f}} \quad (2)$$

where $\mathbf{I}$ is the identity matrix and the frequency f varies from 0 to the Nyquist rate. To alleviate the effect of mutual sources within surface EEGs affected by spatial smearing in the tissue layer, the orthogonalization process is done at the level of MVAR coefficients [42]. The generalized version of OPDC by taking the effect of time series scaling into consideration is:

$$\tilde{\Psi}_{p,q}(n, f) = \frac{1}{\lambda_{p,p}^2 \sqrt{a_q^H(n, f) \Sigma_w^{-1} a_q(n, f)} \sqrt{a_p^H(n, f) \Sigma_w^{-1} a_p(n, f)}} \frac{|\text{Re}\{A_{p,q}(n, f)\}|}{|\text{Im}\{A_{p,q}(n, f)\}|} \quad \text{if } p \neq q \quad (3)$$

where λ are the diagonal elements of covariance matrix $\Sigma_w = \langle ww^H \rangle$ (where $\langle \cdot \rangle$ is the expected value operator), the superscript H denotes the Hermitian operator and $a_q(n, f)$ is the q th column of $A(n, f)$. For detailed mathematical derivation of gOPDC, please refer to [38].

3.2 Effective Connectivity of microFE-EEGs

To assess the particularity of brain connectivity under microFEs, effective connectivity with the resting-state-EEGs was firstly computed as a standard. Such resting-state threshold was calculated as the 99th percentile gOPDC to eliminate outliers and form a connectivity baseline. By comparing with the threshold, only higher gOPDCs were retained to emphasize the stronger connectives. To reduce the computation, EEGs were down-sampled to 512 Hz.

Focusing on the typical EEGs frequency range, gOPDCs were averaged into three representative bands as low

frequency [4 Hz, 12 Hz), medium frequency [12 Hz, 30 Hz) and high frequency [30 Hz, 50 Hz) [43]. Fig. 5 illustrates the normalized microFE-averaged connectivity of three EEG bands. Among three bands, high frequency shows the strongest connectivity. Among all channels, electrodes arranged on the motor cortex show relatively more information exchange than others (where ID.12-14 Cz & C3 & C4 show more information outflow and ID.19-20 CP5 & CP6 show more information inflow).

Focusing on the dynamic process of microFEs, gOPDCs during the first 0.5 s (from 7.00 s to 7.50 s in each trial), the middle 0.5 s (from 8.75 s to 9.25 s) and the last 0.5 s (from 10.50 s to 11.00 s) were detailedly assessed to reveal the connectivity changes from the very beginning to the end. Directed information flows with gOPDCs higher than other 90th percentile were marked in Fig. 6, along with the channels performing more information interactions.

Among all 30 channels, those on and surround the motor cortex show more involvements and interactions. Typically, in micro-Left-Smirk, more interactions flow out of

the right area into the left area of the brains; while in micro-Right-Smirk, more from the right to the left. The participation of the visual cortex may result from the UI prompt. Some slight asymmetry between the channels on the left and the right regions may be caused by the majority of right-handed.

Fig. 5. The normalized microFE-averaged gOPDC over Normal threshold of (a) low frequency, (b) medium frequency and (c) high frequency, where the value between the same channels were assigned as 'NaN', and the Channel ID.1 to ID.30 were listed as: Fp1, Fp2, Fz, F3, F4, F7, F8, FC1, FC2, FC5, FC6, Cz, C3, C4, T3, T4, CP1, CP2, CP5, CP6, Pz, P3, P4, T5, T6, PO3, PO4, Oz, O1 and O2. The block in i th row and j th column represents the gOPDC from Channel ID. j to Channel ID. i .

Fig. 6. The dynamic change of normalized subjects-averaged gOPDC during microFE, and the directed information flow with 90% percentile connectivity and channels with more interaction, where the list of Channel ID.1 to ID.30 is the same as it in Fig. 5.

4 MICROFE-BCI: ALGORITHM

To meet the goal of practicality, the fundamental demands for one control approach are stability, accuracy, real-time, and user-friendliness. As for an EEG-based control paradigm, the specific technique details can be listed as: (1) Using fewer EEGs for each decoding, to improve the real-time ability; (2) Providing asynchronous strategy, to ensure users start or stop paradigm as needed; (3) Adopting a paradigm which requires no additional stimulators and adaptation, and has no strict requirement for high concentration; (4) Ensuring high decoding accuracy with adequate instruction set; (5) Giving an allowance to users' unrelated movements, without affecting the manipulation performance; (6) Reducing the common problem of misoperation, thus enhancing the stability.

In the real-time aspect, [44] stated that any delay greater than 200 ms would degrade the performance of one EEG-based task accomplishment. Considering the process of data acquisition, signal processing, and instruction generation, the EEGs window length used for once decoding in microFE-BCI is chosen as 100 ms.

The processing strategy in microFE-BCI is demonstrated in Fig. 7. The algorithm can be divided into two stages as '*Asynchronous "ON" detection*' and '*microFE-BCI based real-time control*', including four subdivided parts: (1) 'Is this probably microFE-EEGs or obvious 'NON'', aiming at excluding obvious non-microFE-EEGs at the beginning; (2) 'Asynchronous interface detection', turning on or off the paradigm depends on users' will; (3) 'microFE-EEGs real-time decoding', classifying the microFE-EEGs and keep an extra 'NON' to give a respite for users, meanwhile a hold-on command for the system; (4)

‘Validity judgment’, judging the validity of the label first to reduce misoperation instead of directly converting it into instruction.

Such step-by-step design is to shorten the processing time for EEGs unrelated to current system status (e.g., exaggerated facial-expression-EEGs would be rejected from the very beginning; EEGs would not be complexly classified until the asynchronous interface has been turned ON), meanwhile offering an allowance for other slightly physical movements, and improving the stability. The detailed core algorithm is illustrated in Fig. 8.

Fig. 7. The processing strategy in microFE-BCI.

4.1 Step A: Obvious non-microFE-EEGs exclusion

The first step aims at using a simple computation to exclude EEGs that are apparently non-microFE-EEGs, while not let go of any probably microFE-EEGs. To save the computing time thus improving the efficiency, one junior method was chosen: Threshold Comparison.

Due to the EMG artifacts, when performing regular or exaggerated facial expressions, channels placed closer to facial muscles (Fp1, Fp2, F7, F8, T3, T4) tend to show wider amplitude range than microFEs, leading to larger temporal energy in higher EEG frequency [55 Hz, 95 Hz], as shown in Fig. 9. These six channels were used as reference channels for obvious ‘NON’ exclusion.

Instead of uniformly larger than one constant, the temporal energies are relatively larger within each reference channel itself and presents different distributions among microFEs and subjects. For lacking a uniform threshold, such Threshold Comparison was designed: When facing the latest unknown 100 ms EEGs, if there exist one or more channels whose temporal energy exceeds 105% of its maximum, the current EEGs would be judged as ‘NON’ and be excluded. Those mistakenly-accepted EEGs, similar but not microFE-EEGs, would be processed by the next step.

4.2 Step B: Interface ‘ON’ detection

This step enables users to start the microFE-BCI whenever they need, which means system would not reply to any EEGs and keep a standby mode until the interface has been

turned on. Such design guarantees users the option of not controlling the peripherals and handling other affairs in with the EEG cap worn and all devices powered on.

Fig. 9. The boxplot of subject S1's normalized temporal energy under microFE versus regular amplitude.

To switch between the non-control (NC) state and the in-control (IC) state, one of the eight microFEs was chosen as the state-switching microFE: micro-Raise-Brow. The decoding for asynchronous ‘ON’ is realized by a binary classifier. Only micro-Raise-Brow-EEGs were labeled as ‘ON’, while other EEGs including resting, relaxing, other microFEs, regular or exaggerated facial expressions, and EEGs mistakenly-accepted by *Step A* were all labeled as ‘else’. Instead of deep learning algorithms, one traditional machine learning algorithm was adopted to speed up the process: Support Vector Machine (SVM).

Considering of the low frequency solution resulted from the short time window, feature engineering was realized by a classic spatial filtering method: Common Spatial Pattern (CSP) [21]. The CSP features were calculated as:

$$f_k = \frac{\log(\text{var}(Y_{i,k}^j))}{\sum_{k=1}^{2m} \log(\text{var}(Y_{i,k}^j))}, k=1, \dots, 2m \quad (4)$$

where $Y_{i,k}^j, i \in \{1, 2\}$ is the new signal generated through the spatial filters from raw data, in which i indicates the i^{th} category and j indicates the j^{th} sample, k is the number of pairs of spatial filters and was set to be 2 in this paper.

Corresponding to pair number, a 4-dimensional feature vector was formed. The kernel function in SVM was set to be scaled gaussian (Equation (5)), according to the F1 score [45]. Seeing **RESULTS** for detailed comparison.

$$\begin{cases} G(x_j, x_k) = \exp(-\gamma \|x_j - x_k\|^2) \\ \gamma = \frac{1}{n_{\text{feature}} * \text{var}(\mathbf{X})} \end{cases} \quad (5)$$

where $G(x_j, x_k)$ denotes elements in the Gram matrix, γ is the hyperparameter for gaussian kernel, $\mathbf{X}$ is the features sets and n_{feature} is the dimension of feature channels.

Every 100 ms EEGs that passed through *Step A* was re-filtered into the typical EEG band as [5 Hz, 50 Hz] with all 30 channels and processed by this *Step B*.

Fig. 8. The detailed core algorithm of microFE-BCI.

4.3 Step C: microFE-EEGs real-time decoding

After switching ON the microFE-BCI, the algorithm enters the 2nd stage: *microFE-BCI based real-time control*. In the 2nd stage, similarly, only those latest 100 ms EEGs accepted by *Step A* can enter *Step C*. In this step, 9 targets were set in total, including: 7 microFEs corresponding to specified control instructions, the state-switching microFE corresponding to interface OFF, and a 'NON' category as the hold-on command for system. Instead of setting a separate asynchronous 'OFF' detection ahead, such design with the control instruction and interface OFF combined together, is to speed up the efficiency; Otherwise, any microFE-EEGs intend for control have to pass through two classifiers [25].

This multi-classification was realized by the deep-learning framework. To take fully advantage of the translation invariance and the spatial hierarchy of the Convolutional Neural Network (CNN) [46], meanwhile retaining the time sequential characteristics of EEGs, the variant of Recurrent Neural Network (RNN) [47] and the CNN were combined to form this classifier. The classifier structure (namely microFE-Net) was summarized in Table 1. In microFE-Net, one-dimensional Convolutional (Conv) layer along

channels was adopted to extract the information at the same timestamp. Then, to lower the computational cost, the Gated Recurrent Unit (GRU) [48] layer was adopted instead of the Long Short-Term Memory (LSTM) [49]. To reduce the overfitting problem, the dropout and the recurrent dropout [50] were added within the GRU layer.

TABLE 1
SUMMARY OF MICROFE-NET

Layer (type)	Method	Parameter	Value
Conv1D_1	Temporal Dimension	Kernel Size	3
		Strides	1
		Filters	64
Pool-ing1D_1	Max Pooling	Pool Size	3
		Strides	3
		Padding	valid
Conv1D_2	Temporal Dimension	Kernel Size	3
		Strides	1
		Filters	128
GRU_1	---	Activation	tanh
		Recurrent Activation	sigmoid
		Dropout	0.1
		Recurrent Dropout	0.1
		Return Sequences	false
		Units	128
Dense	---	Units	64
		Activation	ReLU

Dense	---	Units	32
		Activation	ReLU
Dense	One Hot	Units	9
		Activation	Softmax
Loss Function	Categorical Cross Entropy	---	---
Optimizer	RMSprop	Learning Rate	0.001
Training Acceleration	Batch	Batch Size	128

The input of microFE-Net was 30-channel EEGs with 100 sample points, which are judged by *Step A* ahead as probably YES and re-filtered into [5 Hz, 50 Hz]. The outputs of microFE-Net were 9 labels with one-hot code, which corresponding to 8 microFEs and a 'NON'.

4.4 Step D: Validity judgment

For realistic manipulation tasks, any misoperation shall result in a huge impact on the execution. To improve the robustness, instead of directly translating each decoded label into instruction, a *Validity judgment* was added between. Labels generated from *Step B* and *Step C* shall pass through *Step D*. Such judgment was simply realized by the consistency checking: Among n decoded labels, if $x\%$ of them are consistent with the current n^{th} , then the n^{th} will be regarded as valid and translated into an instruction.

Fig. 10. The timing diagram for one valid instruction generation, supposed that all collected data were microFE-EEGs intending for the same label.

During processing, the timespan for each label's decoding is less than 100 ms (referring to **Results**), thus adjacent EEGs entering the algorithm should have an overlap. Giving that there exist $x\%$ decoded labels consistent with the current n^{th} , the timing diagram for instruction generation is exemplified in Fig. 10. The theoretical timespan counting from the EEGs collection to the instruction generation is:

$$T_s = 100 + n \times t_s \quad (6)$$

where T_s is the timespan of one instruction, t_s is the timespan of one decoded label, and n is set to be 20 in this paper comprehensively considering both the robustness and the rapidity.

5 RESULTS

To determine the algorithm parameters and develop the microFE-BCI software, data collected in offline experiments from six subjects were used in the offline assessment first. Then, ten subjects participated in the online manipulation based on the microFE-BCI software to evaluate the practical ability of such EEG-based control paradigm. During the offline assessment, the accuracy, precision and time cost are given more consideration; While in the online evaluation, the controllability and the completion quality of

tasks are more emphasized.

5.1 Offline Datasets

Data in offline experiment were sliced into pieces and stacked. The imbalance for training datasets (in *Step B* and *Step C*) was solved by overlap, as illustrated in Fig. 11.

Fig. 11. The illustration for datasets in offline assessment.

Within *Step B*'s training, the NC dataset consists of EEGs from resting-state, relaxing-state, 8 facial-expressions with regular amplitude, and 7 non-state-switching microFEs; While the IC dataset only generated from state-switching microFE-EEGs. In *Step C*'s training, the dataset for 'NON' was sliced from the resting-state EEG.

5.2 Offline Assessment

• Step A: Obvious non-microFE-EEGs exclusion

Compared to the former FE-BCI [21], by limiting the range of facial muscle movement to the micro level, this microFE-BCI greatly reduces the proportion of EMG artifacts and makes it possible to distinguish between daily facial-expressions and microexpressions in EEG-based control. The contrast of EMG artifacts proportion is particularly obvious in the high frequency of EEG. Fig. 12 shows the comparison between regular facial-expression-EEGs versus microFE-EEGs.

Fig. 12. Comparison between EEGs when performing regular-Raise-Brow versus. micro-Raise-Brow in [55 Hz, 95 Hz] of channel FP1 & FP2.

In Fig. 12, the amplitude range of microFE-EEGs is much smaller than that under regular facial-expressions. To exclude non-microFE-EEGs, several different methods for threshold setting are compared in Table 2.

TABLE 2
COMPARISON AMONG DIFFERENT THRESHOLD SETTING METHODS

Method	Formula	Correctly Acceptance Rate (AR)	Correctly Rejection Rate (RR)	Timespan (Ts)	Score
Maximum	$\max\{ x_i \},$ ($i = 1, \dots, 100$)	99.48%	64.67%	0.0055ms	39.11
Temporal Energy	$\sum_{i=1}^{i=100} x_i^2$	99.45%	68.66%	0.0055ms	40.53
Amplitude Range	$\max\{x_i\} - \min\{x_i\}$ ($i = 1, \dots, 100$)	99.48%	64.80%	0.0055ms	39.15

* The score is calculated as $1/(1/AR + 1/RR + Ts)$

Throughout the three methods, the temporal energy achieves the highest score. By setting the threshold as temporal energy, the correctly acceptance rates (ARs) of

different microFEs are listed in Table 3.

ARs in Table 3 are nearly 99% and shows no typical imbalances. The extremely short timespan, high AR, and high RR prove the feasibility of threshold comparison as the first segment of the algorithm.

TABLE 3
CORRECTLY ACCEPTANCE RATE OF 8 MICROFEs WITH THRESHOLD AS TEMPORAL ENERGY

S	m-RB	m-FB	m-LS	m-RS	m-OM	m-S	m-PM	m-DM
S1	97.19%	100%	99.94%	99.25%	100%	99.31%	99.56%	99.94%
S2	98.38%	98.88%	99.75%	100%	99.94%	99.06%	99.94%	99.25%
S3	98.63%	100%	98.81%	98.81 %	100%	100%	100%	100%
S4	98.06%	99.94%	98.88%	99.75%	100%	99.06%	99.94%	100%
S5	97.94%	99.88%	100%	99.94%	100%	99.94%	99.75%	98.00%
S6	97.75%	100%	99.00%	99.13%	99.88%	100%	99.94%	100%

* m-RB stands for micro-Raise-Brow, m-FB for micro-Furrow-Brow, m-LS for micro-Left-Smirk, m-RS for micro-Right-Smirk, m-OM for micro-Open-Mouth, m-SI for micro-Smile, m-PM for micro-Pout-Mouth, m-DM for micro-Duck-Mouth.

• Step B: Interface ‘ON’ detection

To select one microFE as the most suitable microFE for state-switching, 8 microFEs were first compared using SVMs with 4 different kernel functions, as listed in Table 4.

TABLE 4
THE ACCURACY FOR 8 DIFFERENT STATE-SWITCHING-MICROFEs

MicroFE	SVM kernel			
	Linear Polynomial	Quadratic Polynomial	Scaled Gaussian	Medium Gaussian
micro-Raise-Brow	96.19%	74.59%	96.46%	96.30%
micro-Furrow-Brow	80.90%	50.36%	84.07%	83.28%
micro-Left-Smirk	76.70%	51.54%	81.08%	80.60%
micro-Right-Smirk	80.23%	52.85%	83.33%	82.75%
micro-Open-Mouth	72.84%	53.28%	81.66%	81.41%
micro-Smile	71.49%	50.23%	78.37%	77.27%
micro-Pout-Mouth	68.95%	49.55%	75.32%	74.68%
micro-Duck-Mouth	66.95%	49.14%	77.36%	76.76%

In Tabel 4, micro-Raise-Brow achieves the highest overall accuracy when be set as the state-switching microFE. The detailed performances for SVM kernels are listed in Table 5, with the micro-Raise-Brow as the state-switching microFE. Additionally, the time cost of CSP feature engineering is 0.1328 ms in average.

TABLE 5
THE DETAILED PERFORMANCE OF DIFFERENT SVM KERNELS WITH MICRO-RAISE-BROW AS STATE-SWITCHING MICROFE

SVM kernel	Accuracy	Precision	Recall	F1 Score	Prediction Speed	Training Duration
Linear						
Polynomial	96.19%	94.58%	98.02%	48.14	490000obs/sec	>15min
Quadratic						
Polynomial	74.59%	75.62%	73.23%	37.20	960000obs/sec	>15min
Scaled Gaussian	96.46%	95.29%	97.78%	48.26	1300000obs/sec	<3min
Medium Gaussian	96.30%	94.82%	97.98%	48.19	1700000obs/sec	<2min

* Evaluation with Win10, i5-6500, 3.20GHz, without GPU accelerated.

Among 4 SVM kernels, the linear polynomial, the scaled gaussian, and the medium gaussian achieve higher F1 scores [45]. Comprehensively considering the F1 score,

prediction speed, and training duration, the scaled gaussian performs best. The adaptability of scaled gaussian kernel to each subject is listed in Table 6.

TABLE 6
THE ACCURACY, PRECISION AND RECALL WITH SCALED GAUSSIAN

S	Accuracy	Precision	Recall
S1	97.79%	96.14%	99.57%
S2	96.47%	95.22%	97.85%
S3	96.62%	97.09%	96.13%
S4	94.60%	92.50%	97.06%
S5	97.11%	95.65%	98.70%
S6	96.18%	95.13%	97.34%
Mean	96.46%	95.29%	97.78%
Std	±1.07	±1.54	±1.22

The accuracy, precision, and recall in Table 6 show a relatively small standard deviation (Std) among subjects. Based on all the assessments above, the CSP combining with scaled-gaussian-SVM proves its best applicability, which maintains a stable performance without obvious individual differences.

• Step C: microFE-EEGs real-time decoding

As a multi-classification with 9 targets based on deep-learning, several mature structures are assessed to verify their applicability first, such as VGG16 [51], DenseNet121 [52] and ResNet50 [53]. To match with this specified problem, all network applications were imported without pre-trained weights and slightly modified, as shown in Table 7. Compared with the microFE-Net, their accuracies under 10-fold validation are listed in Table 8.

TABLE 7
STRUCTURE FOR NETWORK APPLICATIONS

Layer (type)	Method	Parameter	Value
Network Applications	---	Pretrained weights	None
		Top layer	Not include
Dense	---	Units	256
		Activation	ReLU
Dropout	---	----	0.5
Dense	One Hot	Units	9
		Activation	Softmax
Loss Function	Categorical Cross Entropy	---	---
Optimizer	RMSprop	Learning Rate	0.001
Training Acceleration	Batch	Batch Size	128

TABLE 8
PERFORMANCE COMPARISON AMONG DEEP-LEARNING STRUCTURES

Deep Learning Network	Training Accuracy	Validation Accuracy
VGG16	11.03%	11.34%
DenseNet121	98.91%	88.94%
ResNet50	98.52%	87.27%
microFE-Net	92.68%	89.48%

Through comparison, DenseNet121 and ResNet50 both achieve higher training accuracy, but also face serious over-fitting problems (even would suddenly drop to a 40% validation accuracy in the late-training-process). Compared with 3 mature network applications, the microFE-Net, although not the highest training accuracy, it shows a more balanced performance between training and validation.

In addition to the network structure, extra feature engineering steps were combined to assess its effectiveness (Table 9). For the microFE-Net model isn’t designed to accept

4-dimensional input tensors, the classifier combined with the Filter Bank Common Spatial Pattern (FB-CSP) [54] feature engineering was selected to be the DenseNet121.

TABLE 9

PERFORMANCE COMPARISON FOR EXTRA FEATURE ENGINEERING

Method	Feature Engineering	Classifier	Training Accuracy	Validation Accuracy
A	CSP (One vs Rest)	SVM (Fine Gaussian)	74.24%	71.45%
B	FB-CSP (3 Frequency Bands)	DenseNet121	89.87%	36.63%
C	--	microFE-Net	92.68%	89.48%

In Table 9, the microFE-Net without any hand-made feature engineering achieves the best performance. The iteration of microFE-Net is shown in Fig. 13. The detailed accuracy of microFE-Net under 10-fold validation and its prediction speed were listed in Table 10.

As demonstrated in Table 10, the microFE-Net achieves a stable performance varying among subjects with a $\pm 1.21\%$ Std; Meanwhile maintains a precise accuracy and relatively small overfitting (with the validation accuracy as 89.48% and the training accuracy as 92.68%). The averaged time cost for one prediction is nearly 0.235 ms. The confusion matrix among 8 microFEs, in other words, 7 control

targets and 1 state-switching target is listed in Table 11.

Fig. 13. The learning process of microFE-Net.

TABLE 10

OFFLINE ACCURACY OF MICROFE-NET WITH 10-FOLD VALIDATION

S	Training Accuracy	Validation Accuracy	Prediction Speed
S1	92.58%	89.59%	256000obs/sec
S2	92.45%	89.06%	256000obs/sec
S3	91.21%	88.00%	257000obs/sec
S4	92.25%	89.34%	254000obs/sec
S5	94.89%	91.69%	254000obs/sec
S6	92.69%	89.17%	256000obs/sec
Mean	92.68%	89.48%	--
Std	± 1.21	± 1.21	--

* Evaluation with Win10, i5-6500, 3.20GHz, accelerated with GTX 960.

TABLE 11

CONFUSION MATRIX AMONG 8 MICROFES

True Label	Predicted Label								
	m-RB	m-FB	m-LS	m-RS	m-OM	m-DS	m-PM	m-DM	NON
m-RB	99.15%	0.07%	0.00%	0.05%	0.05%	0.01%	0.01%	0.03%	0.63%
m-FB	0.08%	94.91%	0.63%	0.48%	0.44%	0.27%	0.21%	0.05%	2.93%
m-LS	0.03%	1.02%	92.17%	0.51%	0.39%	1.12%	0.33%	0.21%	4.23%
m-RS	0.05%	0.22%	0.78%	94.05%	0.20%	1.38%	0.20%	0.27%	2.85%
m-OM	0.10%	0.39%	0.25%	0.18%	93.23%	0.22%	0.82%	0.66%	4.14%
m-DS	0.07%	0.13%	0.99%	0.83%	0.27%	93.20%	0.96%	0.92%	2.63%
m-PM	0.09%	0.23%	0.43%	0.16%	1.07%	1.24%	91.61%	0.90%	4.27%
m-DM	0.05%	0.13%	0.48%	0.36%	1.07%	1.15%	1.05%	90.20%	5.51%

Among the 8 microFEs, the micro-Raise-Brow (corresponding to state-switching) achieves the highest prediction accuracy as 99.15%; While the lowest is micro-Duck-Mouth as 90.20%. The averaged prediction accuracy among such 8 microFEs is 93.56%. In each true label, the confusion with 'NON' is especially higher than the others, which decreases the averaged classification accuracy. The high misrecognition rate between the true label and 'NON' may cause by the small change between the microFEs and the resting-state, which results in similar signal ingredients. Considering the advantage to retain the 'NON' label as a hold-on command, which provides the system a rest even after entering the IC state, such 'NON' label cannot be deleted and is designed to be remained. The stability of the final instruction is enhanced by *Step D* to improve accuracy.

• Step D: Validity judgment

As been detailly assessed above, the timespan (with ample margin) of each step is summarized in Table 12.

The theoretical timespans for different instructions are all less than 200 ms, which meet the specified requirement for real-time control. Considering the various classification accuracy for different targets, the timespan for generating one specific instruction under realistic operation can only

be assessed during online.

TABLE 12

TIMESPAN (WITH AMPLE MARGIN) OF EACH STEP

Step	Timespan
Step A: Obvious non-microFE-EEGs exclusion	≈ 0.01 ms
Step B: Interface 'ON' detection	≈ 0.15 ms
Step C: microFE-EEGs real-time decoding	≈ 0.24 ms

According to the theoretical time cost for generating one instruction in (6), the timespan for different instruction is listed in Tab. 13.

TABLE 13

THEORETICAL TIMESPAN FOR INSTRUCTION GENERATION

Instruction	Theoretical Timespan
Asynchronous interface 'ON'	≈ 103.2 ms
Asynchronous interface 'OFF'	≈ 105.0 ms
microFE-BCI based control instruction	≈ 105.5 ms

5.3 Online Evaluation

Based on the offline assessment, a microFE-BCI software has been developed to facilitate the easy application for the online external device control. This software includes three modules: 'user login', 'data collection and offline learning', and 'online application'. By using this software, the online microFE-BCI controlling task with AUBO-i5 robotic arm

system and the 2-DoFs prosthetic hand were conducted.

In the ‘online application’ module, a ‘debug’ mode is provided to adjust the consistency checking criteria by subject-selves, without peripherals connected. Until the accuracy of valid instruction reached approximately a stable 100%, then the online manipulation experiment would start with the machine connected.

Within the stepping control strategy adopted by these two peripherals, the stepping distances are not elaborately designed for tasks. Due to the visual perspective, stepping distance and some unavoidable random errors, these tasks can hardly be completed with perfect zero deviation, even by using the referred control method (i.e., FlexPendant and Joystick). In the following online evaluation, the practicality and the controllability of the microFE-BCI are of more concerned (e.g., the floating range of the indicator) than the precision. Compared between these two tasks, *Task one* requires higher stability, while *Task two* emphasized more on agility and real-time ability.

• Task one: Object-moving with a Robotic Arm

To manipulate the AUBO-i5 robotic arm system, all 8 microFEs were enabled. The instruction list is listed in Table 14, where the direction for axis X, Y, and Z is previously marked in Fig. 4(a).

Considering the different important levels of instructions (e.g., a trial would be judged as a failure once the electric gripper is mistakenly opened halfway), the microFE with the highest recognition accuracy (except for the

micro-Raise-Brow) is assigned to the most vital instruction, differing from each subject. As an example, the correspondence between the microFEs and the system instruction of subject S7 is listed in Table 15, where micro-Raise-Brow is responsible for the state-switching as mentioned before. Table 15 also lists the consistency checking criteria $x\%$ for subject S7, which is personally tuned under ‘debug’ mode. Fig. 14 demonstrates the time log of a successful online manipulation for *Task one*.

TABLE 14

THE INSTRUCTION LIST OF AUBO-i5 ROBOTIC ARM SYSTEM			
Instruction	System Action	Axis	Stepping
‘Right’	Horizontally move right	+X	30 mm
‘Left’	Horizontally move left	-X	2 mm
‘Forward’	Horizontally move forward	+Y	20 mm
‘Backward’	Horizontally move backward	-Y	3 mm
‘Up’	Vertically rise up	+Z	30 mm
‘Down’	Vertically lower down	-Z	$\begin{cases} 10 \text{ mm (Z > 21 mm)} \\ 3 \text{ mm (Z ≤ 21 mm)} \end{cases}$
‘Open’	Electric gripper open	--	--

TABLE 15

THE OPERATIONAL CORRESPONDENCE, ALONG WITH THE CONSISTENCY CHECKING CRITERIA $x\%$ FOR SUBJECT S7 IN *TASK ONE*

Item	m-RB	m-FB	m-LS	m-RS	m-OM	m-S	m-PM	m-DM
Instruction	--	Open	Left	Right	Up	Down	Backward	Forward
Criteria	0.95	0.95	0.35	0.45	0.45	0.95	0.55	0.80

Fig. 14. The time log of a successful online manipulation in *Task one* performed by subject S7. From bottom to top, the first axis is the timeline, and the second axis is a counter which represents the processing for n th 100 ms EEGs. The five boxes in the lower area illustrate the algorithm results along the timeline step-by-step, and the four boxes in the upper area illustrate the AUBO-i5 robotic arm system movement.

According to Fig. 14, firstly the timestamp 0.000 s begins at the ‘Start’ button being pressed by S7-self; secondly, at 2.186 s S7 switched on the microFE-BCI successfully;

thirdly, after carefully movements, S7 opened the electrical gripper to put down the wooden block at 153.530 s; finally, S7 switched off the microFE-BCI and finished the task at

155.479 s. During the operation, unrelated EEGs were successfully rejected by microFE-BCI system. The final deviation for the wooden block in Fig. 14's trial is -4.5 mm on X-axis and +3.1 mm on Y-axis (Fig. 15). The placement deviation with the microFE-BCI is shown in Fig. 16, along with the deviation by FlexPendant.

Fig. 15. The illustration for placement deviation in **Task one**.

For a reliable control method, under one's visual guidance, the deviation shall appear certain random volatility within a small range. Instead of perfect zero deviation, the variation range of deviation under microFE-BCI is of more concerned. Among all online subjects (S7-S16), the averaged variation range (AVR) of microFE-BCI's deviation is 11.14 ± 6.13 mm along X-axis and 9.78 ± 3.83 mm along Y-axis, and 10.46 ± 5.15 mm in total (while the AVR of FlexPendant is 7.75 ± 7.67 mm in total, and shows no significant difference with $P = 0.2089 > 0.05$). As in Fig. 16, for most subjects, compared with FlexPendant, deviation by microFE-BCI achieves a comparable range of variation, a similar averaged value, and a close Std, which indicates an

approximative level of controllability as FlexPendant. But for few subjects, on one certain axis (i.e., the X-axis of S11) where the median of microFE-BCI's boxplot is marked far from the average, it indicates that there exists uncontrollability during the position adjustment along that axis by using microFE-BCI. Overall, the maximum deviation with microFE-BCI can largely be limited below 20 mm (S8), from which the minimum deviation can sometimes be ± 0.1 mm (S10, S11), and none of the subject's deviations shows significant difference compared between microFE-BCI and FlexPendant. The intersection over union (IoU) between the target location B and the block placement in **Task one** is demonstrated in Fig. 17.

Among all 50 trials, 96% of trials succeed, only 2 trials by S8 failed halfway. The averaged IoU of microFE-BCI is $60.03 \pm 11.53\%$, while $62.05 \pm 6.01\%$ of FlexPendant, and shows no significant difference with $P = 0.6521 > 0.05$. As in Fig. 17, the minimum IoU with microFE-BCI among all is 21.47% (S8) while the maximum is 82.62% (S13 & S15). Compared with FlexPendant, statistical test indicates that the IoU of microFE-BCI shows similar performance overall. But for several subjects (e.g., S8, S9, S11 & S14), the IoU of FlexPendant performed slightly better and scored higher than microFE-BCI, which indicates that during an actual application process the operation under microFE-BCI is more complicated.

Fig. 16. The boxplot of placement deviation in **Task one** with microFE-BCI and FlexPendant, where the short red line indicates the median, and the number indicates the mean.

Fig. 17. The IoU of placement deviation in **Task one** with microFE-BCI and FlexPendant, where the short red line indicates the average.

Fig. 18. The time cost in **Task one** with microFE-BCI, where the timestamp A corresponds to 'System Turn ON', the timestamp B corresponds to 'Gripper Open' and the timestamp C corresponds to 'System Turn OFF' (as demonstrated in Fig. 14).

In terms of time cost (Fig. 18), affecting by different levels of tension and proficiency, the completion time for

Task one varies from less than 60 s to approximately 150 s. The average completion time for **Task one** is 105.07 ± 13.50 s; in which the average time spent for ‘System Turn ON’ is 1.55 ± 0.67 s, for block moving and placing is 100.19 ± 13.17 s and for ‘System Turn OFF’ is 3.27 ± 1.64 s.

• **Task two: Water-pouring with a Prosthetic Hand**

With a 2-DoFs prosthetic hand, only 4 microFEs achieved higher decoding accuracy were enabled. Apart from these 4 microFEs, other valid instructions generated from the rest microFEs would not be transmitted. Slightly differing from **Task one**, **Task two** requires a higher real-time response, because a tiny change in wrist angle will pour several milliliters or even dozens of milliliters of water. Table 16 lists the instruction of the 2-DoFs prosthetic hand. Table 17 shows the correspondence between the microFEs and the instruction (left-handed prosthesis), and the consistency checking criteria. Fig. 19 demonstrates the time log of a successful online process in **Task two**.

TABLE 16

THE INSTRUCTION LIST OF THE 2-DOFS PROSTHETIC HAND

Instruction	System Action	Stepping
‘Open’	Palm open	7.0 mm
‘Close’	Palm close	10.5 mm
‘Extorsion’	Wrist external rotation	11.0°
‘Intorsion’	Wrist internal rotation	12.0°

In Fig. 19, subject switched on the microFE-BCI at 1.329 s, then completed the water-pouring task at 102.367 s, and

Fig. 19. The time log of a successful online manipulation in **Task two**. From bottom to top, the first axis is the timeline, and the second axis is a counter which represents the processing for n th 100 ms EEGs. The five boxes in the lower area illustrate the algorithm results along timeline step-by-step, and the two boxes in the upper area illustrate the 2-DoFs prosthetic hand movement.

Fig. 20. The boxplot of water volume in online experiment **Task two** with microFE-BCI and JoyStick, where the short red line indicates the median, and the number indicates the mean.

finally switched off the interface at 106.261 s; The final deviation of water volume in Fig. 19’s trial is less than 1 ml.

Same as **Task one**, the deviation affected by the visual perspective and the step distance can hardly be zero even by Joystick. The water volume in **Task two** is demonstrated in Fig. 20. Among all 50 trials of **Task two**, 100% trials successfully finished. The averaged water volume by microFE-BCI is 202.5 ± 2.5 ml, while 202.2 ± 2.7 ml similarly by Joystick, between which shows no significant difference with $P = 0.7931 > 0.05$. Compared with Joystick, with such simplified 4 instructions, microFE-BCI achieved almost the same performance as Joystick in water pouring task. The average completion time of **Task two** is shown in Fig. 21.

The time spent for **Task two** varies from approximately 60 s to 150 s. The average completion time for online **Task two** is 68.41 ± 19.52 s; Where the averaged time spent for ‘System Turn ON’ is 1.43 ± 0.45 s, for water pouring is 64.09 ± 19.06 s and for ‘System Turn OFF’ is 2.88 ± 0.74 s.

TABLE 17

THE OPERATIONAL CORRESPONDENCE AND THE CONSISTENCY CHECKING CRITERIA $\alpha\%$ FOR SUBJECT S7 IN **Task two**

Item	m-RB	m-FB	m-LS	m-RS	m-OM	m-S	m-PM	m-DM
Instruction	--	Open	Extorsion	Intorsion	--	Close	--	--
Criteria	0.95	0.95	0.35	0.40	1	0.95	1	1

Fig. 21. The time spent in online experiment **Task two** with the microFE-BCI, where the timestamp A corresponds to ‘System Turn ON’, the timestamp B corresponds to ‘Palm Open’ and the timestamp C corresponds to ‘System Turn OFF’ (as demonstrated in Fig. 19).

6 DISCUSSION

To explore the practicality of developed microFE-BCI, more attention was paid to its online application procedure. The overall situation in the online experiment is as follows:

1) During online, subjects need to wear the EEG cap continuously for at least 4 hours, which includes the time for coating conductive gel, training data collection, individual parameters and classifiers computation, consistency checking criteria debugging without peripherals connected, and external device manipulation. Within the rather long wearing time, subjects would drink, eat, and talk for several times with the EEG cap wore.

2) Considering that in the actual operation environment, electromechanical noise is inevitably involved (e.g., the power supply of AUBO-i5), thus during the whole online experiment, the environmental noise is not deliberately controlled. In online process, mobile phones, air conditioners, and machines are all powered on normally, and other laboratory-mates are allowed to enter and exit at will, observe and communicate softly.

3) To give subjects a more realistic experience, after showing an instruction video and giving a brief explanation, the training data collection was conducted by subjects alone, without the experimenter, by operating the software independently.

In online study, there were the following three factors that had been noticed which would affect the performance, and for which our research group planned to conduct a more in-depth study.

6.1 Long-term Wearing of EEG Cap

For being tightened by the EEG cap fabric, subjects experienced varying degrees of itching, leading to subconscious scratching, which became more frequent over time. Meanwhile, in the manipulation, under a relatively concentrated state, several subjects sweated beneath the EEG cap. In whole online experiment, subjects might eat (or even have dinner) with the EEG cap worn, and some subjects would move the strap fixed to their chin to facilitate chewing.

Reasons above caused the shift of EEG electrodes which enlarges with the increase of wearing time. Such shift resulted in the difference between the EEG detected in online and collected during acquisition. In terms of impedance, as the wear duration lengthens, the impedance reduced to lower than 1 kΩ, meanwhile, the conductive gel got solidified and dried up. Noticing these, with the proceeding of the online, we have gradually reduced the amount of training data gathering to compress the duration.

6.2 Mental State

Being more difficult than commercial control forms (i.e., FlexPendant & Joystick), subjects were relatively more concentrated in the process of microFE-based control tasks, resulting in varying nervousness depended on personal psychology. In operation, subjects with higher levels of tension were found to show greater degradation from the ‘debug’ mode (microFE-BCI without peripherals connected) to the actual microFE-BCI based electromechanics control; On the contrary, the performance of tranquil subjects remained consistent. In addition, by lessening the control instructions, **Task two** shows the decrease of difficulty, the relief of nervousness, and the improvement of proficiency. Thus, even **Task two** requires more operation agility, the overall performance is more excellent than **Task one**.

In the whole online study, we have observed that the mental state of subjects has a great impact on the completion quality of control tasks, inspired by which we’ve also carried out a study on the compensation method of manipulation quality affected by mental state.

6.3 Physical Movements

In online procedure, subjects were asked to sit comfortably, but avoid extra-large physical movements. For most subjects, body movements were found that would reduce the stability of microFE-BCI during applications. But for few subjects, such as subjects S11 & S14 who actively asked to stand up, pace, and softly communicate in **Task one**, physical movements didn’t show much influence on the stability of microFE-BCI. The performance of these trials by subjects S11 & S14 were kept in the result of this paper. Encouraged by these two subjects, we believe that the proposed microFE-BCI is promising of realistic applicability, thereby research work emphasized on the stability under physical movements of microFE-BCI will be conducted later.

7 CONCLUSIONS

In this paper, a novel practical asynchronous real-time EEG-based control paradigm assisted by micro-facial-expressions (microFE-BCI) with 8 valid control instructions was proposed and implemented. It is considered as an upgrade of the FE-BCI, and was applied to various online electromechanical manipulation tasks for evaluating its paracticality, especially stability and agility.

Firstly, with brain connectivity analysis, the high participation of the motor cortex under microFE-BCI was revealed. The directional information interaction conformed

to the contralateral control fact, and demonstrated the domination of motor cortex. This analysis provided a deeper understanding of the microFE-BCI.

Secondly, an asynchronous real-time processing algorithm was proposed, along with the microFE-Net for decoding. This core algorithm enabled users to switch on/off interface asynchronously, expanded the instruction sets (to 8 instructions), and reduced the misoperation in traditional literal translation BCI. Each decoded label was generated by the latest 100 ms EEGs to ensure the real-time capability.

In offline, the microFE-BCI achieved accuracies of $96.46\% \pm 1.07$ for interface switching and $92.68\% \pm 1.21$ for microFE-BCI-based real-time control. The theoretical timespan microFE-BCI-based instruction was 105.5 ms in maximum, timing from the generation of microFE-EEGs.

In online, for *Task one* emphasizing more stability, the microFE-BCI performed overall 96% success rate with $60.03 \pm 11.53\%$ averaged IoU, which showed the same level of controllability as FlexPendant ($P = 0.6521 > 0.05$). For *Task two* emphasizing more agility, the microFE-BCI performed 100% success rate with 202.5 ± 7.0 ml averaged water volume, which achieved almost the same score as Joy-stick ($P = 0.7931 > 0.05$).

The research suggested the capability and flexibility of the microFE-BCI for manipulation applications, with a similar level of controllability and agility as the commercial control methods. During the study, more subtle factors that may affect the online performance have been noticed by us, on which we will carry out more in-depth research. We sincerely look forward to the realization of 'brain control' in real-world applications in the future.

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