Fuzzy Integral With Particle Swarm Optimization for a Motor-Imagery-Based Brain–Computer Interface

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***Abstract*—A brain–computer interface (BCI) system using electroencephalography signals provides a convenient means of communication between the human brain and a computer. Motor imagery (MI), in which motor actions are mentally rehearsed without engaging in actual physical execution, has been widely used as a major BCI approach. One robust algorithm that can successfully cope with the individual differences in MI-related rhythmic patterns is to create diverse ensemble classifiers using the subband common spatial pattern (SBCSP) method. To aggregate outputs of ensemble members, this study uses fuzzy integral with particle swarm optimization (PSO), which can regulate subject-specific parameters for the assignment of optimal confidence levels for classifiers. The proposed system combining SBCSP, fuzzy integral, and PSO exhibits robust performance for offline single-trial classification of MI and real-time control of a robotic arm using MI. The main contribution of this paper is that it represents the first attempt to utilize fuzzy fusion technique to attack the individual differences problem of MI applications in real-world noisy environment. The results of this study demonstrate the practical feasibility of implementing the proposed method for real-world applications.**

***Index Terms*—Brain–computer interface (BCI), electroencephalography (EEG), fuzzy integral, motor imagery (MI), particle swarm optimization (PSO).**

I. Introduction

BRAIN–COMPUTER interfaces (BCIs) [1] based on the user's voluntary modulations of electroencephalography (EEG) [2] signals provide an alternative method of communication between humans and machines. Despite the many pivotal techniques developed by the pattern recognition community that have been applied and evaluated within the context of EEG-based BCI, the overall performance of BCIs is still not robust because of inter- and intrasubject variability. This variability introduces a large number of uncertainties that severely degrade the performance of BCIs.

Among existing BCIs [3], efforts to develop EEG-based BCI systems relying on motor imagery (MI) [4] have attracted increasing attention in recent years. The brain dynamics of MI are predominantly observed in the primary sensorimotor area and resemble those observed during the actual execution of movement. A variety of feature extraction methods have been proposed to differentiate between the brain dynamics of left- and right-hand MI. In addition to event-related potentials [5], many methods [6], [7] focus on observing the difference in spectral power between the cerebral hemispheres during MI. Among the existing feature extraction methods [8]–[11], the common spatial pattern (CSP) method is one of the most effective approaches for constructing optimal spatial filters that are sensitive to differences between left and right imagery [12], [13]. However, the performance of these spatial filters depends on the operational frequency band. Searching for the optimal frequency range for each subject can be very time-consuming. To address this issue, the subband CSP (SBCSP) method [14] employs a filter bank to decompose EEG signals into different subbands as inputs to the CSP analysis. The SBCSP approach is used to extract useful features of brain activity during MI tasks; subsequently, multiple linear discriminant analysis (MLDA) [15] is applied to recognize the EEG signals in each subband spectrum. After the subband decisions are obtained from each LDA, a classifier ensemble is constructed for each subband, and a fusion algorithm is then employed to obtain a final decision. Because the decision is derived from different subband classifiers, a combination of classifiers promises to offer better uncertainty identification performance than a single classifier.

Recently, the fuzzy fusion approach [16], [17] has been shown to improve the BCI performance in terms of classification accuracy and system stationarity. One commonly used fuzzy fusion approach is fuzzy integral [18], [19], which allows the uncertain, imprecise, and incomplete information available from EEG signals to be represented and processed using the concept of fuzzy measures introduced by Sugeno [20]. This study attacks the misclassification problem that many current BCI systems experience because of variations among individuals. A judicious use of multiple sources effectively reduces individual uncertainty, and serves to enhance the reliability of the system's performance. Because the fuzzy integral [21]–[25] integrates

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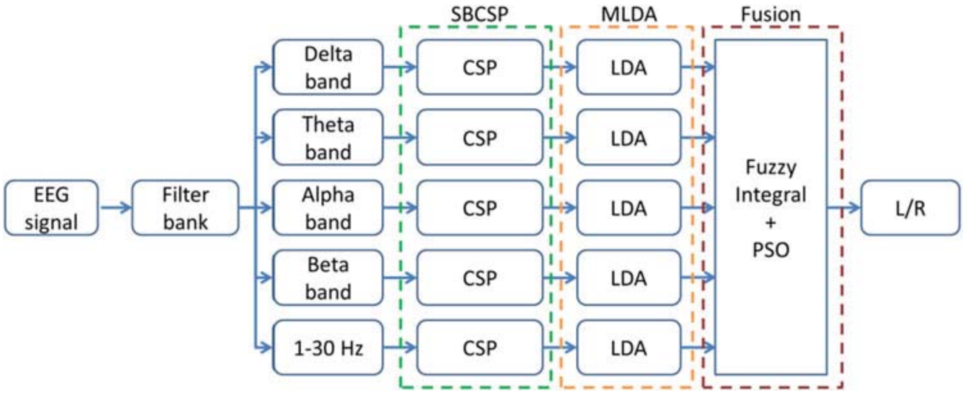

Fig. 1. System architecture of the proposed MI-based BCI fuzzy fusion.

decisions from different sources, using a combination of classifiers holds the promise of achieving better performance in uncertainty identification than the recognition technique based on the single feature. The fuzzy integral [26] is regarded as a numeric-based connective aggregation approach for obtaining collaborative decisions by integrating information from multiple classifiers.

In MI tasks, there are two main difficulties in real-world MI applications: individual difference and noisy environment. The individual differences include not only inter- but also intraindividual differences, which arise from the fact that individuals continually change over time due to factors such as fatigue, attention, and stress. Likewise, physiological signals are nonstationary and can change over time due to movement artifacts, sensor configuration, and intrinsic noise in the environment. Accordingly, features obtained from different subjects under different tempo-spatial environments might vary widely. That is, some effective features can be found in recordings from one subject but not from another. Hence, each possesses its own set of reliabilities and potential uncertainties. As a result, the performance of traditional MI systems using a single classifier to recognize all the feature usually degraded obviously under the situations of individual differences and noisy environments. To solve this problem, the proposed MI-based BCI system in this paper employs the fuzzy integral with particle swarm optimization (PSO) to classify EEG feature vectors. The fuzzy integral is a fusion technique that exploits multiple decisions from different sources to reap collaborative inferences to achieve the objectives under investigation, a result that is infeasible to achieve from each individual source separately.

In this paper, diverse LDA classifiers following the SBCSP approach are established as an ensemble of classifiers to collaboratively recognize the user's mental representation of movements from EEG patterns recorded during an MI task. Two fuzzy integral methods, i.e., the Sugeno integral [27], [28] and the Choquet integral [29], are applied to integrate the information from this ensemble of classifiers and then make a joint decision. To effectively assign confidence levels to particular classifiers, PSO [30] is employed to determine the confidence of the employed classifiers. The proposed method is demonstrated in the real-time MI control of a robotic arm.

The remainder of the paper is organized as follows. In Section II, the proposed BCI for deciphering the mental rehearsal of motor actions is introduced. In Section III, an MI experiment is presented. The classification results obtained using the proposed approach are compared with those obtained using conventional ones. Finally, a brief conclusion is presented and future studies are suggested in Section IV.

II. Materials and Method

The proposed MI-based BCI system is schematically illustrated in Fig. 1. During the MI task, the EEG signals are measured by a wireless acquisition device with dry electrodes. A filter bank is then used to extract frequency components (ranging from 1 to 30 Hz) from the EEG recordings. The CSP method leads to optimal variances for the discrimination of two populations of EEG related to left- and right-hand MI. Multiple LDA classifiers are established that employ CSP features to integral multiclassifiers. Finally, a fuzzy integral with PSO is then applied to fuse the decisions of classifiers and decipher the mental rehearsal of motor actions.

A. EEG Acquisition Device

The EEG acquisition device [31] was designed to measure scalp EEG signals using dry electrodes [32] [see Fig. 2(a)–(c)] from the sensorimotor area [see Fig. 2(d)]. The acquisition device consists of a preamplifier unit, a microcontroller unit, and a Bluetooth transmission unit. The wireless integrated-circuit-based acquisition module has dimensions of approximately $55.08 \times 38.8 \times 5$ mm^3. The gain of the preamplifier unit is set to 1361 V/V, and the cut-off frequency is regulated to 0.2 Hz by a high-pass filter. The microcontroller unit is used to regulate the signal sampling rate and for noise reduction. The microcontroller unit digitizes the analog EEG signal at a sampling rate of 512 Hz. A sinc filter is used to remove frequencies above 128 Hz. Moreover, the ac power line noise (60 Hz) in the amplified EEG signal is reduced by the microcontroller unit using a moving average. Then, the processed EEG signal is transmitted to the computer using Bluetooth (v2.1+ enhanced data rate). The power is supplied by a commercial 700 mAh Li-ion battery, which provides over 10 h of operation.

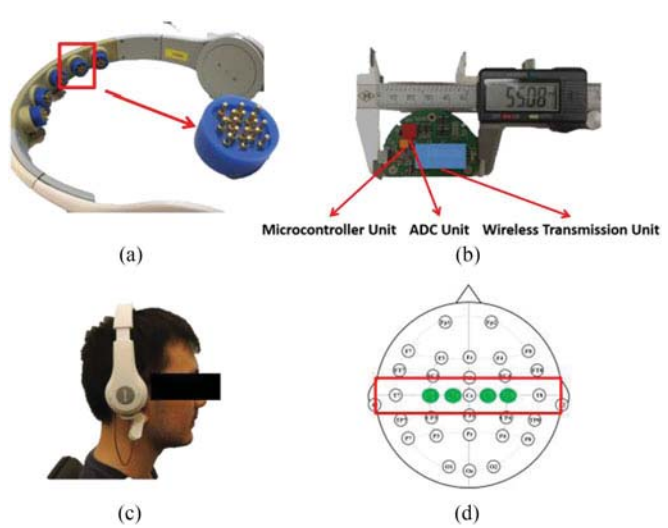

Fig. 2. Wireless and portable EEG device. (a) Dry electrodes. (b) Wireless EEG acquisition system, which consisting a preamplifier, a filter, a microcontroller, and a wireless module. Each circuit board has a width of 55.08 mm. (c) EEG headset. (d) Placement of the four recording electrodes.

B. CSP and Linear Discriminant Analysis

Applying the proper spatial filter can improve the discrimination of data from different classes, thereby facilitating classification. The CSP approach [33] is a popular method that yields the optimal variances for the discrimination of two EEG populations related to left- and right-hand MI. In this study, the CSP method is applied to each set of filtered data E to find a spatial filter matrix W that maximizes the variance of the spatially filtered data of one class Σ_1, and simultaneously minimizes the variance of the spatially filtered data of the other class, Σ_2. Mathematically, the CSP criterion is written as

$$\begin{aligned} &\text{maximize tr}\left(W^{\mathrm{T}}\Sigma_1 W\right)\\ &\text{subject to } W^{\mathrm{T}}\left(\Sigma_1+\Sigma_2\right)W = I \end{aligned} \tag{1}$$

where

$$\begin{aligned} \Sigma_1 &= \underset{E_n\in\{\text{class 1}\}}{\exp}\frac{E_nE_n^{\mathrm{T}}}{\text{tr}\left(E_nE_n^{\mathrm{T}}\right)} \quad \text{and}\\ \Sigma_2 &= \underset{E_n\in\{\text{class 2}\}}{\exp}\frac{E_nE_n^{\mathrm{T}}}{\text{tr}\left(E_nE_n^{\mathrm{T}}\right)}. \end{aligned} \tag{2}$$

This problem can be solved as a generalized eigenvalue problem. With the spatial filter transformation W thus obtained, the spatially filtered data $Z = W^{\mathrm{T}}E$ are then used as the feature vector for LDA classifiers.

LDA [34] is a well-known binary classification method based on the estimation of the mean vectors and covariance matrices of individual classes to find the linear combination of features that maximizes the separability between distinct classes. LDA can be formulated in terms of a Bayes rule that aims to assign each sample to the class with the maximal posterior probability. In this study, multiple LDA classifiers are trained from each subband to serve as base classifiers constituting an ensemble system. The decisions derived from each LDA classifier, i.e., the posterior probabilities of left- and right-hand movements, are then fused by means of a fuzzy integral.

C. Fuzzy Integrals

The purpose of fuzzy integral is to utilize information regarding the uncertainty or confidence of various candidate information sources during the decision-making process as represented using a fuzzy measure. For classifier fusion, an extension of the integral operator is used in the fuzzy integral to gather the objective evidence supplied by the classifiers in the form of certainty measures. Given the aforementioned benefits of this approach, the combination of classifiers based on fuzzy measures and integrals can enhance the robustness and reliability of BCI systems. In this paper, the combination of classifiers is performed by means of the Sugeno integral [27], [28] and the Choquet integral [29], which have been successfully implemented in the pattern recognition community.

The Sugeno integral is a type of integral with respect to a fuzzy measure that is defined for functions whose range is 0–1. Given the outputs of k classifiers $x_k \in [0,1]$, the Sugeno integral over the set $A = \{x_1, \ldots, x_i, \ldots, x_k\}$ of a membership function h with respect to the confidence g is defined as

$$S_g(h) = \int_A h(x_i)^{\circ} g = \sup_{\alpha\in[0,1]}\left[\min\left(\alpha, g\left(A\cap F_\alpha\right)\right)\right] \tag{3}$$

where $F_\alpha = \{\, x | h(x) \geq \alpha \,\}$.

The Choquet integral is another type of integral with respect to a fuzzy measure. The choice of this integral is inspired by both a theoretical property and a practical one. Specifically, it is a proper generalization of the normal integral operator. In addition, the learning task can be regarded as a convex quadratic program and can therefore be solved using well-known algorithms. The Choquet integral is defined as

$$C_g(h) = \sum_{i=1}^{k}\left[h(x_i) - h(x_{i-1})\right] g(A_i) \tag{4}$$

where $h(x_0) = 0$.

Note that the confidence g of each classifier is heuristically assigned. In this study, g is proposed to be determined via PSO (see Section II-D).

The joint confidence of the entire set of sources $g(A_i)$ can be obtained as

$$\begin{aligned} g(A_i) &= g(\{h_1, .., h_{i-1}\}) + g(\{h_i\})\\ &\quad + \lambda \times g(\{h_1, .., h_{i-1}\}) \times g(\{h_i\}) \end{aligned} \tag{5}$$

where $\lambda \in (-1, \infty)$ and λ can be obtained by solving the following equation:

$$\lambda + 1 = \prod_{i=1}^{k}(\lambda g_i + 1). \tag{6}$$

Then, the final decision is determined by the class with the largest fuzzy probability.

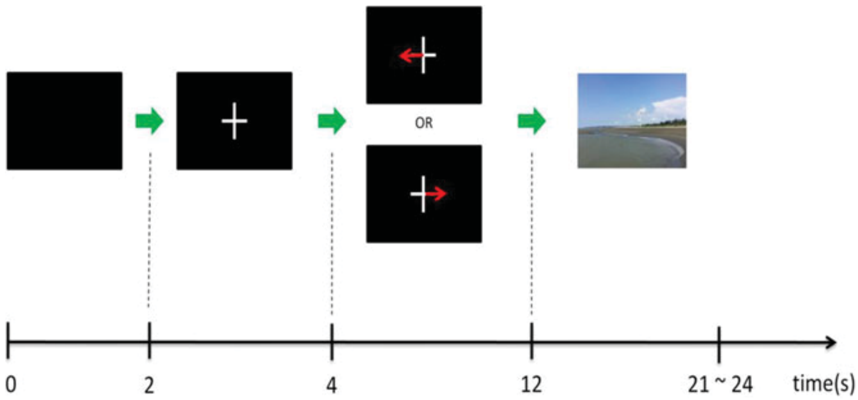

Fig. 3. Experimental paradigm.

D. Particle Swarm Optimization

To effectively assign confidence levels to the classifiers used in the fuzzy integral, PSO [21] is employed to update the confidence of the classifiers. The PSO algorithm is a well-known swarm intelligence technique that was developed to imitate the behavior of a flock of birds or a school of fish. The objective of PSO is to optimize a model by iteratively attempting to improve upon a candidate solution with regard to a given measure of quality. The PSO algorithm involves two critical steps, which are as follows:

1) Initialize a population of particles with a random distribution within the desired range of the search space.
2) Update the particle positions and velocities as follows:

$$v_{i,d} \leftarrow \omega v_{i,d} + \phi_p r_p \left(p_{i,d} - g_{i,d}\right) + \phi_f r_f \left(f_d - g_{i,d}\right), \quad g_i \leftarrow g_i + v_i \tag{7}$$

where f is the best known position of the entire swarm and $p_{i,d}$ is the best known position of particle i. When ω is less than 1, the particle velocities may tend toward 0, causing the particles to fall into a local minimum and delaying convergence.

The confidential weights g of the Sugeno integral and the Choquet integral are determined by PSO in this study. The initial vector that contains the fuzzy integral parameters is randomly chosen; ω is the inertial weight, ϕ_p and ϕ_f are acceleration constants, and r_p and r_f are random numbers drawn from the uniform distribution U (0,1). The confidential weights updated via PSO are calculated according to (7). When a particle finds a better position than its previous best position, the previous position is dropped and the new one is stored in the population. This value is called the personal best position of that particle, i.e., p_{best}. The mechanism retains a satisfactory confidential weight until the predefined number of iterations is reached. Meanwhile, the global best position, i.e., f_{best}, of the particle swam as a whole is updated by the particle swarm optimizer based on the particles that exist in the population. The distances between the positions of the particles and the values of f_{best} and p_{best} decrease during optimization. This procedure allows us to search for the optimal weights for each information source to obtain an optimized output during the training phase.

III. Results and Discussion

Ten male subjects, aged 22–26 years old, were recruited to participate in the MI experiment. All participants were neurologically healthy. Before the experiment, the participants were required to complete an informed consent form. Each participant was seated comfortably in front of a monitor, and the MI task was explained via written instructions on the screen. Five dry electrodes were used (four channels to record the EEG signals and one for reference) to measure EEG signals from the sensorimotor area. The MI experiment consisted of three phases. The first phase was a baseline-constructing task to establish an individual MI model of the proposed system, with the aim of constructing the features for the imagery of left- and right-hand movements. Twenty trials were performed in this baseline-constructing phase for the imagery of both left- and right-hand movements. The second phase was designed to train the participants in imaging left- and right-hand movements for EEG measurements. Each of the two directions was tested 40 times. In each training trial, an arrow pointing either to the left or to the right would randomly appear on the screen. After each imagery trial, a picture was displayed on the screen for a randomly determined period of time to help the subjects relax between trials. The training phase was used to calibrate the parameters of the proposed measurement system for each user, with the aim of identifying each user's EEG features. The last phase was the actual experiment, also with 40 MI trials per direction. Upon seeing an arrow indicating a direction, the users were instructed to perform imagery of the corresponding left- or right-hand movement. The wireless EEG acquisition device was used during the MI experiment.

A. Experimental Procedure

The experimental paradigm is illustrated in Fig. 3. A subject was seated in a comfortable chair, with his hands placed on a table. A blank screen was displayed for 2 s, followed by a cross displayed at the center of the screen for 2 s. Then, the subject was instructed to perform left/right MI as indicated by a left/right-pointing arrow, which was presented for 8 s. Finally, a picture was shown on the screen for 9–12 s to allow the subject to rest.

TABLE I
CLASSIFICATION RESULTS (AUC) FOR THE BASE CLASSIFIERS AND VARIOUS CONVENTIONAL AND FUZZY FUSION APPROACHES WITH FOURFOLD CROSS-VALIDATION APPLIED TEN TIMES

		Area Under ROC Curve	T Test
Single LDA	Delta LDA	0.915 ± 0.020	–
	Theta LDA	0.904 ± 0.027	–
	Alpha LDA	0.890 ± 0.050	–
	Beta LDA	0.880 ± 0.044	–
	All-band LDA	0.900 ± 0.040	–
Conventional Methods	Voting	0.962 ± 0.082	$p < 0.05$
	Weighted Summation	0.990 ± 0.015	$p < 0.05$
	SVM	0.993 ± 0.022	$p < 0.05$
Fuzzy Fusion	Sugeno Integral	0.968 ± 0.063	$p < 0.05$
	Choquet Integral	0.992 ± 0.014	$p < 0.05$

TABLE II
CLASSIFICATION RESULTS FOR THE SUGENO INTEGRAL AND THE CHOQUET INTEGRAL AFTER PSO TRAINING WITH FOURFOLD CROSS-VALIDATION APPLIED TEN TIMES

	Fuzzy Fusion	w/o PSO	w/ PSO
Fuzzy Fusion	Sugeno	0.968 ± 0.063	$\mathbf{0.998 \pm 0.040}$
	Choquet	0.992 ± 0.014	$\mathbf{0.998 \pm 0.003}$

B. Fuzzy Fusion Performance

In MLDA, classifiers are constructed using a combination of features from multiple frequency bands, including four separate frequency bands (i.e., the delta, theta, alpha, and beta bands) and the full-band signal ranging from 1 to 30 Hz. In each frequency band, an LDA classifier is constructed using features extracted via CSP projection. Consequently, the MLDA is established using the spatial pattern features from these five frequency bands. The separate frequency bands provide the features of each band in greater detail and allow more features to be obtained. Accordingly, the Sugeno integral or the Choquet integral is used for fuzzy fusion to integrate the MLDA decisions constructed using the five base classifiers, namely, the delta, theta, alpha, beta, and all-band LDA classifiers, in the proposed system. After the aggregation of the results from different bands, the fuzzy fusion mechanism is applied to make the final decision. Initially, the weights of each classifier in the Sugeno integral and the Choquet integral are all set to 0.2. The PSO algorithm is later applied to update these weights.

The performances of the two fuzzy integrals and of several conventional fusion methods were evaluated in terms of the area under the ROC curve (AUC). As shown in Table I, each fusion technique outperformed each single classifier, with the proposed fusion architecture yielding not only higher AUC values but also smaller standard deviations. In comparison with existing fusion techniques, the weighted summation approach, the support vector machine (SVM) approach [35], and the Choquet integral outperformed the voting approach [36] and the Sugeno integral. As shown in Table II, after the application of PSO to update the weights of the classifiers, the results of both the Sugeno and Choquet integrals exhibited improvements, from 0.968 ± 0.063 to 0.998 ± 0.040 and from 0.992 ± 0.014 to 0.998 ± 0.003, respectively. The AUC was improved and the standard deviation was reduced, indicating that the system achieved higher accuracy and better stability.

C. Proposed Online BCI System and Its Application

The flow chart for a subsequent online experiment is shown in Fig. 4. The offline experiment reported above was initially required for advance model generation. The models thus generated could subsequently be applied in an online experiment using the proposed BCI system. When performing the online experiment, each subject wore an EEG acquisition system on the top of his head along the central sulcus, and the reference was recorded at the earlobes on both sides. Each subject was required to perform a full experiment consisting of four sessions (160 trials), and the model previously derived for that subject was applied in the online system.

In each trial, the user interface of the online system presented a randomly generated cue, namely, an arrow pointing to the left or to the right at the center of the screen. Each classification result was recorded as a score of $+1$ or -1; the total accumulated score was calculated after every trial. If the final score was above $+\ 25$ or below -25, the system made a final decision of either a left command or a right command, respectively. Because the computing speed of the online system was 25 Hz, if the subject wished to issue a left or right command, he was required to continuously think about the same direction for 1 s. After each trial, the classification result accumulated over 1 s was plotted as a bar. The accuracy rate was recorded at the top of the window. The processing time (from the input of the raw data to the output of the result) was 40.1715 ms, as shown in Fig. 5. In other words, this system is capable of computing at a rate of approximately 25 Hz when performing online computations. This computation rate was the basis for the selection of a value of 25 points as the threshold for the online interface. The accuracy rate achieved in the online test was approximately 86%. Depending on the classification result, a robotic arm would immediately grasp a glass to either the left or the right. The robotic arm used in this experiment is commercially available on the rehabilitation market (Kinova, Canada). It consists of a six-axis robotic manipulator arm with a three-fingered hand. This robotic arm can perform a wide variety of functions with graceful movements.

D. Reliability Test

A further test was performed to confirm the model reliability. In this test, the performance of the algorithm was evaluated using data acquired from the same subject but on a different day. The training set included data recorded continuously from four experimental sessions (160 trials) in a single day for one subject. The test set included data from two experimental sessions (80 trials) recorded on a different day for the same subject. After a model was generated from the training set, that model was applied to the test data to evaluate its performance. The accuracy rate of prediction was found to be 91.25%, indicating good model stability.

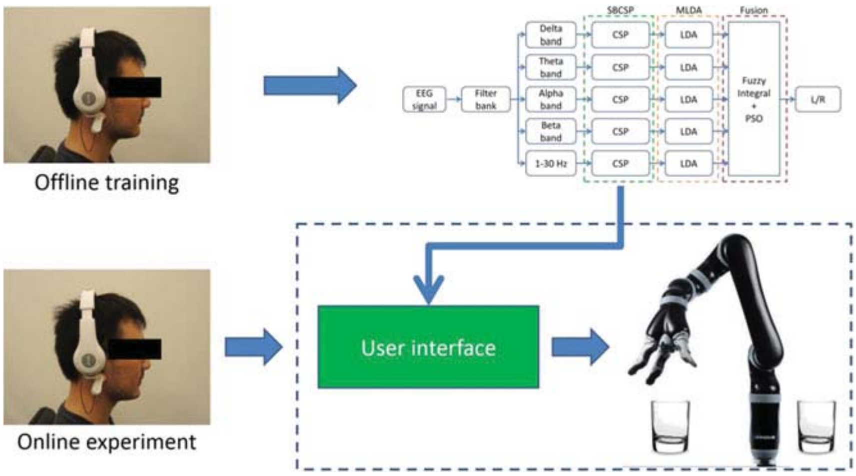

Fig. 4. Flow chart of the proposed MI-based BCI system application.

Fig. 5. Signal processing time within the proposed online system.

IV. Conclusion

In this study, we propose an innovative ensemble method with swarm-optimized fuzzy integral for an MI recognition task. The fuzzy integral provides an effective mechanism for representing and processing the uncertainty of the outputs of individual ensemble members using the concept of fuzzy measures. Furthermore, PSO is used to update the confidence of the employed classifiers. The experimental results derived from a typical MI task show that the best classification accuracy is achieved when applying the Choquet integral with PSO training in the fusion phase. Additionally, the results demonstrate the feasibility of implementing the proposed system in real-time robotic arm control. In the future, developing a more advanced BCI system with fuzzy theory will be necessary to enable the execution of multidirectional movements.

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