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# Improvement of EEG-based motor imagery classification using ring topology-based particle swarm optimization

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ABSTRACT

Mental tasks classification such as motor imagery, based on EEG signals is an important problem in brain-computer interface (BCI) systems. One of the major concerns in BCI is to have an accurate classification. Classifier tuning is one of the most important techniques to increase classification accuracy. In this paper, a ring topology based particle swarm optimization (RTPSO) algorithm is proposed to tune classifiers. Fitness function of RTPSO algorithm is based on the 10-Fold Cross-Validation (CV) or Holdout methods which are used to evaluate performance of classifiers. Feed Forward Neural Network (FFNN) and three types of Support Vector Machine (SVM) classifiers are used to classify mental tasks. The proposed method tunes classifiers efficiently and quickly in a minimum of 10 iterations and outperforms the BCI 2003 and 2005 competition-winning methods and other similar studies on the same Graz datasets. Obtained results of the tuned FFNN proved far better than SVMs and classification algorithms of the other studies on the Graz datasets III and IIIb in all the experiments. According to the criterion of the BCI competition 2003 on the Graz dataset III, the maximal Mutual Information (MI) by tuned FFNN is about 0.81 while by the Least Squares SVM classifiers is about 0.73. FFNN improves misclassification rate comparing with the best of previous methods The mean of the maximal MI steepness is also improved. Our experiments show that the proposed RTPSO together with 10-Fold CV leads to promising results for classifier tuning in motor imagery classification.



## 1. Introduction

A direct communication interface between a brain and an external device is provided by a brain-computer interface (BCI) system. Although a message sent by an individual can be detected by brain signals but it cannot pass through the brain's normal output pathways for people affected by a number of motor disabilities. Such interfaces can be considered as being the only way of communication for them [1–3]. Due to low cost and non-invasive nature of Electro-Encephalogram (EEG), it is one of the most popular techniques for monitoring brain activities in BCIs. There are also another techniques like Magneto-Encephalography (MEG), Near-Infrared Spectroscopy (NIRS), Electro-Cardiogram (ECOG), Positron Emission Tomography (PET) and Functional Magnetic Resonance Imaging (FMRI) those are not common in use as much as EEG [1,4]. Interactions between brain neurons are electrical action potential signals called EEG which can be recorded on the scalp. It is proved that each particular part of the brain, control specific tasks in the human body [1]. Intensive neurological electrical activities generated by neurons firing are big enough to be measured by the non-invasive electrodes placed on specific parts of the brain. The recorded EEG signals contain useful information to decode human thoughts or intents which their amplitude is in the range of 1–100 $\mu$V. Conversion of this information into control signals can be used as input of any BCI based systems [5].

A pattern recognition system involves feature extraction and classification therefore a BCI system involves this two stages. Feature extraction and selection and the classification methods which affect on the performance of a recognition system [6]. Poor signal-to-noise ratio in EEG signals requires employment of robust classification algorithms in order to achieve reasonable classification performance [5]. The main objective here is tuning parameters of some classifier used in this article. Different classification algorithms such as linear discriminant analysis (LDA), linear (or non-linear) Support Vector Machines (SVM), Multilayer Perceptron (MLP), Learning Vector Quantization (LVQ), Radial Basis

*Abbreviations:* EEG, electroencephalogram; BCI, brain-computer interface; RTPSO, ring topology based particle swarm optimization; CV, cross validation; FFNN, feed forward neural network; SVM, support vector machine; MI, mutual information.

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Function (RBF) and many other kinds of classifiers were used in BCI researches [2]. Some well-known evolutionary algorithms (EAs) such as Genetic Algorithm (GA) or particle swarm optimization (PSO) were used to tune parameters of classifiers or used to learning process of a neural network (NN) classifier [7,8]. However large number of iteration in EAs (1500 iteration in proposed method by Lin and Hsieh [8]) leads to achieve good results but to find optimum solutions, the number of iterations should be as little as possible to have a real-time and accurate decision making in a BCI system. In this paper we propose a PSO based on ring topology [9] which namely RTPSO and employ two classifier evaluation method, 10-Fold and Holdout in its fitness function to tune parameters of SVM and FFNN classifiers. The RBF (or Gaussian) kernel is generally used in BCI for SVM classifier [2]. Experimental results have shown that our proposed method can obtain best optimum parameters value of classifiers with minimum 10 iterations and outperform classification results of mental tasks from EEG data.

Most commonly performance evaluation of different pattern recognition techniques is the error (or misclassification) rate. This criterion determines only each pattern class and does not assign membership degree of patterns belongs to that class, so the error rate contains only information about classification accuracy with no confidence of classification outputs. The entropy-based mutual information (MI) [10] containing classification accuracy and confidence is achieved from classifying results which was used as the BCI Competition 2003 criterion to compare the performances of different methods on the Graz dataset. More confidence results can be produced by greater MI of classification outputs. Due to the importance of time delay in the BCI Competition 2005 on the Graz dataset, the maximum increase of MI was considered as validation criterion to evaluate classifiers performance [11]. In this paper the SVM and FFNN classifiers and extracted wavelet features from raw signals as classifier input are used to motor imagery classification. The obtained classification results by the SVM and FFNN were compared with the winners of BCI competitions of 2003 and 2005 [11,12] and other similar studies [6,7] on the same Graz dataset in terms of the competition criteria of the MI and the maximum increase of MI.

## 2. Materials and methods

### 2.1. Data description

In this study the 2-classes motor imagery datasets of III and IIIb (which are part of 2003 and 2005 BCI competitions datasets respectively) were used to evaluate performance of proposed method. This datasets are provided by leaderships of Dr. Gert Pfurtscheller from Graz University of Technology and are available online [13,14]. The Graz dataset III contain 280 trials (140 trials for each class) was recorded from a 25 years subject. Each trial lasts 9 s in a feedback session. In the beginning there is 2 s of silence. At t = 2 s, beginning of trial was informed to the subject by a beep sound and simultaneously a cross "+" was displayed for 1 s. Then in a random state, at t = 3 s, a left (or right) cue stimulus was displayed and subject should control a feedback bar by imagination of her hand movements. The C3, CZ and C4 bipolar EEG channels (Fig. 1 top) were used to record signals with a 128 Hz sampling rate. According to competition criterion, the output of classifiers should be continuous values (<0 class 'left', >0 class 'right', 0 'non-decisive') for each time point. The sign and magnitude of values specify class and confidence of classifications respectively [12,15].

Another motor imagery dataset is the Graz IIIb which consists of 3 sub-datasets recorded from 3 subjects (namely O3, S4 and X11). Positions of recording electrodes are the same as shown in Fig. 1(top). In BCI competition 2005, Classifiers outputs should be provided continuous values like BCI competition 2003, but in this series of competitions the maximum increase of MI (maximum steepness calculated as MI(t)/(t − 3s) for t > 3.5 s) was used as criterion [11]. Fig. 2 shows recording paradigm of trials which was used for the O3 subject and Fig. 3 shows basket paradigm which was used for the S4 and ×11 subjects of the Graz dataset IIIb [16]. A summary of information about each subject are presented in Table 1.

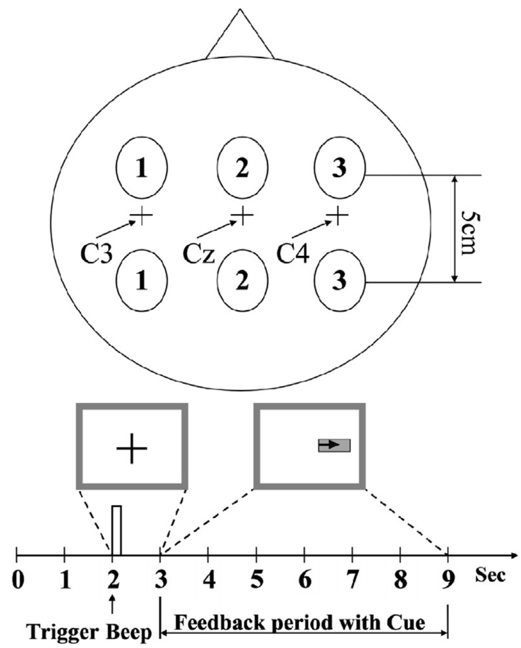


**Fig. 1.** Electrodes positions (top) and timing scheme (bottom) [15].

**Table 1**
Number of training and test trails in the Graz dataset IIIb for each subject.

| Subject | Training trials | Test trials | Total |
|---|---|---|---|
| O3 | 242 | 159 | 401 |
| S4 | 540 | 540 | 1080 |
| X11 | 540 | 540 | 1080 |

**Table 2**
Frequencies corresponding to different levels of wavelet decomposition with a 128-Hz sampling rate [6].

| Decomposed signal | Frequency range (Hz) |
|---|---|
| D1 | 32–64 |
| D2 | 16–32 |
| D3 | 8–16 |
| A3 | 0–8 |

### 2.2. Feature extraction using discrete wavelet transform

In this paper, feature extraction method is based on discrete wavelet transform (DWT) which proposed by Xu et al. [6] and Subasi [17,18]. The signal at different frequency bands is analyzed by decomposition procedure of DWT method and a coarse approximation and detailed information about signal is presented. Daubechies is selected as the wavelet function and level of decomposition is 3. Pfurtscheller et al. [19,20] reported that the $\mu$ rhythm (8–13 Hz) and $\beta$ rhythm (13–22 Hz) contain properly signal features which can be efficient for EEG-based BCI systems. According to decomposition levels demonstrated in Tables 2 and 3, the D2 and D3 sub-bands almost cover $\beta$ and $\mu$ rhythm respectively; so features are extracted base on those sub-bands [6]. To reduce the numbers of extracted features, two statistical measures were used as final fea-