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Evolutionary perspective for optimal selection of EEG electrodes and features

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ABSTRACT

This paper proposes a novel evolutionary approach to the optimal selection of *electroencephalogram* (EEG) electrodes as well as relevant features for effective classification of cognitive tasks. The EEG *electrode and feature selection* (EFS) problem here has been formulated in the framework of an optimization problem with an aim to simultaneously satisfying four criteria. The first criterion deals with maximization of the correlation between the selected features of EEG source signals, before and after the selection of optimum electrodes. It thus ensures the preservation of information of the cortical sources corresponding to a cognitive task even after reducing the number of electrodes. The second criterion is concerned with minimization of the mutual information between the selected features of the EEG signals recorded by the selected electrodes. It helps in identifying the unique information by reducing the redundancy in the EEG signals recorded by the selected electrodes for a specific cognitive task. The third criterion aims at optimal selection of EEG electrodes and EEG features in an attempt to i) minimize the difference between the selected EEG source-features (to ensure their similarity) for a specific cognitive task and ii) maximize the difference between the selected EEG source-features (to ensure the efficient categorization) of different cognitive tasks. The last criterion is concerned with maximization of the classification accuracy of different cognitive tasks based on the selected EEG source-features, corresponding to the selected EEG electrodes. The originality of the paper lies in obtaining the sets of optimum EEG electrodes and EEG features by independent optimization of individual objectives. These sets of optimum EEG electrodes and EEG features are then ranked based on their fuzzy memberships to satisfy individual four objectives. A self-adaptive variant of firefly algorithm (referred to as SAFA) is proposed to optimize individual objectives by proficiently balancing the trade-off between the computational accuracy and the run-time complexity. Experiments undertaken over wide variety of cognitive tasks reveal that the proposed algorithm outperforms the other standard algorithms (applied to the same problem) in terms of accuracy and computational overhead.

1. Introduction

Brain computer interfacing (BCI) [1,2] is a multi-dimensional field of research, concerned with cognition, neurophysiology, psychology, sensors, machine learning, signal detection and processing, to name a few. Now a day, BCI stands alone as the only modality of control and communication for patients suffering from diseases like amyotrophic lateral sclerosis, paralysis, cerebral palsy, and amputees. The BCI interfaces bypass the natural pathways of neuromuscular control and thus aim at serving alternative means of communication/control in case of failure in neural/motor functioning. Several interfacing methodologies including invasive implants, semi invasive implants like *electrocorticography* (ECoG) [3–6] and non invasive modalities like EEG [7–10], *magnetoencephalogram* (MEG) [11–14] and *functional magnetic resonance imaging* (fMRI) [15–18] have emerged to implement BCI successfully. ECoG, MEG and fMRI are invasive procedures to capture brain activity pattern, which require surgery for implantation of electrodes inside human scalp. Although these techniques provide reliable signals but they involve exposure to high magnetic fields and the equipments used are bulky and immobile. Additionally, there are evidences of claustrophobia among the participants [19] during signal acquisition using MEG and fMRI. To overcome these difficulties, EEG is the preferred technology for measuring brain activities for most BCI

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researchers because of its non-invasiveness, portability, easy availability, and high temporal resolution [20].

The basic EEG-based BCI module consists of three steps [21], including i) pre-processing of the EEG signals dealing with artifact removal, identification of relevant electrodes and frequency bands of EEG signals, ii) feature extraction, and iii) classification, concerned with identification of different mental states. The classified results thus obtained, lead to the generation of the control signals required to drive an assistive device. The classification accuracy relies on the extent of detour the redundant information. This paper addresses two crucial factors for effective classification of cognitive tasks using EEG-based BCI systems, including

1. optimal selection of electrodes [39] to facilitate faster processing of EEG signals for different cognitive tasks, and
2. optimal selection of relevant EEG features to enhance the performance of a classifier.

The optimal selection of electrodes [39] is essentially influenced by the estimation of cortical sources. The EEG devices acquire raw cortical current signals (also known as *source* signals), generated from different independent sources, through neuronal firing in outer cortex of the brain. These signals are then transformed to respective voltage signals by passing through different resistive devices. Finally, the voltage signals (also referred to as *sink* signals) are recorded by placing electrodes at specified scalp regions. Due to volume conduction, the signal acquired at the scalp electrodes is found to contain components of different cortical sources. Moreover, for a particular cognitive task, not every electrode placed on the scalp may provide relevant information. In fact, sometimes electrodes generate redundant information. Overlapping information will not only degrade the classifier performance, but it also involves processing of same signal components more than once, which negatively affects the time complexity as well.

Only optimal selection of electrodes is not sufficient for a successful EEG-based BCI implementation. One of the significant concerns in BCI research is to deal with the high dimensionality of the features. Often it is observed that due to the presence of a large number of redundant features in the feature set, the accuracy of the classifier is greatly decreased. Researchers are now taking keen interest to select fewer discriminate features from the high dimensional EEG feature vectors for different cognitive tasks without sacrificing the classification accuracy. The paper proposes a novel evolutionary approach to automatic selection of set of optimum EEG electrodes and EEG features (from the high dimensional feature space).

Following four strategies have been introduced here to determine the optimal set of EEG electrodes and relevant EEG features for effective classification of cognitive tasks.

a) The correlation between the selected EEG source-features, corresponding to the original and the selected EEG electrodes, should be high to prevent the loss of information of the cortical sources, while discarding redundant electrodes.
b) The mutual information between the selected features of the EEG signals, recorded by the selected EEG electrodes, should be small to reduce the redundant information, captured by the EEG electrodes.
c) The difference between the selected EEG source-features for a specific cognitive task should be smaller compared to the difference between the selected EEG source-features of different cognitive tasks. It helps in identifying the unique EEG source-features (corresponding to the selected EEG electrodes) representing each cognitive task.
d) The accuracy of classification of different cognitive tasks based on the reduced set of relevant EEG source-features, corresponding to the optimal set of EEG electrodes, should be high.

Evidently, the efficacy of the optimal *selection* of EEG *electrodes and features* (EFS) for efficient classification of cognitive tasks greatly depends on the proficient optimization of the abovementioned four objectives. Apparently, the problem may be cast as a single objective optimization problem by combining the four objectives into a single composite objective function. One possible combination can be realized by considering the difference of the objectives that need to be maximized and that need to be minimized. There exists plethora of methods for combining the objectives. However, due to non-overlapping dynamic range of the four objective functions, it is evident that mere optimization of the composite objective function (combining all four objectives) does not always assure effective optimization of its constituent four objectives [22]. This difficulty can be overcome by recasting the EFS problem as a multi-objective optimization problem. In the present context, unfortunately, the pre-condition of the conflicting relationships among the four concerned objectives, to formulate the EFS problem in a multi-objective optimization setting, does not hold.

In this paper, we propose a novel approach to solve the EFS problem by independently optimizing four individual objectives with non-overlapping dynamic range. First, the objective function value (or fitness) $f_l^{\max}$ of the optimal solution (representing the optimal set of EEG electrodes and features), obtained by individual optimization of the objective function f_l is recorded for $l = [1, 4]$. Next, a set $\mathbf{\Omega}_l$ of solutions is identified for each objective function f_l, comprising solutions with fitness in the interval $[0.95 f_l^{\max}, f_l^{\max}]$. Next, we prepare a set $\mathbf{\Omega}$ by taking the union of all four solution sets $\mathbf{\Omega}_l$s for $l = [1, 4]$. Evidently, each of the four objectives is satisfied to an extent of 95% or more by at least one solution of the union set $\mathbf{\Omega}$ [22].

A new ranking score is developed to sort the solutions of $\mathbf{\Omega}$ based on their degree of satisfying each individual objectives. For each objective function f_l, a sigmoid-type membership function is used to signify the degree of membership of a solution of $\mathbf{\Omega}$ to satisfy the objective function f_l. The composite membership of each solution of $\mathbf{\Omega}$ is obtained by taking the *t*-norm (here, product) of their four membership functions, representing the extent of their confidence in satisfying all four objectives. Next, the solutions of $\mathbf{\Omega}$ are sorted in descending order of their *t*-norm ranking scores. Thus, a solution with the highest score is declared as the representative of the optimum EEG electrodes and features for effective categorization of cognitive tasks under consideration.

A self-adaptive variant of the traditional firefly algorithm (FA) [23] is proposed here to select an optimal set of appropriate EEG electrodes and features by independently optimizing individual objectives f_ls for $l = [1, 4]$. FA is selected here partly heuristically and partly due to its established performance with respect to computational accuracy and run-time complexity [23]. The self-adaptive variant of FA (referred to as SAFA) assists the potential candidate solutions (of the optimization problem) to confine their search in their local neighborhood in the parameter space. On the other hand, the inferior members are equipped with the global exploration capability.

The present paper is a thorough and detailed extension of our previous work reported in [24] as given below. First, the present version includes the fourth objective, concerned with maximization of classification accuracy while categorizing different cognitive tasks based on the selected EEG source-features corresponding to the selected EEG electrodes. Second, a fuzzy set based novel policy is proposed for independent optimization of individual objectives, in contrast to the single objective formulation of the problem as