Neurocomputing 82 (2012) 109–116

Contents lists available at SciVerse ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

A subject transfer framework for EEG classification

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ARTICLE INFO

Article history:
Received 21 December 2010
Received in revised form
3 June 2011
Accepted 9 October 2011
Communicated by D. Erdogmus
Available online 27 December 2011

Keywords:
EEG classification
Transfer learning
Ensemble learning
Sparse representation

ABSTRACT

This paper proposes a subject transfer framework for EEG classification. It aims to improve the classification performance when the training set of the target subject (namely user) is small owing to the need to reduce the calibration session. Our framework pursues improvement not only at the feature extraction stage, but also at the classification stage. At the feature extraction stage, we first obtain a candidate filter set for each subject through a previously proposed feature extraction method. Then, we design different criterions to learn two sparse subsets of the candidate filter set, which are called the robust filter bank and adaptive filter bank, respectively. Given robust and adaptive filter banks, at the classification step, we learn classifiers corresponding to these filter banks and employ a two-level ensemble strategy to dynamically and locally combine their outcomes to reach a single decision output. The proposed framework, as validated by experimental results, can achieve positive knowledge transfer for improving the performance of EEG classification.

1. Introduction

During recent years, the development of brain computer interface (BCI) technology has both theoretical and practical significance. BCIs have the ability to enable their users to manipulate an external device by means of translating brain activities into a command for a computer or machine [1]. They are communication and control systems that do not require any peripheral muscular activities, and therefore can be a very helpful aid to people suffering from motor disabilities [2]. As Fig. 1 shows, BCIs can be seen as a complex pattern recognition system [3], where the user's ability to reliably produce changes of electroencephalogram (EEG) signals and subsequent stages of feature extraction and classification are equally important and can complement one another.

Improving classification performances of EEG-based BCI systems faces a great challenge today. One problem is that, for a new subject (user), a long calibration session (e.g., more than 1 h) is needed to collect sufficient training samples to construct subject-specific feature extractors and classifiers, which are used later in the test session to classify brain signals of this subject. In recent research in BCIs, reducing training sessions is a task of great sense since the calibration session is a boring and time-consuming process. Therefore, it is more desirable to conduct performance improvement with a small labeled set, rather than on an abundant one. However, because a short calibration session means only a few training samples of the target user are available, which may lead to suboptimal or overfitting feature extractors or classifiers, we have to find appropriate methods to enhance the performance.

One promising way to reduce training sessions is to utilize samples collected from other subjects (we call them as “source subjects”) to aid the subject whose brain signals would be classified in the test session (we call this subject as “target subject”). This strategy can be termed “subject transfer”. However, owing to the large inter-subject variabilities, it is unwise to simply add training samples of source subjects to the training set of the target subject. This is often unhelpful and even degrades the performance. How to properly use the data of source subjects is the key to achieving positive subject transfer for EEG classification.

Several related works also focusing on the small training sample problem in EEG classification are described here. Semi-supervised learning with local temporal regularization [5] has been proposed to utilize test samples to solve the small training sample problem. However, for real BCI systems, collecting a lot of test samples are sometimes unpractical, so that semi-supervised technology may be unsuitable. Another important work for this problem is the session transfer strategy [6]. However, this method assumes the target user has already performed some training sessions, so that it can not work for a new user who did not perform any training session before. Moreover, there are several works on adaptive learning also related to this problem [7–9]. This paper proposes a framework for achieving the subject transfer strategy. It can be applied to users with few training samples and it handles test samples with the one-after-one manner, which is similar to the real situation of most BCI systems.

This paper proposes a framework for improving EEG classification performance. It can achieve positive subject transfer with

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doi:10.1016/j.neucom.2011.10.024

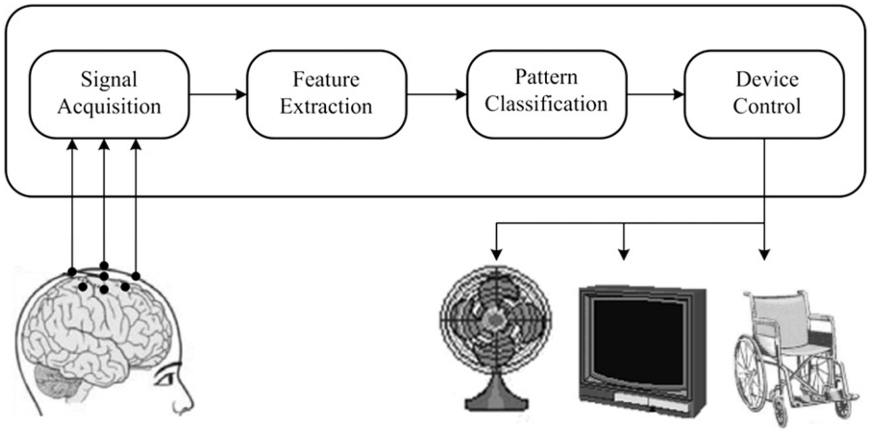

Fig. 1. A general EEG-based BCI [4].

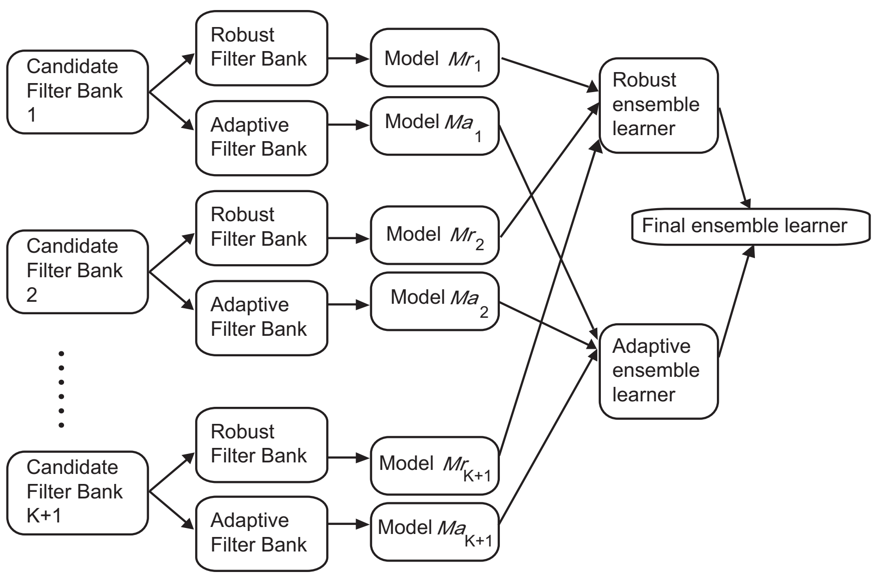

Fig. 2. The proposed subject transfer framework for EEG classification.

improvement on both feature extraction and classification stages. Traditional spatial filtering algorithms often have some important limitations: It is not flexible enough and often overfitts or underfits, especially in the small training sample situation (for details, see [10–13]). Thus, we design a method to obtain two banks that ensure robustness and adaptiveness of spatial filtering, respectively. Specifically speaking, it uses a previous method called extreme energy ratio (EER) to obtain candidate filter banks, and then extracts its two subsets with 1-norm regularization and different performance criterions. Given multiple classifiers corresponding to these banks, we employ an ensemble strategy to combine them. The proposed fusion method assigns dynamic weights to these base models according to the local structure of a given test sample in the feature space. These weights represent the prediction consistency of the model. With this weighting approach, we can learn robust ensemble learner and adaptive ensemble learner, respectively. Finally, a parameter weighting combination of them makes the final prediction on the category of the given test sample. Fig. 2 provides a structural illustration of our framework. The experiment is performed on public datasets from nine subjects and the results demonstrate the excellent performance of our method.

The rest of this paper is organized as follows. Subject transfer based BCI systems are introduced in Section 2. Section 3 displays main notations used in this paper. Next, the feature extraction stage and classification stage of our framework are shown in Section 4 and Section 5, respectively. In Section 6, experimental results and performance analysis are provided. At last, conclusions and plans for future work are given in Section 7.

2. Subject transfer based BCI systems

In this part, the subject transfer based BCI system is proposed. It wishes to use data from other subjects to reduce training burden of the current user.

It is known that the procedure of using BCI devices includes two parts: training and test sessions. Before a BCI device can be served for users, users should first perform training sessions to provide enough training samples to systems. This can be achieved by two steps: First, devices show a command by offering a visual or audible cue and users should act accordingly. By that way, BCI systems can collect enough training samples to learn a model for performing later tasks The training session of a BCI device often consumes half to 1 h.

However, long time-consuming training sessions bring huge difficulties to the practical wide use of BCI devices. First, not all users can perform training sessions (e.g., people who have visual or audible handicaps) and sometimes users who wish to use the