Multitask Learning for EEG-Based Biometrics

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Abstract

Biometrics based on electroencephalogram (EEG) signals is an emerging research topic. Several recent results have shown its feasibility and potential for personal identification. However, they all use a single task (e.g., signals recorded during imagination of repetitive left hand movements or during resting with eyes open) for classifier design and subsequent identification. In contrast with this, in this paper multiple related tasks are used simultaneously for classifier learning. This mechanism has the advantage of integrating information from extra tasks and thus hopefully can guide classifier learning in a hypothesis space more effectively. Experimental results on EEG-based personal identification show the effectiveness of the proposed multitask learning approach.

1. Introduction

Biometrics, with the aim to recognize and distinguish people based on their physical or behavioral features, has received an increasing attention during the past years [1, 2]. It can not only be applied to criminal identification and police work, but also to many civilian purposes, such as access control and financial security. Biometric systems can employ different kinds of features, e.g., features of fingerprint, face, iris or posture. Since each biometric modality has its own perspectives and constraints, people have been exploring new modalities for usage in different situations. Besides, multi-modal biometrics combining these alternative modalities is also a research direction in progress, which is promising to improve performance and reduce the possibility of forgery. The focus of this paper is on biometrics using electroencephalogram (EEG) signals, an emerging research topic.

EEG signals are brain activities recorded from electrodes mounted on the scalp. Compared to other means for monitoring brain activities, such as magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI), electroencephalography is the most recipient and practical one. Up to the present, EEG signals have been successfully applied to the research and development of brain-computer interfaces whose main goal is to enhance the communication and control abilities of motor-disabled people [3, 4]. For biometrics, without regard to the somewhat cumbersome data recording process the modality of EEG signals has several advantages. It is confidential and hard to imitate, since EEG signals are a reflection of individual-dependent inner mental tasks [5]. In addition, one can not force a person to give ideal EEG signals as those recorded in normal situations, as brain activity is easy to be influenced by the stress and mood of a person [5]. In this sense, EEG-based biometrics can protect personal safety of its users.

Till now, little work has been done on EEG-based biometrics. With a data set of four subjects and 255 EEG trials (subjects were at rest with eyes closed) Poulos et al. adopted two classification algorithms and obtained the accuracies of around 80% and 95% respectively [6, 7]. Paranjape et al. analyzed a data set of 40 subjects and 349 EEG trials (subjects were resting with eyes open and closed) and got a classification accuracy of about 80% [8]. Palaniappan and Mandic carried out a personal identification experiment with 102 subjects based on visual evoked potentials and the accuracies were around 95-98% [9]. With a data set of nine subjects performing mental imaginary tasks of left hand movements, right hand movements and word generation beginning with a same letter, Marcel and Millán got a highest accuracy rate for personal verification of 93.4% [5].

The above early work has played an important role

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in studying the feasibility of EEG signals for usage in biometrics. However, when learning a classifier, they all adopted only one kind of brain activity. Recent research on multitask learning indicates that the performance of a main task can be improved by learning related tasks together [10, 11]. In this paper, we make an attempt to include signals of a different task for classifier learning. The inductive bias provided by the extra task is supposed to favor the learning of the main task.

The rest of the paper is organized as follows. Section 2 introduces multitask learning briefly and our approach for EEG-based biometrics. Section 3 reports experimental results of personal identification with motor imaginary tasks. Finally, concluding remarks are given in Section 4.

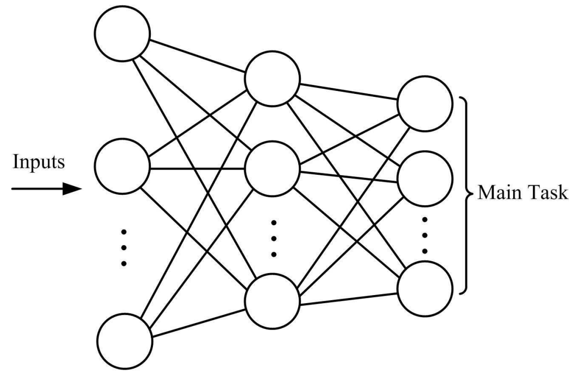

Figure 1. A neural network for STL.

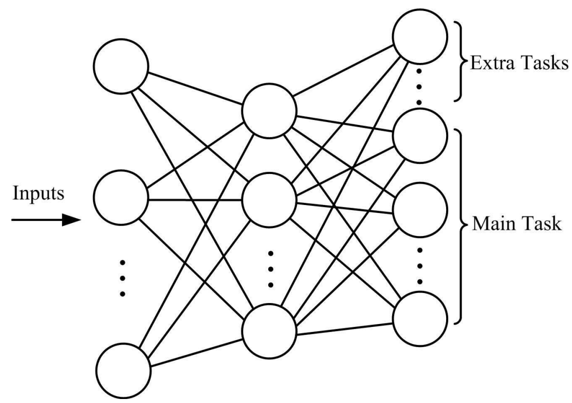

Figure 2. A neural network for MTL.

2. Methodology

2.1. Multitask learning

Usually in pattern recognition and machine learning a large problem is divided into some small problems. After learning these small problems (each serves as a main task) separately, people then recombine them. This is the traditional single task learning (STL) mechanism. Though STL makes the large problem easier to learn in some sense, it ignores a potentially rich information source provided by extra related tasks [10]. On the contrary, multitask learning (MTL) trains several related tasks in parallel with some shared representation, and can take advantage of the latent domain-specific information in extra tasks. For MTL extra tasks actually serve as an inductive bias which causes a learner to prefer the hypotheses best explaining the main task and the extra tasks simultaneously [10].

MTL can be used with many learning methods, such as k-nearest neighbor, decision trees and neural networks. In our present study, neural networks are adopted as they are direct and intuitive for MTL, i.e., in terms of a shared hidden layer representation [10].

2.2. MTL for EEG-based biometrics

Previous research on EEG-based biometrics is a STL mode. Specifically, only one kind of mental activity is used for personal identification or verification. With the terminology of neural networks, STL for this sort of biometrics can be depicted as Figure 1, where inputs mean features of recorded EEG signals (e.g., imagining repetitive left hand movements or resting with eyes open) and the main task is personal identification or verification. For illustration, a feedforward neural network with two layers is used, though any neural network can be chosen.

Different from the former STL approach, our method for EEG-based biometrics adds extra but related tasks to the current neural network, as shown in Figure 2. Now the number of output nodes increases to accommodate the inclusion of the extra tasks. The main task and extra tasks have a shared hidden layer representation which can integrate the inductive bias provided by extra tasks and thus hopefully benefit the learning of the main task [10]. As an instantiation, consider the example where we have two kinds of mental activities: imagination of left hand movements or right hand movements. STL will use either of the mental activity as inputs for personal identification. But our MTL approach will add an extra task of discriminating the mental activity type to the current problem. EEG signals from both mental activities will be used to train a MTL neural network. After training, the resultant neural network can be used to classify signals from either imagination of left hand movements or imagination of right hand movements.

3. Experiment

3.1. Data description

The EEG data used in this study were made available by Dr. Allen Osman of University of Pennsylvania during the NIPS 2001 BCI workshop [12]. There were totally nine subjects denoted S1, S2, ..., S9 respectively. For each subject, the task was to imagine moving his or her left or right index finger in response to a highly predictable visual cue. EEG signals were recorded with 59 electrodes mounted according to the international 10-10 system [3]. Totally 180 trials were recorded for each subject. Ninety trials with half labeled left and the other half right were used for training, and the other 90 trials were for testing. Each trial lasted six seconds with two important cues. The preparation cue appeared at 3.75 s indicating which hand movement should be imagined, and the execution cue appeared at 5.0 s indicating it was time to carry out the assigned response.

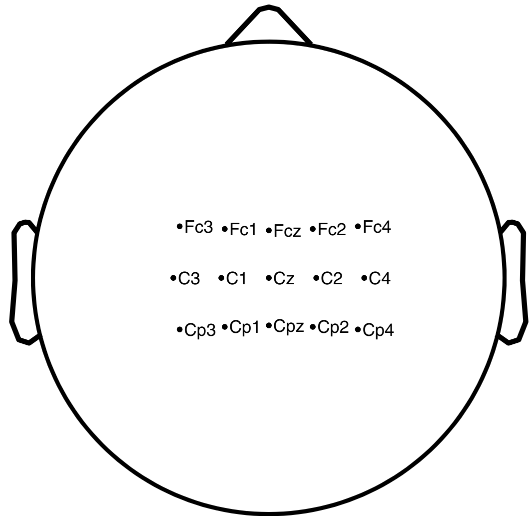

Figure 3. The top view of the names and locations of the 15 electrodes used.

3.2. Preprocessing and feature extraction

Signals from 15 electrodes (as given in Figure 3) over the sensorimotor area are used in this paper, and for each trial the time window from 4.0 s to 6.0 s is retained for analysis. Other preprocessing operations include common average reference, 8-30 Hz bandpass filtering, and signal normalization to eliminate the energy variation of different recording instants [13]. Then the method of common spatial patterns (CSP) is employed to carry out subsequent energy feature extraction [13, 14]. As a result, each trial is modeled by a 8-dimensional vector (4 sources from each kind of mental task is assumed in this paper). Based on these features, neural network classifiers can be learned, e.g., from a part of the entire training set.

3.3. Neural network design choice

As a neural network with two layers of appropriate units can approximate every bounded continuous function [15, 16], we use neural networks of one hidden layer and one output layer for experiments. Sigmoid units are adopted whose ranges for the hidden layer and the output layer are respectively taken as -1 to 1 and 0 to 1. For STL, nine distinct output units, each representing one of the nine subjects, are used. If an EEG trial belongs to subject 1, we encode the output of the nine units as $(0.9, 0.1, ..., 0.1)$. For other subjects, the location of 0.9 will change accordingly. Namely, for subject i ($i = 1, ..., 9$) the ith entry of the output units is 0.9 while the rest is all 0.1. This 1-of-n output encoding increases the representation freedom of the network, and often works well in practice [15]. For MTL, two more units are added to the output layer, which respectively correspond to the tasks of imaging left and right index finger movements. The same encoding mechanism is applied to these two units.

The stopping criterion for neural network training is its performance on a separate validation set whose size is one-ninth of the size of the training set. Levenberg-Marquardt algorithm, a variant of the backpropagation algorithm [15, 16], is used to carry out error minimization over the rest of the training set. After every 50 gradient descent steps, the personal identification performance on the validation set is evaluated. And if it drops down, the neural network will stop training.

With respect to the number of hidden units for STL and MTL neural networks, different numbers from 4 to 20 with an interval of 2 are tried. For each configuration, neural networks are trained five times with different random initializations. The number of hidden units with the highest average performance on the validation set is selected.

3.4. Result

With the selected configuration of hidden units, we run each neural network ten times with different random initializations. Then we can obtain the average accuracy and its standard deviation for personal identification. For STL, EEG signals of imagining left and right index finger movements are separately used and

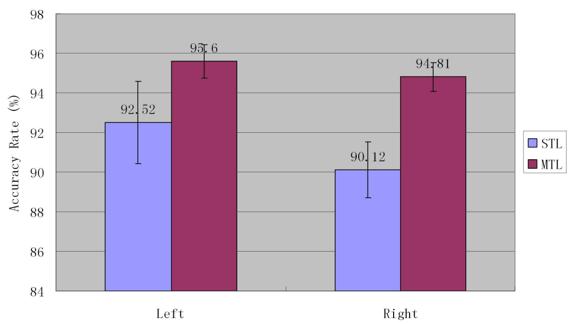

Figure 4. Biometrics results using STL and MTL for imagining left and right index finger movements.

thus two accuracy evaluations are obtained. For MTL, both signals are used for training as indicated earlier in the paper, and to facilitate comparisons the performance of the learned network is tested respectively using each kind of signals.

The results for personal identification are shown in Figure 4, from which we get two conclusions given as follows. 1) Imagining left index finger movements is more appropriate for personal identification. Interestingly, Marcel and Millán got a similar conclusion for personal verification in another context of imaginary hand movements [5]. 2) For the current problem, the performance of MTL is superior to that of STL consistently according to the obtained accuracies and standard deviations.

4. Conclusion

In this paper, the MTL approach to EEG-based biometrics is proposed, whose performance is evaluated by the neural network learner. Compared to the usual STL approach, it brings a large improvement for personal identification. This indicates that simultaneously training related tasks in EEG-based biometrics is effective to bias the induction of the main task. In addition, we also validated a conclusion drawn by other researchers which states that imagination of left hand movements is more effective for biometrics than imagination of right hand movements. Maybe there exists some physiological explanation for this phenomenon.

In the future, investigating the performance of EEG-based biometrics on a large database and the feasibility of combining multiple extra tasks for EEG-based biometrics are worth studying.

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