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Transductive domain adaptive learning for epileptic electroencephalogram recognition

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ABSTRACT

Objective: Intelligent recognition of electroencephalogram (EEG) signals is an important means for epilepsy detection. Almost all conventional intelligent recognition methods assume that the training and testing data of EEG signals have identical distribution. However, this assumption may indeed be invalid for practical applications due to differences in distributions between the training and testing data, making the conventional epilepsy detection algorithms not feasible under such situations. In order to overcome this problem, we proposed a transfer-learning-based intelligent recognition method for epilepsy detection.
Methods: We used the large-margin-projected transductive support vector machine method (LMPROJ) to learn the useful knowledge between the training domain and testing domain by calculating the maximal mean discrepancy. The method can effectively learn a model for the testing data with training data of different distributions, thereby relaxing the constraint that the data distribution in the training and testing samples should be identical.
Results: The experimental validation is performed over six datasets of electroencephalogram signals with three feature extraction methods. The proposed LMPROJ-based transfer learning method was compared with five conventional classification methods. For the datasets with identical distribution, the performance of these six classification methods was comparable. They all could achieve an accuracy of 90%. However, the LMPROJ method obviously outperformed the five conventional methods for experimental datasets with different distribution between the training and test data. Regardless of the feature extraction method applied, the mean classification accuracy of the proposed method is above 93%, which is greater than that of the other five methods with statistical significance.
Conclusion: The proposed transfer-learning-based method has better classification accuracy and adaptability than the conventional methods in classifying EEG signals for epilepsy detection.

1. Introduction

Epilepsy is one of the most common diseases in human brain that affects a population of 50 million people in the world [1]. It is a transient brain dysfunction phenomenon caused by abnormal brain neurons. There has been increasing interest in the use of intelligent recognition technology for the detection of epilepsy based on electroencephalogram (EEG) signals. It has become an important means for epilepsy detection since many physiological and pathological information in brain can be obtained from the EEG signals.

At present, a variety of intelligent recognition methods [2–7] have been applied to EEG signal identification, including decision tree algorithm (DT) [6], naïve Bayes algorithm (NB) [4,6], support vector machine algorithm (SVM) [3], nearest-mean algorithm (NM) [4], linear discriminant analysis method (LDA) [2,5,7]. Although these existing methods have demonstrated both effectiveness and feasibility for epilepsy detection, they all face a critical challenge – the effectiveness of these methods are dependent on the premise that the training data and testing data are drawn from samples of identical distribution. However, this assumption cannot be satisfied in many practical application scenarios. For instance, when drifting exists between the distributions of the training

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and testing EEG samples, the performance of the conventional intelligent recognition methods would deteriorate significantly.

In fact, the distributions of EEG data collected from both epileptic patients and normal people may vary from time to time depending on multiple factors, such as health status, drug actions and the timing of EEG measurements. Typically, the EEG signals collected can be divided into three classes, including (1) Class 1: EEG signals obtained from healthy people in normal conditions; (2) Class 2: EEG signals derived from epileptic patients during seizure free interval (preictal); and (3) Class 3: EEG signals obtained from epileptic patients during seizure (ictal). The data distribution characteristics of these three classes of signals are somewhat independent. Generally, the conventional recognition methods use the labeled data from the first two classes of signals to build a classification model. If this model is used to identify Class 3 EEG signals, the identification accuracies will decline greatly, and the existing intelligent recognition methods would no longer be appropriate for handling such situations. Hence, an epileptic EEG identification method that is more adaptable to differences in EEG data distributions is needed to meet the challenge.

In this paper, a novel epileptic EEG signal recognition method based on transfer learning is proposed. The method is advantageous in that it allows for differences in distributions between the training and testing data, which greatly improves the adaptation ability of epileptic EEG signal identification. The rest of this paper is organized as follows. In Section 2, classical feature extraction and recognition methods on EEG signals for epilepsy detection are reviewed briefly. In Section 3, the EEG signal recognition classifier based on transfer learning method is proposed. The experimental studies are reported in Section 4, and the conclusion is given in the last section.

2. Related work

2.1. EEG signals processing methods

Identification of epileptic EEG signals is generally divided into two steps. First, feature extraction methods are employed to extract useful features from the original EEG signals. A classifier is then obtained by using the EEG training data, which is subsequently used to classify the testing data of epileptic EEG signals. This section provides a brief review of several classical feature extraction and classification methods that have been widely applied in EEG signals recognition for epilepsy detection.

2.1.1. Feature extraction methods

The major feature extraction methods used for epileptic EEG signals can be divided into three types, namely (1) time-domain analysis, (2) frequency-domain analysis and (3) time-frequency analysis. In time-domain analysis, features are extracted by analyzing the waveform parameters of EEG signals, such as average value of waveform, wave amplitude and wave variance. Spike wave, sharp wave and slow wave in EEG signals can all be reflected in the time domain [10]. For example, Litt et al. used time-domain analysis method to obtain useful features in EEG signals and identified regular pattern of epilepsy seizure [8]. In frequency-domain analysis, features in EEG signals are analyzed in the frequency domain. Power spectrum analysis of EEG signals is performed to transform changes in EEG signal amplitude into changes in EEG signal power so that the variations in brain waves at different frequencies can be directly observed. Feature extraction method for EEG signals based on FFT and principal component analysis has been proposed [9]. Time-frequency analysis is based on the fact that EEG signals do not only contain distinctive features in the time domain but also energy distribution characteristics in the frequency domain. According to the known characteristics of epileptic waveforms, the typical frequency ranges of slow waves, sharp waves and spike waves are 1–2.5 Hz, 5–12.5 Hz, and 13.5–50 Hz, respectively [10]. Wavelet transform method can be used to convert the EEG signals and exactly split them into waves of these three frequency bands. This method provides a convenient way to extract features from the EEG signals and thereby making it a widely used approach for epilepsy detection. Susana et al. applied EEG time-frequency analysis to identify the characteristics in the frequency bands of EEG signal and studied the dynamic changes and time evolution [11]. Besides, a modified fast wavelet transform method was proposed to achieve high computational speed and improve accuracy [12].

2.1.2. Classification methods

Many intelligent classification methods have been applied for the identification of epileptic EEG signals since 1990s [13–20]. A brief introduction of the commonly used methods is given as follows. (1) *Support vector machine*: SVM is an effective tool for solving pattern recognition and function estimation problems [3]. It is particularly useful for classification involving small size and high dimension datasets, and has been widely used in epileptic EEG intelligent detection [13]. (2) *Decision tree*: Decision tree and rules for classification are generated by processing the training data using induction method. The testing data are then classified by using the obtained decision tree and the rules. Decision tree classifiers have been used for the recognition of EEG signals with features extracted by Fast Fourier Transform [14]. (3) *Naïve Bayes algorithm*: The algorithm is derived from the Bayes theorem in probability theory. Automatic detection of spike waves between epileptic periods has been realized by using a data mining model based on NB [15]. (4) *Linear discriminant analysis*: While LDA is a classical and widely used feature extraction method, it can be further exploited for classification [16]. For EEG signals, LDA has been used for feature extraction and identification by employing the extracted features as new features for classification [17]. (5) *Nearest mean algorithm*: NM is a well-known algorithm that has been used in classification problems involving high dimensional data [18,19]. It has been successfully applied for the detection of epileptic EEG spikes [20].

2.2. Challenges for the conventional methods

The existing intelligent recognition methods described above have achieved success in applications concerning epileptic EEG detection, demonstrating a high level of classification accuracy and validity. However, all these methods are based on the same assumption that the training data and testing data are originated from samples of identical distribution. When the training and testing datasets are acquired from different, yet related distributions, the performance of these conventional methods would degrade significantly. In order to tackle this challenge, this paper proposes a more adaptive identification algorithm for epileptic EEG signals based on transfer learning technology.

3. Epileptic EEG signal recognition based on transfer learning

3.1. Transfer learning technology

Conventional classification methods employ a large amount of labeled training data to obtain a decision function which is then applied to categorize the unlabeled test samples. These classification methods are all based on the premise that the training data and testing data have the same distribution. When the distribution characteristics of EEG signal samples do not meet this requirement, satisfactory classification results could not be achieved with the conventional methods. In recent years, transfer learning is being