Transfer Components Between Subjects for EGG-based Driving Fatigue Detection

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Abstract. In this paper, we first build up an electroencephalogram (EEG)-based driving fatigue detection system, and then propose a subject transfer framework for this system via component analysis. We apply a subspace projecting approach called transfer component analysis (TCA) for subject transfer. The main idea is to learn a set of transfer components underlying source domain (source subjects) and target domain (target subjects). When projected to this subspace, the difference of feature distributions of both domains can be reduced. Meanwhile, the discriminative information can be preserved. From the experiments, we show that the TCA-based algorithm can achieve a significant improvement on performance with the best mean accuracy of 77.56%, in comparison of the baseline accuracy of 66.56%. The improvement shows the feasibility and efficiency of our approach for subject transfer driving fatigue detection from EEG.

Keywords: EEG, Driving Fatigue Detection, Transfer Learning, Domain Adaptation

1 Introduction

Among all the driving accidents, driving fatigue is believed to be the most significant one [1]. When people feel tired, the ability to maintain essential vigilance and avoid accidents gets worse. In this case, to develop an efficient method for detecting drivers' fatigue during driving is an essential issue for many transportation safety researchers. Up till now, various methods have been studied to analyze fatigue status during driving. Among them, EEG is believed to be the most reliable one [2].

To present, most machine learning based Brain-Computer Interface systems [3] rely on a calibration session to train the models. This calibration is time-consuming for real world applications [4]. The intuitive approach is to train the classifiers on a set of collected data from the previous experiments and then

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make prediction on the unseen data from a new subject. However, it becomes technically difficult as the nonstationary nature of EEG signals and the variance of environment enlarges the distribution difference between subjects. Traditional machine learning methods assume that the training data and test data follow the same distribution and they have the same feature space [5]. However, this assumption can not be always satisfied between different subjects for EEG-based driving fatigue detection.

Domain adaptation, one of the branches of transfer learning, is feasible to address this problem. Here, we introduce a domain adaptation method to driving fatigue detection across subjects. Let $X \in \mathcal{X}$ be the feature space and $y \in \mathcal{Y}$ be the corresponding drivers' fatigue labels. In this case, $\mathcal{X} = \mathbb{R}^{C \times d}$, where C is the number of samples and d is the number of feature dimensions. Let $P(X)$ be the marginal probability distribution of X. In our case, the source and target subjects share the same feature space, $\mathcal{X}_S = \mathcal{X}_T$, but the marginal distributions are different, $P(X_S) \neq P(X_T)$. The key assumption in most domain adaptation methods is that $P(Y_S|X_S) = P(Y_T|X_T)$.

The major problem for subject transfer is how to reduce the difference between the distributions of the source and target subject data. In this paper, we introduce a feature reduction based transfer learning method called transfer component analysis (TCA) [6] to subject transfer driving fatigue detection from EEG. Although the distributions of source domain and target domain in high dimensional space are different, there still exist a low dimensional manifold space where the distributions of both domains are similar [7]. TCA tries to learn a set of common transfer components underlying both domains. When projected to this subspace, the difference of feature distributions of both domains can be reduced, and at the same time, the discriminative information can be preserved. There exists a transformation function $\phi(.)$ such that $P(\phi(X_S)) \approx P(\phi(X_T))$ and $P(Y_S|\phi(X_S)) \approx P(Y_T|\phi(X_T))$. We demonstrate that TCA can be used to improve the performance of driving fatigue detection system for subject transfer from EEG.

This paper is organized as follows. In Section II, a systematic description of feature extraction and TCA method is given. Section III describes the fatigue driving simulation experiment, the data collection and pre-processing, the fatigue measurement by PERCLOS rule, as well as the parameters we used for data processing. In Section IV, we compare the performance of the proposed method with that of the baseline. Finally, in Section V, we make conclusion and future work.

2 Algorithm Description

2.1 Feature Extraction

The raw EEG data is firstly downsampled to 200Hz in order to reduce computing complexity. After that, the EEG data is processed with a bandpass filter between 0.3Hz and 60Hz in order to filter the noise and artifacts. Each channel of EEG data is divided into 10s segments without overlapping.

The existing studies indicate that differential entropy (DE) features can achieve better performance than conventional EEG features such as power spectral density [8]. Thus, we employ the DE features in this study. If a random variable obeys the Gaussian distribution $N(\mu, \sigma^2)$, the DE can simply be calculated by the following formulation,

$$\begin{aligned} h(X) &= -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\frac{(x-\mu)^2}{2\sigma^2} \log \frac{1}{\sqrt{2\pi\sigma^2}} \exp\frac{(x-\mu)^2}{2\sigma^2} dx \\ &= \frac{1}{2}\log 2\pi e\sigma^2. \end{aligned} \tag{1}$$

For a fixed length EEG segment, DE is proven to be equivalent to the logarithm energy spectrum in a certain frequency band [9]. Then, we choose the differential entropy of each frequency band and each channel as features. The choice of frequency bands and channels are discussed in Section 3.4.

2.2 Transfer Component Analysis

The major computational problem in transfer learning is how to reduce the difference between the distributions of the source and target domain data. As the feature distributions of different subjects cannot be ignored, discovering a good feature representation across domains is crucial.

As mentioned in Section I, we need to find a transformation $\phi(.)$ such that $P(\phi(X_S)) \approx P(\phi(X_T))$ and $P(Y_S|\phi(X_S)) \approx P(Y_T|\phi(X_T))$. Since we have no labeled data of target subject, $\phi(.)$ cannot be learnt through minimizing the distance between $P(Y_S|\phi(X_S))$ and $P(Y_T|\phi(X_T))$. Pan et al. [6] proposed an efficient approach called transfer component analysis to learn $\phi(.)$.

Let Gram matrices defined on the source domain, target domain and cross-domain data in the embedded space be $K_{S,S}$, $K_{T,T}$, $K_{S,T}$ and $K_{T,S}$, respectively. The kernel matrix K is defined as

$$K = \begin{bmatrix} K_{S,S} & K_{S,T} \\ K_{T,S} & K_{T,T} \end{bmatrix} \in \mathbb{R}^{(n_1+n_2)\times(n_1+n_2)}. \tag{2}$$

By the virtue of kernel trick, the distribution distance can be written as $tr(KL)$, where $K = [\phi(x_i)^T\phi(x_j)]$, and L is defined as

$$L_{ij} = \begin{cases} \frac{1}{n_1^2}, & x_i, x_j \in X_S \\ \frac{1}{n_2^2}, & x_i, x_j \in X_T \\ -\frac{1}{n_1 n_2}, & otherwise \end{cases}. \tag{3}$$

A matrix $\widetilde{W} \in \mathbb{R}^{(n_1+n_2)\times m}$ transforms the empirical kernel map K to an m-dimension space (where $m \ll n_1 + n_2$). The resultant kernel matrix is

$$\widetilde{K} = (KK^{-1/2}\widetilde{W}(\widetilde{W}^T K^{-1/2}K)) = KWW^TK, \tag{4}$$

where $W = K^{-1/2}\widetilde{W}$. With the definition of $\widetilde{K}$ in (4), the distance between empirical means of the two domain $X_S^{'}$ and $X_T^{'}$ can be written as

$$Dist(X_S^{'}, X_T^{'}) = tr((KWW^TK)L) = tr(W^TKLKW). \tag{5}$$

A regularization term $tr(W^TW)$ is usually added to control the complexity of W, while minimizing (5).

Besides reducing the difference of the two distributions, $\phi(.)$ should also preserve the data variance which is related to the target learning task. From (4), the variance of the projected samples is W^TKHKW, where $H = I_{n_1+n_2} - \frac{1}{n_1+n_2}\mathbf{1}\mathbf{1}^T$ is the centering matrix, $\mathbf{1} \in \mathbb{R}^{n_1+n_2}$ is the column vector with all 1s and $I_{n_1+n_2}$ is the identity matrix.

Therefore, the objective function of TCA is

$$\begin{aligned} \min_W \quad & tr(W^TKLKW) + \mu tr(W^TW) \\ s.t. \quad & W^TKHKW = I_m \end{aligned} \tag{6}$$

where $\mu > 0$ is a tradeoff parameter, and $I_m \in \mathbb{R}^{m\times n}$ is the identity matrix.

According to [6], the solutions W are the m leading eigenvectors of $(KLK + \mu I)^{-1}KHK$, where $m < n_1 + n_2$. The algorithm of TCA for subject transfer is summarized in Algorithm 1. The detailed descriptions of TCA can be refered to [6]. After obtaining the transformation matrix W, standard machine learning methods can be used in the subspace KW across domains.

Algorithm 1 TCA-based Subject Transfer

Input: Source domain data set $\mathcal{D}_S = \{(x_{S_i}, y_{src_i})\}_{i=1}^{n_1}$ and the target domain data set $\mathcal{D}_T = \{x_{T_j}\}_{j=1}^{n_2}$;

Output: New feature matrix Φ;

1: Construct kernel matrix K from $\{x_{S_i}\}_{i=1}^{n_1}$ and $\{x_{T_j}\}_{j=1}^{n_2}$, matrix L and centering matrix H;

2: Eigendecompose the matrix $(KLK + \mu I)^{-1}KHK$ and select the m ($m \ll n_1 + n_2$) leading eigenvectors to construct the transformation matrix W;

3: **return** transformation matrix $\Phi = KW$.

3 Experimental Setup

3.1 Subjects and Procedure

In order to collect EEG data under different mental states, subjects are asked to drive in a car in a simulated driving environment. The experimental scene is shown in Fig. 1. A NeuroScan4.3 system is used to collect the original EEG data and the SMI eye tracking glasses are set for eye closure data. All the actions of each subject are recorded in each section in order to guarantee the appearance of both fatigue and wake period. Six healthy subjects of 20-23 years old in total have participated in this experiment. Before each session, the subjects have a short time to be acquainted with the driving simulation system. Each subject has performed three experiments on different days. Each of the experiments is carried out about 1h and 30min in a quiet and comfortable room with normal illumination.

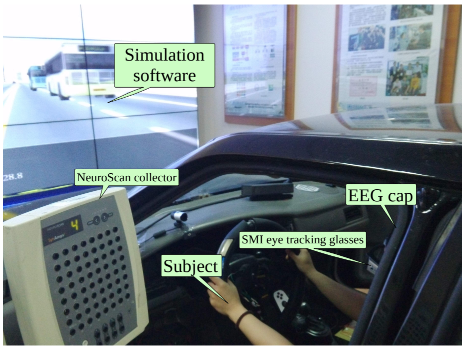

Fig. 1. The experimental scene

3.2 Data Collection and Pre-processing

For each experiment, a total of 62 EEG channels are recored and sampled at 1000Hz. Then, the original data is down-sampled to 200Hz to reduce computational complexity and filtered between 0 and 60 Hz to eliminate some artifacts. The 1h 30min sequence of each experiment is divided with a 10s windows, and thus get nearly 540 fragments for each experiment.

3.3 Feature Smooth

As driving fatigue is a relatively stable variable, the sudden changes of feature values are mostly caused by noisy and artifact, especially for the artifact caused by electromyography (EMG). Moving Average algorithm is used to choose the average value of a successive sequence as the value of a certain point. By using the Moving Average algorithm, the sudden changes caused by artifact can be removed.

3.4 Feature Extraction

Although we have 62 channels of EEG data collected, not all these channels are related to fatigue. Some unrelated signals may disturb the detection of fatigue. According to [10] [11], occipital lobe region has strong relation with fatigue status. Fig. 2(a) shows the chosen channels.

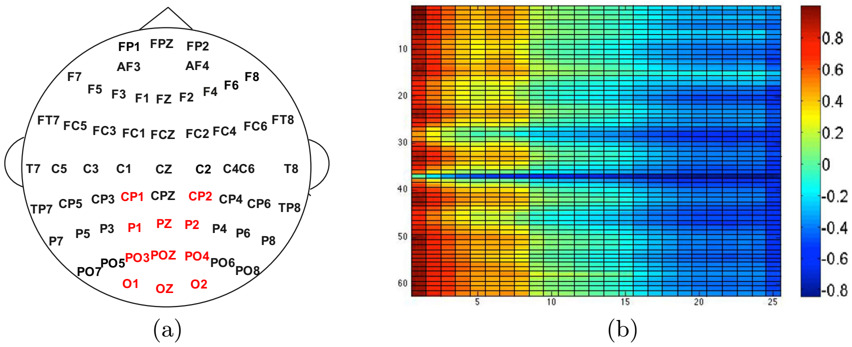

Fig. 2. The chosen channels in occipital lobe region (a), and the power spectrum in relation to 62 channels and 25 frequency bands (b).

We extract the DE features in twenty-five frequency bands (1-2Hz, 2-4Hz,..., 48-50Hz), rather than the normal five frequency bands, with a 2048 point short-time fourier transform. The existing studies show that the increased number of frequency bands has a benefit of preserving more information of EEG signals [12]. From Fig. 2(b), we can see that, the power of adjacent frequency bands shows dynamic differences for different mental states. In contrast, the rough five frequency bands-separation will lose some important information.

3.5 Fatigue Measurement

Along with the EEG data, the eye closure data is recorded by the SMI eye tracking glasses. The glasses use infrared lighting sources to track the eye gaze and eye movements [13]. Then, the information of eye movement is used to calculate the proportion of time that a subject's eyes are closed over a specified period, namely the PERCLOS value. According to the existing work [14], we set the threshold to be 0.75. If the PERCLOS value is above 0.75, the subject is considered in fatigue state. Otherwise, it corresponds to normal state.

3.6 Detailed Parameters for Training

Here, we present the details about the parameters for training and the baseline for comparison. For baseline method of subject transfer for driving fatigue detection, a straightforward and intuitive method is to concentrate all the data of all the subjects and employ the leave-one-subject-out cross validation. We employ support vector machine with 'RBF' kernel as the classifiers.

For TCA, there are three parameters, kernel parameter σ, parameter μ, and the dimensionality of latent space D. We fix two parameters and adjust the remaining parameter one by one to find out the optimal three values. We first set $\mu = 1, m = 10$ and search for the best σ value in the range $[10^{-5}, 10^{5}]$. Afterwards, we set μ and m in the same manner as TCA. The range of searching for μ and m are $[10^{-3}, 10^{3}]$ and $[3, 220]$ respectively. After the searching process, the optimal parameter combination is $\sigma = 100, \mu = 2$ and $m = 7$.

4 Experiment results

From our parameter searching results, we observe that TCA-based subject transfer algorithm is a parameter-stable algorithm. The valus of σ and μ influence little on the results. For the dimension m, this value has great effect on the result. If m is too big, the transferred feature matrix involves too much redundant features. Meanwhile, if m is too small, it contains little useful information. As a result, $m = 7$ is the best dimension for our driving fatigue detection problem.

From Fig. 3, we see that TCA-based SVM performs much better than conventional SVM for our 18 experiments. In experiment 1, 2, 8, TCA-based subject transfer does not show great improvements compared to the baseline as the noise in original EEG is strong. Even in experiment 8, there are two bad electrodes after the whole process. But for others, when the inherent structure of EEG data is good, the TCA gets more significant improvement. After eliminating the data of experiment 1, 2, 8, the improvement grows up to 10.46% from the conventional SVM (66.56%) to TCA-SVM (77.02%).

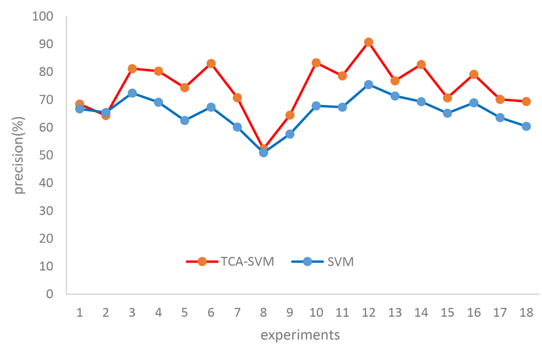

Fig. 3. The comparison of TCA-based framework and SVM

5 Conclusion and Future Work

In this paper, we have proposed a subject transfer framework for EEG-based driving fatigue detection via shared common components. We have introduced a domain adaptation method called TCA to address the structural and functional variability across subjects. This method can learn transfer components in a low-dimensional latent space from the source domain and target domain. Meanwhile, we present our experiment details for driving fatigue detection. The experimental results show that TCA can achieve a significant improvement of 10.46% in accuracy compared to the conventional method.

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References

1. Steven Nobe, Fei-Yue Wang, et al. An overview of recent developments in automated lateral and longitudinal vehicle controls. In *2001 IEEE International Conference on Systems, Man, and Cybernetics*, volume 5, pages 3447–3452. IEEE, 2001.
2. Christian Cajochen, Sat Bir S Khalsa, James K Wyatt, Charles A Czeisler, and Derk-Jan Dijk. Eeg and ocular correlates of circadian melatonin phase and human performance decrements during sleep loss. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*, 277(3):R640–R649, 1999.
3. Ethan Buch, Cornelia Weber, Leonardo G Cohen, Christoph Braun, Michael A Dimyan, Tyler Ard, Jurgen Mellinger, Andrea Caria, Surjo Soekadar, Alissa Fourkas, et al. Think to move: a neuromagnetic brain-computer interface (bci) system for chronic stroke. *Stroke*, 39(3):910–917, 2008.
4. Matthias Krauledat, Michael Tangermann, Benjamin Blankertz, and Klaus-Robert Müller. Towards zero training for brain-computer interfacing. *PLOS ONE*, 3(8):2967–2976, 2008.
5. Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. *IEEE Transactions on Knowledge and Data Engineering*, 22(10):1345–1359, 2010.
6. Sinno Jialin Pan, Ivor W Tsang, James T Kwok, and Qiang Yang. Domain adaptation via transfer component analysis. *IEEE Transactions on Neural Networks*, 22(2):199–210, 2011.
7. Shai Ben-David, John Blitzer, Koby Crammer, Fernando Pereira, et al. Analysis of representations for domain adaptation. *Advances in neural information processing systems*, 19:137, 2007.
8. Ruo-Nan Duan, Jia-Yi Zhu, and Bao-Liang Lu. Differential entropy feature for eeg-based emotion classification. In *IEEE EMBS Conference on Neural Engineering*, pages 81–84. IEEE, 2013.
9. Li-Chen Shi and Bao-Liang Lu. Eeg-based vigilance estimation using extreme learning machines. *Neurocomputing*, 102:135–143, 2013.
10. Ruben Kuzniecky. Symptomatic occipital lobe epilepsy. *cortex*, 3(12):13, 1998.
11. Shyh-Yueh Cheng and Hong-Te Hsu. *Mental Fatigue Measurement Using EEG*. INTECH Open Access Publisher, 2011.
12. Ha Truong Ngoc, Thanh Hai Nguyen, and Cuong Ngo. Average partial power spectrum density approach to feature extraction for eeg-based motor imagery classification. *American Journal of Biomedical Engineering*, 3(6):208–219, 2013.
13. Qiang Ji and Xiaojie Yang. Real-time eye, gaze, and face pose tracking for monitoring driver vigilance. *Real-Time Imaging*, 8(5):357–377, 2002.
14. Xiang-Yu Gao, Yu-Fei Zhang, Wei-Long Zheng, and Bao-Liang Lu. Evaluating driving fatigue detection algorithms using eye tracking glasses. In *IEEE EMBS Conference on Neural Engineering*, pages 767–770. IEEE, 2015.