2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) | 979-8-3503-2447-1/23/$31.00 ©2023 IEEE | DOI: 10.1109/EMBC40787.2023.10340605

KL Divergence-based transfer learning for cross-subject eye movement recognition with EOG signals

RuiZhi Su[1] Zheng Zeng[1] LinKai Tao[2] ZaiHao Wang[1] Chen Chen[3] Wei Chen[1,3]

Abstract— **Human-machine interfaces (HMIs) based on Electro-oculogram (EOG) signals have been widely explored. However, due to the individual variability, it is still challenging for an EOG-based eye movement recognition model to achieve favorable results among cross-subjects. The classical transfer learning methods such as CORrelation Alignment (CORAL), Transfer Component Analysis (TCA), and Joint Distribution Adaptation (JDA) are mainly based on feature transformation and distribution alignment, which do not consider similarities/dissimilarities between target subject and source subjects. In this paper, the Kullback-Leibler (KL) divergence of the log-Power Spectral Density (log-PSD) features of horizontal EOG (HEOG) between the target subject and each source subject is calculated for adaptively selecting partial subjects that suppose to have similar distribution with target subject for further training. It not only consider the similarity but also reduce computational consumption. The results show that the proposed approach is superior to the baseline and classical transfer learning methods, and significantly improves the performance of target subjects who have poor performance with the primary classifiers. The best improvement of Support Vector Machines (SVM) classifier has improved by 13.1% for subject 31 compared with baseline result. The preliminary results of this study demonstrate the effectiveness of the proposed transfer framework and provide a promising tool for implementing cross-subject eye movement recognition models in real-life scenarios.**

I. INTRODUCTION

EOG signal is the recording of potential differences between the cornea and retina, which has the ability to reflect eye movements. By recognizing multiple eye movements, various HMI applications based on EOG have been proposed in the literature including digital recognition, quadcopter control, and smart home environment control [1] [2] [3]. However, existing methodologies mainly focus on subject-specific eye movement recognition and are only verified via k-folds cross-validation, failing to achieve favorable performance among cross-subjects. For example, there was only one subject in [4], and k-folds cross-validation was used in [1] [5]. Despite these studies having achieved favorable performance in intra-subject eye movement recognition, it can be outdated when the model is applied to a new subject. This performance compromise indicates the necessity of adapting the cross-subjects variations when a new subject occurs. In practice, many factors can lead to individual variability including individual specific, current activity, level of stress, tiredness, etc. [6] [7]. These factors may bias the data distribution for model training, thus further hindering performance. In essence, the cross-subject problems can be regarded as domain shift issues. Recently, many studies have tried to align the source domain and target domain, improving the cross-subject performance in practical applications. Specifically, J. Li, et al. used the accuracy of k classifiers to metric the similarities between target subject and k source subjects, and used the Style Transfer Mapping (STM) to reduce the difference. Although the performance improved by 12.72%, the computation was expensive and the method needs labeled target data [8]. A. M. Azab, et al. used the KL Divergence to modify the parameters of the classifier to improve the performance [9], but the method used the data of all existing subjects to train the model and was strong coupled with classifier. Inspired by these studies, the performance of cross-subject eye movements classification can also be improved by aligning source and target domains.

In this paper, a Kullback-Leibler (KL) divergence-based approach to improve the cross-subject performance of eye movement recognition is proposed. It automatically selects partial subjects who suppose to have similar distributions to the target subject from the source domain. Thus, for each target subject, a dedicated training dataset will be generated, and via this training dataset, it can maximize the contributions of similar subject data and minimize the negative effect of dissimilar subject data. K-Nearest Neighbor (KNN),SVM, and Random Forests (RF) are used as the primary classifiers to get the baseline performance. Then, the proposed method is compared with three classical transfer learning methods, namely, CORAL, TCA, and JDA. The leave-one-subject-out cross-validation on 50 subjects demonstrates a performance improvement compared with baseline and classical transfer learning methods.

The rest part of the paper is organized as follows. Section II introduces the dataset, data pre-processing, and features extraction. Section III describes the methods used in this paper. Section IV presents the results. Section V provides

*This work was supported in part by Shanghai Municipal Science and Technology International R&D Collaboration Project (Grant No.20510710500), and in part by the National Natural Science Foundation of China under Grant No.62001118.

[1]RuiZhi Su, Zheng Zeng, and ZaiHao Wang are with the Center for Intelligent Medical Electronics, Department of Electronic Engineering, School of Information Science and Technology, Fudan University, Shanghai 200433, China (e-mail: 21210720218@m.fudan.edu.cn; zceng20@fudan.edu.cn; zhwang20@fudan.edu.cn).

[2]LinKai Tao is with the Department of Industrial Design, School of Industrial Design, Eindhoven University of Technology, Eindhoven 513 5600MB, The Netherlands (e-mail: 148243215@qq.com).

[3]Chen Chen is with Human Phenome Institute, Fudan University, Shanghai 201203, China (e-mail: chenchen_fd@fudan.edu.cn).

[1,3]Wei Chen is with the Center for Intelligent Medical Electronics, Department of Electronic Engineering, School of Information Science and Technology, Fudan University, Shanghai 200433, China, and also with Human Phenome Institute, Fudan University, Shanghai 201203, China (e-mail: w_chen@fudan.edu.cn).

TABLE I
FEATURES FOR CLASSIFICATION

No	Features	Abbreviation
1	Power Spectral Density (1-20Hz)	PSD (1-20Hz)
2	Energy	-
3	Variance	Var
4	Mean value	Mean
5	Maximum value	Max
6	Minimum value	Min
7	Nonlinear energy	NLE
8	Kurtosis	Kurt
9	Area under curve	AUC
10	Root mean square	RMS
11	Form factor	FF
12	Crest factor	CF

the conclusions of the paper.

II. MATERIALS

A. Dataset

The dataset used in this paper was EEG eye artifact dataset, which was collected from five sub-studies, with a total of 50 participants and 59 recordings. The dataset includes HEOG signals and vertical EOG (VEOG) signals, which have been pre-processed by a notch filter with 49Hz and 51Hz cut-off frequencies along with a 0.4Hz high-pass filter (2nd Butterworth filter) [10]. According to the experiment protocol, subjects were asked to perform 5 types of eye movements including upward eye movement, downward eye movement, rightward eye movement, leftward eye movement and blink. The details of the dataset can refer to the GitHub (https://github.com/rkobler/eyeartifactcorrection).

B. Data Pre-processing and Features Extraction

1) Data Pre-processing: Since the EOG data from five studies were sampled with different sampling rates. We first downsampled the data to 100Hz. Then, according to the label of five kinds of eye movements, the HEOG and VEOG were intercepted and each eye movement was divided into a 1s sample.

2) Features Extraction: As shown in Tab. I, we extracted 12 kinds of temporal and spectral features for eye movement recognition [1] [11]. As for the PSD, we used the Welch's method to estimate the PSD (segment length=10, overlapped samples=5, and window=Hamming window). We further selected the PSD from 1Hz to 20Hz to construct the spectral features, which are also the main frequency of eye movements. We also used the total energy of segmented signals as an alternate spectral feature.

III. METHODOLOGY

Subject-transfer approaches transfer the labeled training data of existing subjects to a new subject with limited unlabeled data. The underlying assumption is that individual differences will minor if their have comparable EOG responses to the same kind of eye movement. Because of the high dimensionality of EOG signals, it is challenging to identify the subject similarity. To effectively measure the subject similarity, in this paper, KL divergence based on the log-PSD features of HEOG was used.

Given two distributions presented as $Q(x)$ and $P(x)$, the definition of KL divergence is carried out by Equation (1).

$$KL(Q||P) = \sum_i Q(i) log \frac{Q(i)}{P(i)} \tag{1}$$

When the two distributions are normal distributions presented as $N_0(\mu_0, \sum_0)$ and $N_1(\mu_1, \sum_1)$, the KL divergence can be calculated as the Equation (2).

$$\begin{aligned} KL(N_0||N_1) &= 0.5\big[(\mu_1 - \mu_0)^T \Sigma_1^{-1} (\mu_1 - \mu_0) \\ &+ trace(\Sigma_1^{-1}\Sigma_0) - ln(\frac{det(\Sigma_0)}{det(\Sigma_1)}) - K\big] \end{aligned} \tag{2}$$

Where det, T and K denote the determinant function, transpose of the matrix and the dimension of the data, respectively. The features of EEG signals are commonly assumed normally distributed [16], but it is not the same for EOG signals. According to the experiment, the Kurt of log-PSD of HEOG from 1Hz to 20Hz are about 3, so they can be assumed normally distributed, but the features of VEOG not.Thus, in this paper, we used the PSD of HEOG to calculate the KL divergence between target subject and each source subject by Equation (2). First, the PSD features of HEOG were processed by log function and Principal Component Analysis (PCA) algorithm for each subject, and preserved 4 main components for 95% of the explained variance. Second, we calculated the KL divergence between the target subject and each source subject based on the components. Third, we selected similar subjects from source subjects to construct the new training set according to the KL divergence. Finally, the recognition was performed by the primary classifiers based on the new training set with features in Tab. I. The structure of the KL divergence-based transfer learning framework is shown in Fig. 1.

IV. RESULTS AND DISCUSSION

A. Baseline Results

In this paper, we used KNN, SVM, and RF as the primary classifiers to classify the five kinds of eye moments. The

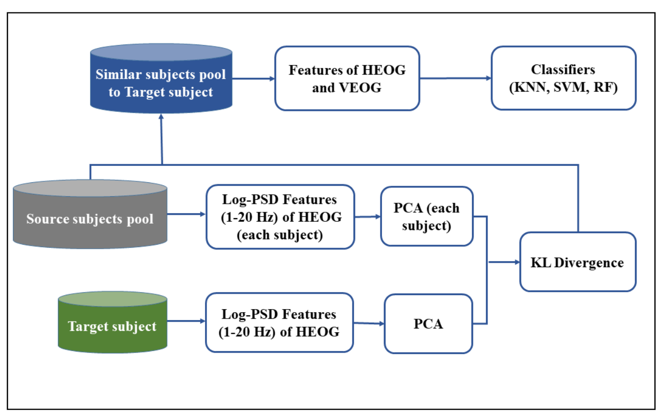

Fig. 1. The flowchart of KL Divergence-based transfer learning for cross-subject eye movement recognition with EOG signals.

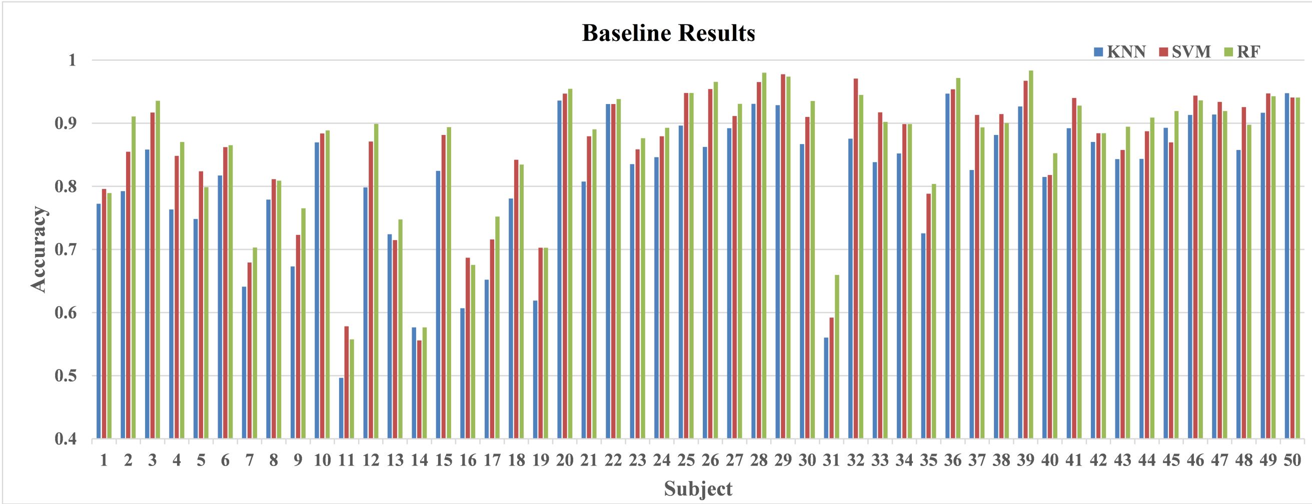

Fig. 2. The accuracy of each subjects based on primary classifiers

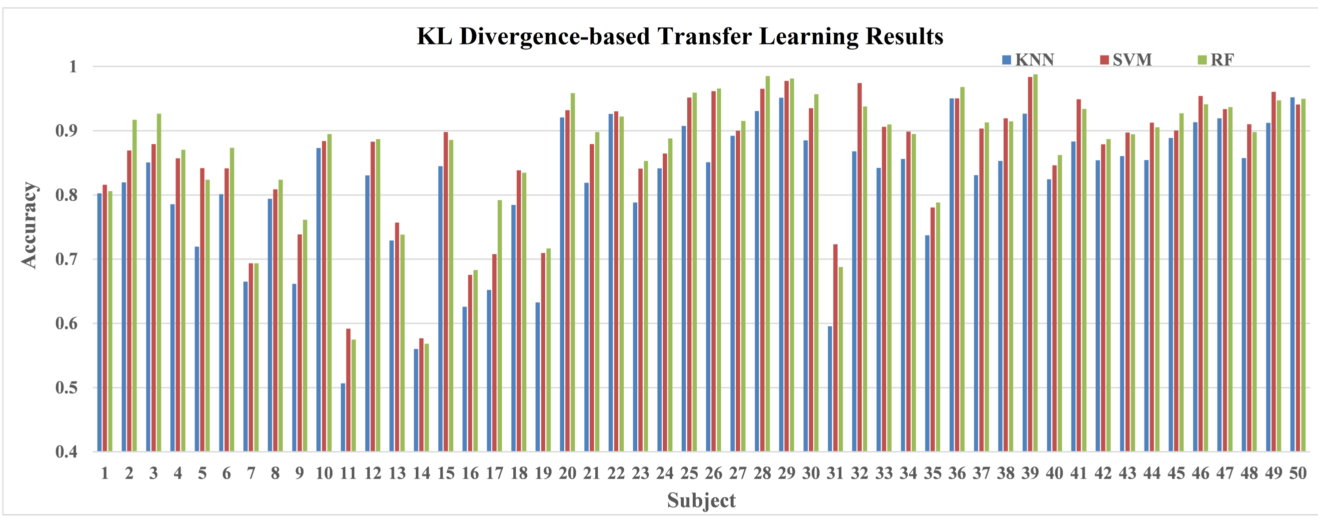

Fig. 3. The accuracy of each subject based on KL Divergence-based transfer learning method

TABLE II
THE PERFORMANCE OF THREE CLASSICAL TRANSFER LEARNING METHODS

Methods	Average Accuracy	Methods	Average Accuracy	Methods	Average Accuracy
KNN-CORAL	74.0%	**SVM-CORAL**	73.1%	**RF-CORAL**	61.5%
KNN-TCA	78.1%	**SVM-TCA**	80.0%	**RF-TCA**	83.8%
KNN-JDA	79.6%	**SVM-JDA**	81.0%	**RF-JDA**	84.4%
KNN-Our	**81.7%**	**SVM-Our**	**86.3%**	**RF-Our**	**86.9%**

cross-subject validation was used to evaluate the model performance, and the average accuracy was obtained by Equation (3). The average accuracy of KNN, SVM and RF is 81.3%, 85.6%, and 86.5%, respectively. The accuracy of each subject are shown in Fig. 2. The results of SVM and RF model are superior to the KNN model. Subject 7, 11, 14 and 31 have poor performance.

$$AverageAccuracy = \frac{\sum_i Accuracy(subject(i))}{50} \quad (3)$$

B. Results of Classical Transfer Learning Methods

Regarding the domain shift of EOG signals, domain adaption methods can be used to improve the performance of the models. In this experiment, we used the data of 49 subjects as source domain and data of the remaining subject as target domain. The recognition was performed by three feature-based domain adaptation methods: CORAL, TCA, and JDA. The goal of CORAL is to align the second-order statistics of the source and target domains which aims to learn a matrix that minimizes the distance between the source domain and the target domain [12]. The goal of TCA is to find a projection with the minimum Maximum mean discrepancy (MMD) [13] of the source domain and target domain in a reproducing kernel Hilbert space [14]. JDA aims to minimize the MMD distance of marginal distribution and conditional distribution between source domain and target domain [15].

Recognition was performed by the three primary classifiers combined with three kinds of classical transfer learning methods. The average accuracy is shown in Tab. II. Compared with the baseline results, the results of classical transfer learning methods all present negative transfer.

C. Results of KL Divergence-based Transfer Method

We select 38 closest subjects for KNN, 23 closest subjects for SVM and 35 closest subjects for RF to construct the new training set. Finally, the recognition was performed by the primary classifiers based on the new training set with features in Tab. I, the average accuracy of KNN, SVM and RF is 81.7%, 86.3% and 86.9%, respectively. The accuracy of each subject are showed in the Fig. 3. Compared with the baseline results, the average accuracy has increased by 0.4%, 0.7% and 0.4% for KNN, SVM and RF, respectively. Compared with the TCA method, the average accuracy has increased by 3.6%, 6.2% and 3.1% for KNN, SVM and RF, respectively. Compared with the JDA method, the average accuracy has increased by 2.1%, 5.3% and 2.5% for KNN, SVM and RF, respectively. Especially for subject who has the poor performance, SVM improved by 1.4%, 1.4%, 2.1%, and 13.1% for subject 7, 11, 14 and 31 compared with baseline result, respectively. Because the new training set was constructed by selected subject, the computation was reduced significantly compared to the original training set. And, the selected subjects were closed to the target subject, which can take full advantage of similar distribution to improve the performance, especially for subjects who have the poor performance in baseline. However, the number of selected subjects was obtained by sequential selection.

To our best knowledge, this is the first study to improve the cross-subject performance of eye movement recognition via subject transferring. With the preliminary results, the proposed method can effectively enhance the performance for cross-subject and exhibit the great potential for real applications.

V. CONCLUSIONS

In this paper, we proposed a novel KL divergence-based transfer learning approach for the recognition of eye movement. Our approach takes the advantage of using similar source subjects to train the model robustly. Hence, it can maximize the contribution of similar source domains to adapt the cross-subject variations. Compared with the baseline results, the average accuracy has increased by 0.4%, 0.7% and 0.4% for KNN, SVM and RF, respectively. Compared with the TCA method, the average accuracy has increased by 3.6%, 6.2% and 3.1% for KNN, SVM and RF, respectively. Compared with the JDA method, the average accuracy has increased by 2.1%, 5.3% and 2.5% for KNN, SVM and RF, respectively. Since the similarities were considered, the proposed method is superior to classical methods, and the computational consumption decrease. The Preliminary results from this paper suggest that the KL divergence-based transfer learning approach is promising for handling the human variability of EOG. In this way, our work can broaden the horizons of current studies on cross-subject eye movement models.

REFERENCES

[1] A. Rakshit, A. Banerjee, and D. N. Tibarewala, "Electro-oculogram based digit recognition to design assitive communication system for speech disabled patients.", in 2016 International Conference on Microelectronics, Computing and Communications (MicroCom), pp. 1–5, Jan. 2016.

[2] S. Milanizadeh and J. Safaie, "EOG-Based HCI System for Quadcopter Navigation.", IEEE Transactions on Instrumentation and Measurement, vol. 69, no. 11, pp. 8992–8999, 2020.

[3] R. Zhang et al., "An EOG-Based Human–Machine Interface to Control a Smart Home Environment for Patients With Severe Spinal Cord Injuries.", IEEE Transactions on Biomedical Engineering, vol. 66, no. 1, pp. 89–100, Jan. 2019.

[4] B. O'Bard and K. George, "Classification of eye gestures using machine learning for use in embedded switch controller.", in 2018 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), pp. 1–6, May 2018.

[5] E. Dong, C. Li, and C. Chen, "An EOG signals recognition method based on improved threshold dual tree complex wavelet transform.", in 2016 IEEE International Conference on Mechatronics and Automation, pp. 954–959 Aug. 2016.

[6] J. R. Davis and B. Shackel, "Changes in the electro-oculogram potential level.", The British Journal of Ophthalmology, 44(10): 606, 1960.

[7] M. Liu, H. Zhu, J. Tang, H. Chen, C. Chen, J. Luo, and W. Chen, "Overview of a Sleep Monitoring Protocol for a Large Natural Population.", Phenomics, 2023.

[8] J. Li, S. Qiu, Y.-Y. Shen, C.-L. Liu, and H. He, "Multisource Transfer Learning for Cross-Subject EEG Emotion Recognition.", IEEE Transactions on Cybernetics, vol. 50, no. 7, pp. 3281–3293, Jul. 2020.

[9] A. M. Azab, L. Mihaylova, K. K. Ang, and M. Arvaneh, "Weighted Transfer Learning for Improving Motor Imagery-Based Brain–Computer Interface.", IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 7, pp. 1352–1359, Jul. 2019.

[10] P. Sawangjai, et al., "EEGANet: Removal of Ocular Artifacts From the EEG Signal Using Generative Adversarial Networks.", IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 10, pp. 4913–4924, Oct. 2022.

[11] J. F. Wu, et al., "Efficient Implementation and Design of a New Single-Channel Electrooculography-Based Human–Machine Interface System.", IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 62, no. 2, pp. 179–183, Feb. 2015.

[12] B. Sun, J. Feng, and K. Saenko, "Return of Frustratingly Easy Domain Adaptation.", arXiv, Dec. 09, 2015. Accessed: Feb. 05, 2023.

[13] A. Gretton, K. Borgwardt, M. Rasch, B. Scho¨lkopf, and A. Smola, "A Kernel Method for the Two-Sample-Problem.", in Advances in Neural Information Processing Systems, 2006, vol. 19. Accessed: Feb. 05, 2023.

[14] S. J. Pan, I. W. Tsang, J. T. Kwok, and Q. Yang, "Domain Adaptation via Transfer Component Analysis.", IEEE transactions on neural networks, 22(2): 199-210, 2010.

[15] M. Long, J. Wang, G. Ding, J. Sun, and P. S. Yu, "Transfer Feature Learning with Joint Distribution Adaptation.", in 2013 IEEE International Conference on Computer Vision, Sydney, Australia, pp. 2200–2207, Dec. 2013.

[16] W. Samek, M. Kawanabe, et al., "Divergence-Based Framework for Common Spatial Patterns Algorithms.", IEEE Reviews in Biomedical Engineering, vol. 7, pp. 50–72, 2014.