2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Online Cross-subject Emotion Recognition from ECG via Unsupervised Domain Adaptation

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***Abstract*— Performing cross-subject emotion recognition (ER) using electrocardiogram (ECG) is challenging, since inter-subject discrepancy (caused by individual differences) between source and target subjects (new subjects) may hinder the generalization for new subjects. Recently, some ER methods based on unsupervised domain adaptation (UDA) are proposed to address inter-subject discrepancy. However, when being applied for online scenarios with time-varying ECG, existing methods may suffer performance degradation due to neglecting intra-subject discrepancy (caused by time-varying ECG) within target subjects, or need to re-train ER model, leading to time-and resource-consuming. In the paper, we propose an online cross-subject ER approach from ECG signals via UDA, consisting of two stages. In a training stage, we propose to train a classifier on a shared subspace with a lower inter-subject discrepancy. In an online recognition stage, an online data adaptation (ODA) method is introduced to adapt time-varying ECG via reducing the intra-subject discrepancy, and then online recognition results can be obtained by the trained classifier. Experimental results on Dreamer and Amigos with emotions of valence and arousal demonstrate that our proposed approach improves the classification accuracy by about 12% compared with the baseline method, and is robust to time-varying ECG in online scenarios.**

I. INTRODUCTION

Emotion recognition (ER) is an evolving direction in the human-machine interaction [1]. In many real-life applications, to meet the real-time requirements, there is a need to recognize emotions in an online manner. For example, mastering a patient's emotional state in time is helpful for the psychiatrist to monitor the patient's mental health status. Electrocardiogram (ECG)-based ER has gathered increasing attention due to the rapid development of inexpensive and wearable ECG recording devices [2]–[5].

For ER using ECG, the individual differences make it difficult to acquire a general ER model that can be across subjects [6]. The individual differences (such as personality) may cause a inter-subject discrepancy between source and target subjects, which may hinder the generalization of ER models for new subjects. The conventional method is to develop a subject-dependent model which trains a new model for a new subject using labeled data [2], [7], yet labeled data is costly to collect [8], [9].

This work is supported in part by a grant from the National Natural Science Foundation of China (No. 61976047), in part by grants from the Science & Technology Department of Sichuan Province of China (No. 2020YFG0087, 2020YFG0326 and 2021YFG0331), in part by a grant from the Fundamental Research Funds for the Central Universities (No. ZYGX2021YGLH016), and in part by a grant from the Open Innovation Fund of 55 Institute of China North Industries Group.

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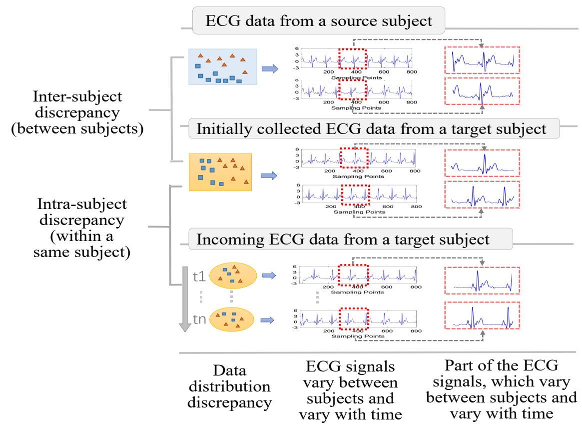

Fig. 1. Example showing inter-subject and intra-subject discrepancies. Because of individual differences, ECG morphology varies between subjects, resulting in inter-subject discrepancy. Due to the nonstationarity of ECG, ECG morphology varies with time, leading to intra-subject discrepancy.

Recently, some ER methods proposed to address inter-subject discrepancy by unsupervised domain adaptation (UDA), which personalized a general ER model for new subjects in an unsupervised way with knowledge transfer from source subjects [10]–[12]. For example, Zheng *et al.* [10] suggested to exploit transfer component analysis (TCA) [13] to learn a shared subspace where the difference between subjects is reduced. In this way, only unlabeled data are required for target subjects. These methods mainly focus on offline scenarios where target data are collected in advance. However, existing methods neglect the data discrepancy within target subjects when being applied for online scenarios, which may lead to performance degradation in online ER scenarios using ECG signals.

In many real world applications, ECG signals often arrive in an online way, and ECG signals are time-varying [14] due to the nonstationary nature which may result in a intra-subject discrepancy between incoming ECG and previous ECG from a same target subject. Thus, in online cross-subject ER, apart from the inter-subject discrepancy between subjects, there is a intra-subject discrepancy within a same target subject, as shown in Fig. 1. As a result, the intra-subject discrepancy may hinder the generalization of ER model for online scenarios.

Only a few methods [15] considered both inter-and intra-subject discrepancies in online scenarios. Chai *et al.* [15] proposed an UDA method (adaptive subspace feature matching, ASFM) to reduce the inter-subject discrepancy and handle the intra-subject discrepancy by re-training a new ER model periodically. However, re-training model may be time-consuming and resource-consuming, which may limit the applications of ER model in the real world.

In this paper, a method for ECG-based online cross-subject ER is proposed via jointly reducing inter-subject and intra-subject discrepancies, consisting of two stages. In a classifier training stage, UDA is exploited to reduce inter-subject discrepancy by projecting source and target data into a shared subspace where a classifier can be trained. In an online recognition stage, online data adaptation (ODA) is first introduced to reduce intra-subject discrepancy, and then online ER results can be obtained by the trained classifier. The contributions of this work can be summarized as follows.

- An online cross-subject ER approach using ECG is proposed. Compared with previous works which may suffer a decline in performance due to neglecting intra-subject discrepancy or need to re-train a new classifier in online scenarios, our approach can adapt to time-varying ECG to ensure the online ER performance.
- The intra-subject discrepancy is introduced to represent the nonstationary nature of ECG in online ER using ECG. To reduce the intra-subject discrepancy, an ODA strategy is proposed to minimize the discrepancy within a same subject.
- Experiments results on datasets of Dreamer [2] and Amigos [4] proved that the proposed approach can achieve better performance than previous methods and is robust to the intra-subject discrepancy.

II. Methods

Fig. 2 shows the framework of the proposed approach. The training stage is to build an ER classifier for a target subject. UDA is to reduce inter-subject discrepancy, obtaining a shared subspace where a classifier can be trained. The online recognition stage is to adapt to time-varying ECG via ODA, and make recognition for transformed online data (obtained by ODA) using the trained classifier.

A. Training stage

The training stage is used to construct an ER classifier for a target subject, consisting of two steps, namely UDA-based subject transfer used for reducing the inter-subject discrepancy, and classifier training used to train a classifier.

1) UDA-based subject transfer: This part is to exploit UDA to alleviate the inter-subject discrepancy by learning a shared subspace between source subjects (source domain) and a target subject (target domain). Fig. 3(a) shows that the data distribution of two domains can be aligned in a shared subspace. UDA algorithm, namely balanced domain adaptation (BDA) [16], is chosen because it can minimize both marginal and conditional distribution discrepancies.

Here, we let $\mathbf{X}^s \in \mathbb{R}^{m \times n_s}$ and $\mathbf{X}^t_r \in \mathbb{R}^{m \times n_t}$ denote the ECG recordings in source and target domain respectively, where n_s and n_t denote the number of source and target samples respectively, and m is the number of ECG features.

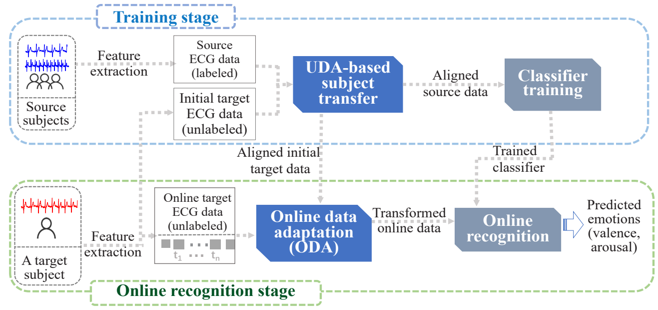

Fig. 2. The framework of our proposed online cross-subject ER from ECG arriving in an online manner.

$\mathbf{P}_r \in \mathbb{R}^{m \times d}$ is a projection matrix to map two domains into a shared subspace.

BDA [16] is to minimize the discrepancy between source ECG data and target ECG data, as follows:

$$\begin{aligned} &\min_{\mathbf{P}_r} \operatorname{tr}\left(\mathbf{P}_\mathrm{r}\mathbf{X}\left((1-\theta)\mathbf{M}_0+\theta\sum_{c=1}^{C}\mathbf{M}_c\right)\mathbf{X}^\mathrm{T}\mathbf{P}_\mathrm{r}\right)+\lambda\left\|\mathbf{P}_\mathrm{r}\right\|_F^2 \\ &\text{s.t. } \mathbf{P}_\mathrm{r}{}^\mathrm{T}\mathbf{X}\mathbf{H}\mathbf{X}^\mathrm{T}\mathbf{P}_\mathrm{r}=\mathbf{I}, 0\le\theta\le 1, \end{aligned} \tag{1}$$

where θ is balance factor, and λ is regularization parameter with $\|F\|_2$ being the Frobenius norm, C is the number of emotion categories. $\mathbf{X}$ is composed of source data $\mathbf{X}^s$ and initial target data $\mathbf{X}^t_r$, and $\mathbf{P}_r$ is a projection matrix, and $\mathbf{I} \in \mathbb{R}^{d \times d}$ is the identity matrix, and $\mathbf{H} \in \mathbb{R}^{(n_s+n_t)\times(n_s+n_t)}$ is the centering matrix, and $\mathbf{M}_0$ and $\mathbf{M}_c$ are Maximum Mean Discrepancy (MMD) matrices [17] of marginal and conditional distribution. $\mathbf{P}_r$ can be obtained by finding the d smallest eigenvectors of the equation:

$$\left(\mathbf{X}\left((1-\theta)\mathbf{M}_0+\theta\sum_{c=1}^{C}\mathbf{M}_c\right)\mathbf{X}^\mathrm{T}+\lambda\mathbf{I}\right)\mathbf{P}_r=\mathbf{X}\mathbf{H}\mathbf{X}^\mathrm{T}\mathbf{P}_r\Phi, \tag{2}$$

where Φ denotes the Lagrange multiplier, d is the dimension of a shared subspace. The details of solving equation(1) to obtain $\mathbf{P}_r$ can refer to the reference [16].

Using $\mathbf{P}_r$, the source data $\mathbf{X}^s$ are transformed into a shared subspace, obtaining aligned source data $\mathbf{Z}^s \in \mathbb{R}^{d \times n_s}$ ($\mathbf{Z}^s = \mathbf{P}_r{}^\mathrm{T}\mathbf{X}^s$). And aligned initial target data $\mathbf{Z}^t \in \mathbb{R}^{d \times n_t}$ can be obtained by $\mathbf{Z}^t = \mathbf{P}_r{}^\mathrm{T}\mathbf{X}^t_r$.

2) Classifier training: This part is to train a classifier based on the aligned source data $\mathbf{Z}^s$. The classifier we chose is support vector machine (SVM) with a Radial Basis Function (RBF) kernel in the package of sklearn with default parameter. We denote the trained classifier by f. Using f, we can classify the aligned initial target data $\mathbf{Z}^t$, obtaining the emotion state of initial target data.

B. Online recognition stage

The stage aims to make recognition for incoming ECG data, consisting of ODA used to adapt to time-varying ECG by reducing intra-subject discrepancy, and online recognition used to recognize the online data using the classifier f.

1) Online data adaptation: The aim is to adapt to time-varying ECG by alleviating the intra-subject discrepancy. As shown in Fig. 3, although $\mathbf{P}_r$ can be used to map incoming data into the shared subspace, there may be a difference for online data and initial data in the subspace. In specific, some

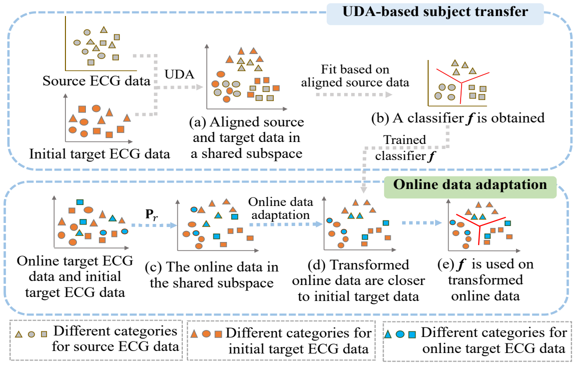

Fig. 3. The principles of UDA-based subject transfer and ODA. (a) the subspace obtained by UDA. (b) a classifier f for the target subject. (c) online data after using $\mathbf{P}_r$. (d) the online data after ODA. (e) transformed online data can be classified by f.

online data with a certain category may be far from the initial samples of the corresponding category. As a result, the online data may be misclassified by trained classifier f.

Before introducing ODA, some variables are defined. Denote $\mathbf{x}_i^t \in \mathbb{R}^{m\times n_c}$ by incoming recordings ($i = 1,\ldots,N$, N is number of batches of online data), where n_c denotes the number of online data at each batch. Besides, $\mathbf{P}_i \in \mathbb{R}^{d\times d}$ is a projection matrix to project the subspace of incoming data $\mathbf{x}_i^t$ into the subspace of initial data, where d denotes the dimension of a shared subspace.

To address intra-subject discrepancy, an ODA strategy is designed to align incoming data and initial data. In specific, the subspace ($\mathbf{z}_i \in \mathbb{R}^{d\times n_c}$) of online data is projected onto the subspace $\mathbf{Z}_n \in \mathbb{R}^{d\times n}$ (related to $\mathbf{Z}^t$) of initial data, obtaining transformed data $\mathbf{z}_i^n$ closer to initial data. Here we compute $\mathbf{z}_i$ of and $\mathbf{Z}^n$ as follows: $\mathbf{z}_i = \mathbf{P}_r^{\mathrm{T}}\mathbf{x}_i^t$. $\mathbf{Z}^n$ is obtained by updating the subspace $\mathbf{Z}^t$ ($\mathbf{Z}^t = \mathbf{P}_r{}^{\mathrm{T}}\mathbf{X}_r^t$). $\mathbf{Z}^t$ is updated to make the category proportion in the online data and initial data close to avoid negative transfer due to the difference in the proportion. First, the initial classification of online data is obtained based on $\mathbf{P}_r$ and f; then the category proportion in online data is computed; finally, some samples are selected from $\mathbf{Z}^t$ according to the proportion, obtaining an updated subspace $\mathbf{Z}_n$ related to initial data.

The ODA strategy is mainly composed of three steps. First, we define a projection matrix $\mathbf{P}_i \in \mathbb{R}^{d\times d}$ used to align $\mathbf{z}_i$ and $\mathbf{Z}^n$, expressed as:

$$\mathbf{P}_i = \sigma\mathbf{P}_c + \mathbf{I}, \tag{3}$$

where $\mathbf{P}_c \in \mathbb{R}^{d\times d}$ denotes the projection matrix used to project $\mathbf{z}_i$ onto $\mathbf{Z}^n$, $\mathbf{I} \in \mathbb{R}^{d\times d}$ is the identity matrix, σ is to alleviate negative transfer.

Then, to obtain $\mathbf{P}_c$, Correlation Alignment (CORAL) [18] is used to align the second-order statistics (covariance) between $\mathbf{z}_i$ and $\mathbf{Z}^n$, which is chosen due to its simplicity and efficiency.

Finally, using the online projection matrix $\mathbf{P}_i$, $\mathbf{z}_i$ can be projected onto $\mathbf{Z}^n$, getting the online data $\mathbf{z}_i^n$ closer to initial target data, expressed as follows:

$$\mathbf{z}_i^n = \mathbf{P}_i\mathbf{z}_i. \tag{4}$$

2) Online recognition: Based on the classifier f obtained in the training stage, we can classify the online ECG data $\mathbf{z}_i^n$, obtaining the emotion state of current online ECG data by $p_i = f(\mathbf{z}_i^n)$, where p_i is the predicted emotion state.

III. EXPERIMENTS SETUP

A. Datasets description

The proposed approach is evaluated using two datasets of Dreamer [2] containing 23 subjects, and Amigos [4] containing 40 subjects. In the paper, we focus on two binary tasks: negative/positive valence, low/high arousal, where valence represents the emotion is positive (such as glad, excited and satisfied) or negative (such as angry, sad and afraid), and arousal means the emotional intensity is low (such as sleepy and relaxed) or high (such as excited and amused). For Amigos, 4 subjects with lots of nan ECG value are eliminated. We divide ECG signal into time windows with a time window of W seconds to increase the amount of data, where a longer time window with W of 30 seconds is set to ensure sufficient emotional information in a time window.

B. Feature extraction

In this part, we introduce extracted ECG features. Some features that are proven to be related with emotions are extracted [19]. The extracted features are from time-domain features (related to heart rate variability, heart rate [20] and R-R intervals), frequency-domain features (in different frequency ranges of ECG signals), and nonlinear features (Poincaré-related, approximate entropy and Multiscale entropy at 5 levels [21]). The detailed introduction of the extracted features can refer to [19]. Note that, although a lot of features are extracted, feature selection is not adopted, since domain adaptation covers part of the function of feature selection. In specific, domain adaptation is to transform the original data into a shared subspace in order to find significant and domain invariant features, and feature section is to select siginificant features from original features.

C. Evaluation details

We adopt leave-one-subject-out for evaluation, where one subject is used as target domain and the other subjects are used as source domain. The target data is randomly divided into initial data and online data, where initial data accounts for half of all target data, and the other half was divided into different batches. The online data are arriving sequentially in a small batch at a time. Besides, to ensure the performance of UDA, the initial data consists of all categories.

IV. EXPERIMENTAL RESULTS

In this part, we carry out experiments to demonstrate the effectiveness of our proposed online cross-subject ER method. In our experiments, the baseline method is SVM. In addition, our proposed approach is compared with some UDA-based ER approaches, including seven UDA methods: joint probability distribution adaptation (JPDA) [22], Transductive SVM (TSVM) [23], kernel principle analysis (KPCA) [24], selective pseudo-labeling (SPL) [25], ASFM

TABLE I

VALENCE CLASSIFICATION ON DREAMER. ACCURACY COMPARISON OF SVM (BASELINE), SOME UDA METHODS, AND OUR PROPOSED APPROACH.

	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15	s16	s17	s18	s19	s20	s21	s22	s23	Ave(std)
SVM	0.59	0.72	0.73	0.47	0.66	0.53	0.44	0.70	0.53	0.57	0.42	0.64	0.65	0.56	0.47	0.56	0.51	0.55	0.63	0.63	0.67	0.56	0.45	0.58(0.09)
JPDA [22]	0.56	0.72	0.76	0.64	0.51	0.54	0.49	0.58	0.57	0.66	0.50	0.61	0.75	0.52	0.56	0.68	0.54	0.53	0.69	0.66	0.50	0.46	0.40	0.58(0.09)
TSVM [23]	0.58	0.73	0.73	0.47	0.67	0.51	0.45	0.68	0.55	0.60	0.41	0.65	0.69	0.55	0.48	0.57	0.52	0.55	0.65	0.63	0.66	0.57	0.41	0.58(0.09)
KPCA [24]	0.52	0.67	0.73	0.64	0.57	0.50	0.50	0.50	0.53	0.70	0.42	0.57	0.75	0.61	0.56	0.50	0.55	0.60	0.77	0.68	0.72	0.67	0.42	0.59(0.10)
SPL [25]	0.56	0.63	0.58	0.64	0.72	0.48	0.55	0.79	0.57	0.64	0.46	0.64	0.65	0.57	0.56	0.52	**0.57**	0.62	0.65	0.71	**0.78**	0.59	0.36	0.60(0.10)
ASFM [15]	0.50	0.52	0.47	0.54	0.53	0.56	0.52	0.45	0.49	0.50	0.46	0.46	0.57	0.51	0.51	0.48	0.53	0.49	0.65	0.47	0.53	0.52	0.47	0.51(0.04)
TCA [13]	0.53	0.68	0.76	0.59	0.73	0.47	0.61	0.80	0.59	0.73	0.45	0.68	0.80	0.63	0.55	0.64	0.52	0.63	0.83	0.70	0.74	0.72	0.47	0.65(0.11)
JDA [26]	0.59	0.68	0.78	0.57	0.70	0.49	0.61	0.79	0.57	0.73	0.41	0.60	0.80	0.63	0.43	0.62	**0.57**	0.64	0.83	0.68	0.72	0.70	0.44	0.63(0.12)
BDA [16]	0.62	0.73	0.76	0.64	0.72	0.60	0.61	0.80	**0.63**	0.70	0.58	0.61	0.75	0.61	0.56	0.67	0.54	0.63	0.78	0.71	0.72	**0.70**	0.56	0.66(0.08)
Proposed	**0.71**	**0.82**	**0.79**	**0.69**	**0.77**	**0.65**	**0.70**	**0.84**	**0.63**	**0.79**	**0.65**	**0.69**	**0.86**	**0.70**	**0.58**	**0.70**	0.56	**0.67**	**0.88**	**0.72**	0.74	**0.74**	**0.62**	**0.72(0.08)**

TABLE II

AROUSAL CLASSIFICATION ON DREAMER. ACCURACY COMPARISON OF SVM (BASELINE), SOME UDA METHODS, AND OUR PROPOSED APPROACH.

	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15	s16	s17	s18	s19	s20	s21	s22	s23	Ave(std)
SVM	0.53	0.40	0.56	0.71	0.54	0.58	0.31	0.62	0.77	0.65	0.67	0.57	0.47	0.61	0.64	0.68	0.62	0.60	0.60	0.60	**0.78**	0.45	0.56	0.59(0.11)
JPDA [22]	0.57	0.51	0.52	0.27	0.48	0.68	0.50	0.60	0.73	0.50	0.68	0.67	0.43	0.53	0.45	0.42	0.55	0.51	0.44	0.42	0.68	0.70	0.62	0.54(0.11)
TSVM [23]	0.55	0.37	**0.62**	0.72	0.57	0.62	0.44	0.56	0.44	0.47	0.74	0.53	0.52	0.54	0.59	0.58	0.62	0.55	0.53	0.55	0.60	0.51	0.55	0.56(0.08)
KPCA [24]	0.48	0.51	0.54	0.27	0.54	0.66	0.49	0.68	0.50	0.74	0.68	0.54	0.60	0.50	0.51	0.42	0.49	0.66	0.61	**0.67**	0.54	0.71	0.46	0.56(0.11)
SPL [25]	0.48	0.43	0.43	0.27	0.54	0.42	0.22	0.58	0.23	0.60	0.66	0.41	0.48	0.42	0.49	0.67	0.59	0.68	0.47	0.45	0.56	0.14	0.59	0.47(0.14)
ASFM [15]	0.57	0.48	0.44	0.42	0.48	0.49	0.40	0.45	0.62	0.55	0.46	0.44	0.46	0.62	0.51	0.55	0.16	0.49	0.53	0.42	0.36	0.47	0.61	0.48(0.10)
TCA [13]	0.44	0.57	0.58	0.58	**0.66**	0.45	0.52	0.80	0.49	0.69	0.45	0.48	**0.80**	0.63	0.46	0.57	0.55	0.63	0.85	0.68	0.64	0.68	0.47	0.60(0.12)
JDA [26]	0.62	0.40	0.59	0.65	0.55	0.68	0.45	0.68	0.64	0.68	0.72	0.55	0.56	0.64	0.59	0.65	0.56	0.70	0.59	0.52	0.61	0.72	0.55	0.61(0.08)
BDA [16]	0.66	0.60	0.60	0.75	0.54	**0.71**	0.41	0.71	**0.70**	0.76	0.74	0.67	0.61	0.66	0.68	**0.84**	0.74	**0.73**	0.82	0.63	0.71	**0.78**	0.52	0.68(0.10)
Proposed	**0.67**	**0.61**	0.60	**0.76**	0.60	**0.71**	**0.58**	**0.75**	**0.70**	**0.83**	**0.82**	**0.72**	0.62	**0.76**	**0.69**	**0.84**	**0.77**	**0.73**	**0.83**	**0.67**	0.72	0.75	**0.64**	**0.71(0.09)**

TABLE III

VALENCE CLASSIFICATION ON AMIGOS. ACCURACY COMPARISON OF SVM (BASELINE), SOME UDA METHODS, AND OUR PROPOSED APPROACH.

	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15	s16	s17	s18	s19	s20	s21	s22	s23	s24	s25	s26	s27	s28	s29	s30	s31	s32	s33	s34	s35	s36	Ave (std)
SVM	0.44	0.70	0.59	0.55	0.52	0.68	0.61	0.66	0.55	0.53	0.39	0.65	0.49	0.65	0.49	0.56	0.54	0.69	0.47	0.59	0.57	0.77	0.61	0.52	0.38	0.71	0.77	0.74	0.31	0.74	0.49	0.59	0.52	0.64	0.59	0.69	0.58(0.11)
JPDA [22]	0.56	0.67	0.63	0.49	0.61	0.54	0.66	0.64	0.41	0.58	0.58	0.65	0.53	0.51	0.42	0.54	0.57	0.61	0.56	0.57	0.53	0.53	0.61	0.51	0.67	0.62	0.61	0.74	0.44	0.57	0.52	0.58	0.59	0.59	**0.69**	0.60	0.58(0.07)
TSVM [23]	0.45	0.67	0.59	0.71	0.56	0.67	0.59	0.57	0.63	0.53	0.64	0.67	0.51	0.43	0.57	0.49	0.64	0.67	0.49	0.58	0.57	0.57	0.57	0.53	0.48	0.63	0.50	0.77	0.28	0.65	0.48	0.53	0.57	0.52	0.57	0.74	0.57(0.09)
KPCA [24]	0.49	0.61	0.63	0.72	0.61	0.76	0.63	0.41	0.61	0.53	0.58	**0.68**	0.50	0.44	0.57	**0.68**	**0.68**	0.66	0.54	**0.64**	0.62	0.62	0.63	0.57	0.67	0.67	0.57	0.86	0.67	0.71	0.43	0.58	0.48	0.49	0.59	0.59	0.60(0.09)
SPL [25]	0.43	0.67	**0.70**	0.49	0.61	0.70	0.67	0.52	0.41	0.45	**0.81**	0.64	0.54	0.50	0.47	0.50	**0.68**	0.66	0.60	0.58	0.41	0.52	0.65	0.53	0.52	0.62	0.57	0.57	0.46	0.57	0.49	0.54	0.58	0.55	0.56	0.64	0.57(0.09)
ASFM [15]	0.48	0.45	0.63	0.52	0.58	0.63	0.50	0.41	0.47	0.18	0.56	0.54	0.62	0.46	0.53	0.62	0.68	0.60	0.44	0.52	0.49	0.68	0.65	0.50	0.43	0.51	0.27	0.57	0.51	0.45	0.52	0.47	0.51	0.48	0.60	0.49	0.51(0.10)
TCA [13]	0.55	0.63	0.67	0.76	0.56	**0.77**	0.59	0.52	**0.71**	0.51	0.67	0.64	0.51	0.65	0.60	0.60	0.57	0.69	0.58	0.59	0.54	0.80	0.67	0.54	0.67	0.66	0.55	0.83	0.72	0.78	0.49	0.57	0.55	0.65	0.63	0.66	0.63(0.09)
JDA [26]	0.53	0.66	0.63	0.82	0.56	0.73	0.60	0.52	0.68	0.52	0.67	0.64	0.51	0.66	0.58	0.63	0.61	0.69	0.59	0.58	0.62	0.80	0.65	0.54	0.67	0.67	0.55	0.83	0.69	**0.80**	0.57	0.59	0.55	0.64	0.65	0.67	0.64(0.08)
BDA [16]	0.59	0.72	0.67	0.79	0.56	**0.77**	0.69	0.70	**0.71**	0.72	0.64	0.64	0.57	0.65	0.53	0.62	0.61	0.70	0.61	**0.64**	0.62	0.83	0.67	0.58	0.67	0.68	0.70	0.83	0.77	0.77	0.57	**0.60**	0.55	0.65	0.65	0.79	0.67(0.08)
Proposed	**0.61**	**0.81**	**0.70**	**0.85**	**0.64**	**0.77**	**0.76**	**0.80**	**0.71**	**0.76**	0.67	0.66	**0.59**	**0.76**	**0.61**	0.65	**0.68**	**0.73**	**0.63**	**0.64**	**0.63**	**0.87**	**0.70**	**0.63**	**0.67**	**0.73**	**0.82**	**0.89**	**0.79**	**0.80**	**0.59**	**0.60**	**0.61**	**0.65**	0.65	**0.77**	**0.71(0.08)**

TABLE IV

AROUSAL CLASSIFICATION ON AMIGOS. ACCURACY COMPARISON OF SVM (BASELINE), SOME UDA METHODS, AND OUR PROPOSED APPROACH.

	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15	s16	s17	s18	s19	s20	s21	s22	s23	s24	s25	s26	s27	s28	s29	s30	s31	s32	s33	s34	s35	s36	Ave
SVM	0.54	0.39	0.66	0.85	0.52	0.47	0.67	0.55	0.57	0.63	0.81	0.69	0.65	0.61	0.60	0.58	0.66	0.23	0.58	0.55	0.57	0.68	0.59	0.67	0.52	0.50	0.65	0.57	0.70	0.59	0.64	0.73	0.70	0.50	0.51	0.60	0.59(0.11)
JPDA [22]	0.41	0.32	0.50	0.87	0.57	0.47	**0.76**	0.41	0.48	0.05	0.58	0.49	0.77	0.26	0.27	0.60	0.50	0.34	0.38	0.42	0.29	0.74	0.45	0.52	0.69	0.52	0.56	0.58	0.50	0.49	0.51	0.50	0.52	**0.66**	0.51	0.44	0.50(0.16)
TSVM [23]	0.56	0.32	0.67	0.83	0.51	0.47	0.62	0.57	0.48	0.63	0.77	0.76	0.48	0.30	0.55	0.53	0.71	0.23	0.62	0.47	0.57	0.59	**0.64**	0.63	0.52	0.44	0.65	0.66	0.65	0.45	0.59	0.79	0.57	0.34	0.49	0.53	0.56(0.13)
KPCA [24]	0.48	0.32	0.67	0.72	0.57	0.38	0.74	**0.63**	0.53	0.58	0.92	0.62	0.61	0.26	0.53	0.63	0.75	0.14	0.47	0.50	0.19	0.74	0.48	0.65	0.31	0.40	**0.66**	0.62	0.59	0.42	0.75	0.81	**0.93**	0.53	0.39	0.44	0.55(0.18)
SPL [25]	0.52	0.32	0.68	0.92	0.43	0.26	0.74	0.47	0.31	0.37	0.69	0.76	0.68	0.17	0.26	0.58	0.61	0.11	0.48	0.65	0.24	0.56	0.50	0.41	0.62	0.56	0.62	0.63	0.65	0.38	0.64	0.83	0.56	0.42	0.39	0.47	0.51(0.18)
ASFM [15]	0.59	0.42	0.41	0.38	0.55	0.59	0.53	0.51	0.52	0.68	0.42	0.37	0.48	0.35	0.53	0.50	0.42	0.32	0.40	0.50	0.62	0.44	0.64	0.56	0.52	0.48	0.41	0.43	0.57	0.45	0.41	0.58	0.52	0.47	0.46	0.56	0.49(0.08)
TCA [13]	0.53	0.39	0.62	0.89	0.52	0.53	0.74	0.60	0.59	0.79	0.89	**0.79**	0.77	0.61	0.62	0.64	0.74	0.16	0.57	0.62	0.62	0.85	0.55	0.59	0.52	0.56	0.62	**0.74**	0.70	0.48	0.71	0.81	0.87	0.55	0.61	0.71	0.64(0.15)
JDA [26]	0.53	0.42	0.66	0.92	0.52	0.53	0.74	0.60	0.60	0.79	0.89	**0.79**	0.77	0.61	0.62	0.64	0.74	0.16	0.57	0.62	0.62	0.85	0.57	0.59	0.52	0.52	0.65	**0.74**	0.72	0.46	0.71	0.81	0.87	0.55	0.61	0.69	0.64(0.15)
BDA [16]	0.63	0.58	0.68	0.92	**0.61**	0.58	0.74	0.60	0.70	0.75	0.86	0.78	**0.84**	0.61	0.62	0.61	0.75	0.57	0.65	0.62	0.62	0.85	0.59	**0.76**	**0.79**	0.52	0.56	0.71	0.65	0.60	0.72	0.81	0.79	0.61	0.61	0.71	0.68(0.10)
Proposed	**0.66**	**0.55**	**0.79**	**0.96**	**0.61**	**0.71**	**0.76**	**0.63**	**0.74**	**0.89**	**0.89**	0.78	**0.84**	**0.65**	**0.62**	**0.67**	**0.78**	**0.59**	**0.67**	**0.68**	**0.62**	**0.88**	0.61	**0.76**	**0.79**	**0.60**	0.59	0.73	**0.74**	**0.72**	**0.74**	**0.85**	0.89	0.61	**0.63**	**0.71**	**0.72(0.10)**

[15], TCA [13], and joint distribution adaptation (JDA) [26]. To apply these UDA methods for ECG-based online ER, SVM is used as the final classifier. Note that, TSVM, KPCA and TCA are presented in one related ER work [10], and ASFM is from the ER work in [15].

Table I to Table IV list accuracies on valence and arousal recognition, where bold numbers represent optimal results. From the four tables, we observe that:

- Our proposed approach improves the classification accuracy by about 12% over SVM, indicating the effectiveness of the proposed approach. In addition, our proposed approach performs better than other UDA methods. Also, the tables give the performance of BDA [16] which is the proposed without ODA. our proposed method performed better than BDA, meaning the effectiveness of the ODA, and the robustness of the proposed method to time-varying ECG in online scenarios.
- TCA [13] and JDA [26] performed better than SVM, indicating the benefit of the two methods to reduce inter-subject discrepancy. Since both our method and the two methods exploit MMD distance [17] to represent the difference between two domains, the results suggest that MMD-based methods may be effective for alleviating the inter-subject discrepancy in ECG-based ER. In contrast, some UDA methods (JPDA [22], TSVM [23], KPCA [24], SPL [25]) performed worse than SVM on arousal classification, and ASFM [15] failed in most cases, meaning that negative transfer may occur. The reason may be that they can not adapt to the time-varying nature of ECG.

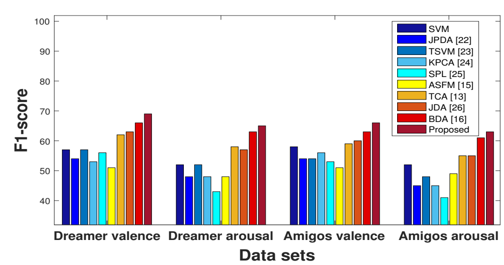

Fig. 4. Comparison of F1-scores based on different methods.

Moreover, to better compare different methods, Fig. 4 gives the macro F1-scores (the average of score for both

TABLE V

COMPARISONS OF OUR PROPOSED METHOD AND SOME EXISTING ECG-BASED ER WORKS. - MEANS THAT THE RESULT IS NOT GIVEN.

	model comparison			Dreamer valence		Dreamer arousal		Amigos valence		Amigos arousal	
	subject depedent or cross-subject model	online or offline	ER classification schemes	Acc	F1	Acc	F1	Acc	F1	Acc	F1
Katsigiannis *et al.* [2]	subject depedent	-	SVM	0.62	0.53	0.62	0.58	-	-	-	-
Miranda-Correa *et al.* [4]	cross-subject	-	SVM	-	-	-	-	-	0.55	-	0.55
Tung *et al.* [3]	cross-subject	-	XGBoost	-	-	-	-	-	0.63	-	0.56
Proposed	cross-subject	online	UDA + online data adaptation + SVM	0.72	0.69	0.71	0.65	0.71	0.66	0.72	0.63

classes) of different methods. Fig. 4 shows that our method is better than the other methods, again indicating the advantage of our proposed method for online cross-subject ER using ECG. Further, the running time of the online recognition stage for our proposed method is computed based on the environment using pycharm 2020 with an Intel core i5-10400 2.90 GHz processor and 16 GB of RAM. The online recognition of our method (feature extraction + ODA + SVM classification) consumes 4.91 seconds, which is the latency of the our emotion recognition algorithm. The number is less than the arrival time of ECG data (30 seconds), which implies that our proposed method can complete the classification before the next batch of online data arrives, indicating the practical value of the proposed method in real world application scenarios. Besides, Table V lists the comparison of our proposed approach and some existing ECG ER works [2]–[4]. The table shows that our proposed approach outperforms the methods of the other works, showing the benefits of our proposed method.

V. CONCLUSION

In this paper, an approach for online cross-subject ER is proposed, where ECG signals arrive in an online manner. Unlike previous methods that may need to re-train ER model, our proposed approach adopts UDA-based subject transfer and ODA to reduce both inter-and intra-subject discrepancies to ensure the performance of online cross-subject ER using ECG. The experimental results have demonstrated the effectiveness of the proposed approach, and the robustness to the intra-subject discrepancy. In future works, we will exploit deep learning-based feature extraction or transfer learning techniques to further improve the performance.

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