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# Self-adjustable domain adaptation in personalized ECG monitoring integrated with IR-UWB radar

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To enhance electrocardiogram (ECG) monitoring systems in personalized detections, deep neural networks (DNNs) are applied to overcome individual differences by periodical retraining. As introduced previously [4], DNNs relieve individual differences by fusing ECG with impulse radio ultra-wide band (IR-UWB) radar. However, such DNN-based ECG monitoring system tends to overfit into personal small datasets and is difficult to generalize to newly collected unlabeled data. This paper proposes a self-adjustable domain adaptation (SADA) strategy to prevent from overfitting and exploit unlabeled data. Firstly, this paper enlarges the database of ECG and radar data with actual records acquired from 28 testers and expanded by the data augmentation. Secondly, to utilize unlabeled data, SADA combines self organizing maps with the transfer learning in predicting labels. Thirdly, SADA integrates the one-class classification with domain adaptation algorithms to reduce overfitting. Based on our enlarged database and standard databases, a large dataset of 73200 records and a small one of 1849 records are built up to verify our proposal. Results show SADA's effectiveness in predicting labels and increments in the sensitivity of DNNs by 14.4% compared with existing domain adaptation algorithms.



## 1. Introduction

How to provide a personal diagnosis becomes a trend of the mobile electrocardiogram (ECG) monitoring, after the precise medicine is presented. The reliability of mobile ECG monitoring system is affected by the detection error caused by individual differences. Overcoming the issue of individual differences promotes the clinical usage of mobile ECG monitoring based on the Internet of Things. A mobile cloud hybrid solution for mobile ECG monitoring [1] is put forward to enhance the adaptation to individual differences. This solution applies the deep neural network (DNN) in the arrhythmia detection on the mobile side, and dynamically retrains this neural network on cloud using new personal data. Through the process of periodical retraining, the neural network is adjusted as adaptive to individual differences.

Though such DNN-based mobile ECG monitoring solution achieves the adaptation to individual features due to the virtue of periodical retraining procedures, it is subject to personal data used for fine-tuning. In real mobile health applications, new collected data are almost unlabeled and corresponding categories are imbalanced. Besides, on condition that the size of personal datasets is small, the retraining procedure tends to over-fit. These situations brings about issues on how to exploit unlabeled data, how to prevent over-fitting during retraining, and how to keep the recognition sensitivity for each class on the imbalanced dataset in the ECG monitoring solution.

The domain adaptation is able to relieve over-fitting of neural networks in the target domain, since it controls the learning in target domain with matching to the source domain. As a few labels are available in the target domain in real ECG monitoring applications, the domain adaptation is performable in a semi-supervised way, which exploits unlabeled data by predicting pseudo labels with a basic classifier [14] such as the support vector machine (SVM) [2] or the self-organizing maps (SOM) [19]. Since SOM offers unsupervised morphological clustering, it is adopted in this paper for classifying ECG waveforms. The SOM serves as a rough clustering method and therefore it is employed together with other clustering algorithms, such as the fuzzy c-means (FCM) clustering. However, existing SOM-based clustering is unable to integrate multiple data. Besides, the real ECG monitoring scenarios cannot meet the con-

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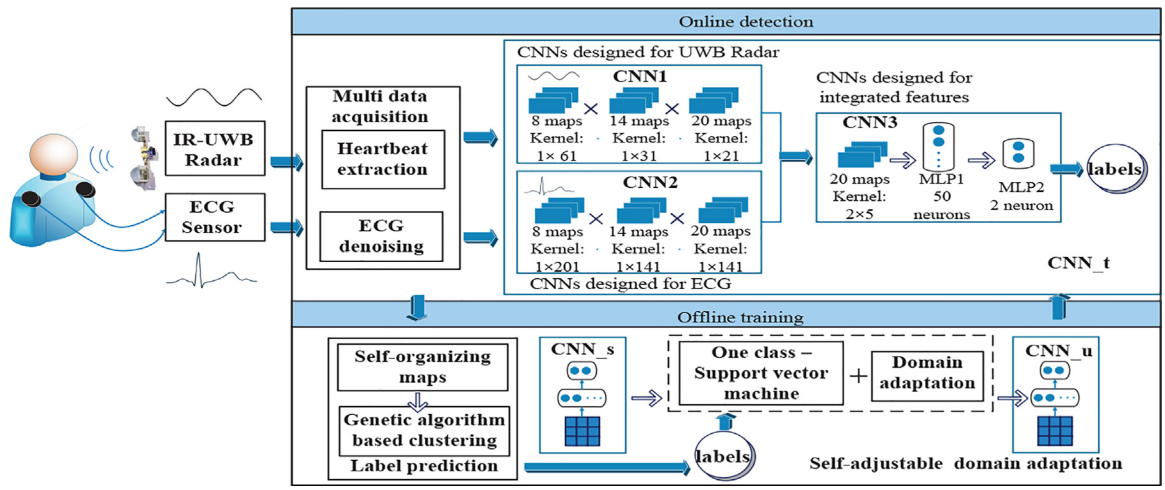


**Fig. 1.** Proposed strategy for mobile ECG monitoring. $CNN_s$ denotes a standard neural network trained on the MIT-BIH database. $CNN_u$ is adjusted by SADA. $CNN_t$ is updated with weights of $CNN_u$ and used for personalized diagnoses.

straint of existing domain adaptation algorithms that the set of classes is the same across domains. It is common that the target domain only acquires the normal category from a specific person.

This paper proposes a self-adjustable domain adaptation (SADA) strategy in the DNN-based mobile ECG monitoring system to prevent from overfitting to individual differences. Fig. 1 illustrates the architecture of a mobile ECG monitoring solution which is extended by SADA. To fuse ECG and radar data for relieving interferences of motion artifacts and individual differences, SADA adopts a cascade convolutional neural network introduced previously [4]. SADA modifies the SOM-based clustering to fuse multiple data and broadens the application scenarios of domain adaptation algorithms. Firstly, SADA extends the SOM-based clustering by the transfer learning (TL). Secondly, SADA applies the one-class SVM (OC-SVM) with the domain adaptation. By breaking the restriction of domain adaptation with the OC-SVM in our scenario, SADA increases the sensitivity of DNNs. Experimental results verify the effectiveness of SADA by comparisons with existing domain adaptation algorithms.

The rest of this paper is organized in the following. Section 2 gives a summary of related works on the domain adaptation and states details of the personalized ECG monitoring system integrated with IR-UWB radar. Section 3 presents the modification that SADA made to SOM-based clustering, describes issues on the consistency of class sets across domains and explains the extension of existing domain adaptation algorithms by applying the OC-SVM. Section 4 presents experimental results and their analyses. Finally, Section 5 concludes our paper.

## 2. Related works

### 2.1. Related works in domain adaptations

The deep structure of DNN is capable of extracting transferable features [13] specific to data and tasks. Since such features are domain-invariant, the deep domain adaptation dependent on DNNs benefits in these domain-invariant features in reducing distribution discrepancies across domains. The deep domain adaptation aligns domains through adding restrictions to the training loss of DNNs with an extra loss of domain fusion or domain classification. The domain fusion loss enables classifiers indistinguishable across domains, while the domain classification loss maintains extracted features distinct on target and source domains. The network architecture in [8] is adjusted to import the domain classification loss into the back-propagation. The network in [9] achieves the domain classification loss and the domain fusion loss simultaneously with a compromise deal. Works in [5–7,15] append the domain fusion loss by calculating the maximum mean discrepancy (MMD) of extracted features on source and target domains.

Specifically, the domain fusion loss is decreased by reducing discrepancies of the marginal distribution or the conditional distribution across domains [3]. The deep transfer network (DTN) [5] poses constraints to both marginal distribution and conditional distribution. The deep adaptation network (DAN) [6] presents a strategy for the optimal multi-kernel selection, to improve the marginal matching performance across multiple layers. The joint adaptation network (JAN) [7] restricts the joint distribution across multiple layers in the neural network. It is no longer necessary to separately adapt the marginal and conditional distribution.

As in [16], the domain adaptation requires that the class space keeps exactly consistent across target and source domains, which hinders its application in real-world scenario such as the mobile health monitoring. Though the network in [9] is applicable in situation that a part of categories lack labeled target data, it still obey the consistency constraint on class space. It is necessary to develop a flexible domain adaptation which is usable in either consistent or inconsistent class space. Then SADA makes a first attempt to broaden the application of domain adaptation to the situation that the class space shrinks in the target domain.

### 2.2. Personalized ECG monitoring integrated with IR-UWB radar

#### 2.2.1. Multi data acquisition

In addition to the ECG monitoring, it is feasible to apply other contactless heart rate (HR) detections achieved through the capacitively coupled ECG measurement, the radar-based displacement measurement and the audio-based HR measurement [21]. The radar-based HR measurement outperforms other noncontact means due to its robustness in long distances (>10 cm) [22]. Besides, the radar-based HR measurement suppresses the affects of motion artifacts by applying multi antennas [23] or by adopting the generalized warblet transform to cancel random body movements [24]. Therefore, it is effective to apply the radar-based HR measurement to assist in vital sign monitoring scenarios such as the sleep apnea detection based on ECG or electroencephalograms [31–42].

Radar-based HR monitoring is achieved by the continuous-wave (CW) radar and the UWB radar, which includes the stepped frequency CW radar, the frequency-modulated CW radar and the IR-UWB radar [46]. Except the IR-UWB radar, other three kinds