Adversarial Deep Feature Extraction Network for User Independent Human Activity Recognition

Sungho Suh†, Vitor Fortes Rey∗† and Paul Lukowicz∗†
*German Research Center for Artificial Intelligence (DFKI), 67663 Kaiserslautern, Germany
†Department of Computer Science, TU Kaiserslautern, 67663 Kaiserslautern, Germany
Email: {sungho.suh, vitor.fortes_rey, paul.lukowicz}@dfki.de

Abstract—User dependence remains one of the most difficult general problems in Human Activity Recognition (HAR), in particular when using wearable sensors. This is due to the huge variability of the way different people execute even the simplest actions. In addition, detailed sensor fixtures and placement will be different for different people or even at different times for the same users. In theory, the problem can be solved by a large enough data set. However, recording data sets that capture the entire diversity of complex activity sets is seldom practicable. Instead, models are needed that focus on features that are invariant across users. To this end, we present an adversarial subject-independent feature extraction method with the maximum mean discrepancy (MMD) regularization for human activity recognition. The proposed model is capable of learning a subject-independent embedding feature representation from multiple subjects datasets and generalizing it to unseen target subjects. The proposed network is based on the adversarial encoder-decoder structure with the MMD realign the data distribution over multiple subjects. Experimental results show that the proposed method not only outperforms state-of-the-art methods over the four real-world datasets but also improves the subject generalization effectively. We evaluate the method on well-known public data sets showing that it significantly improves user-independent performance and reduces variance in results.

Index Terms—human activity recognition, domain generalization, adversarial learning, multi-task learning

I. INTRODUCTION

Human Activity Recognition (HAR) using wearable sensors is an important field in Ubiquitous computing where the task is to recognize which activity is being performed (sitting, walking, hammering, etc) given the data provided by the on-body sensors (IMU on the smartphone, watch, etc). This field spans more than two decades of research [1], [2]. Recently, deep learning methods have achieved state-of-the-art performance in HAR by using convolutional neural networks (CNNs) as in [3] or by combining them with long short-term memory networks (LSTMs) as in [4]. Even more recently, transformer-like approaches have reached state-of-the-art results by employing self-attention [5].

While much has been achieved, creating models that can generalize to unseen subjects is still a major challenge. As many studies have shown [6], [7], different people perform the same activities in different ways, which makes user recognition possible, but activity recognition more challenging. This is observed in practice by the gap in performance when evaluating by leaving out subjects instead of leaving out sessions. Approaches to deal with those limitations can be classified into classic approaches and deep learning-based methods. Classic approaches include directly selecting user-invariant classical features [9] or directly building one model per user [9]. Building user models requires labeled data for all users, which is not realistic for many HAR applications as it may increase costs and deployment time. Selecting hand-crafted features is a possible solution, but may not be feasible as developing said features requires expertise in the target domain. Moreover, this approach may weaken the overall performance depending on the quality of the features available.

Our work follows recent trends in deep learning approaches in this field: multi-task and adversarial learning. Recently, deep learning has been applied to this problem by exploring multi-task or even adversarial learning. In [10], authors exploit user labels by combining HAR with subject identification in a multi-task learning framework that allows the model to focus on the relevant features for each user. This shows that taking user information into account can improve classification results, but it is not clear if models can learn to generalize beyond the available training subjects as they were not evaluated when leaving users out. Still, their work shows that deep learning models can clearly benefit from taking user information into account. Other works such as [11] have shown that differences in the environment can, to some extent, be mitigated by employing similarity-based multi-task learning, but they have also not evaluated their model leaving users out and, moreover, their representation tends to create one cluster per subject with sub-clusters per activity, which may not favor generalization, being more similar to user-models.

In the other direction, [12] use adversarial learning to generate a feature representation more robust regarding user variations. That is, instead of allowing the model to exploit user-specific information for classification, it should avoid leaking it as there is an adversary (a discriminator) whose objective is to separate subjects in the feature space. They achieve this by employing a Wasserstein Generative Adversarial Network (WGAN) [13] and Siamese networks and showed that their method can generalize to new subjects without sacrificing performance, that is, still proving state of the art results. This may have other advantages besides performance, as neural networks are known to leak subject information [14] and applying adversarial learning can mitigate those concerns.

While the deep learning-based methods such as [12] have
achieved significant improvements, most of these methods still have limitations. Although adversarial learning improved the performance of the activity recognition by generalization, they cannot measure the degree of generalization of the latent features in the training procedure. In the adversarial learning procedure, feature representation modules as generators are trained to fool a discriminator, while the discriminator conducts binary classification to distinguish between two different features from representation modules with randomly chosen two subjects. Thus, it cannot measure the degree of generalization for all subjects and cannot generalize the feature representation over all subjects. Furthermore, their multi-view data representation module comprises three different networks to merge the sub-representations of different views. It requires large amounts of annotated data for human activity recognition to train this complex multi-view data representation module. However, it is challenging to collect a sufficiently large amount of datasets in personalized human activity recognition applications. Annotated medical datasets are limited due to the laborious labeling process, and sometimes legal issues associated with publicly sharing private personal information.

To overcome these problems, we propose an adversarial subject-independent feature extraction for human activity recognition. The proposed model is capable of learning a subject-independent embedding feature representation from multiple subjects datasets and generalizing it to unseen target subjects by using an adversarial learning procedure. The adversarial learning between a feature extractor and a discriminator, which distinguishes the extracted features from multiple subjects, learns the distributions of multiple subject data and extracts subject-invariant generalized features for activity recognition. To measure the degree of the feature generalization and align the distributions among the multiple subjects, we use the Maximum Mean Discrepancy (MMD) \cite{9,10} regularization. The MMD regularization helps enhance the generalization ability of the proposed adversarial learning method. Additionally, the proposed model adopts an encoder-decoder structure to preserve the characteristic of the original signals, which has been utilized in weakly supervised learning and feature representation \cite{23, 24}.

The contributions of this paper can be summarized as follows.

- A novel adversarial subject-independent feature extraction method is proposed for human activity recognition. We formulate the adversarial learning between feature extraction and subject discriminator and improve the performance of the activity recognition.
- We use the MMD regularization to enhance the generalization of the feature representation and measure the degree of the generalization.
- We design the feature extractor and reconstruction based on the encoder-decoder network structure to preserve the characteristic of the original input signals and extract important information for activity recognition.
- To validate the proposed method, we conducted experiments with four public real-world activity recognition datasets: Opportunity \cite{19}, PAMAP2 \cite{20}, MHEALTH \cite{21} and MoCapaci \cite{22}. By the experiments on multiple datasets, we can verify the advantages and effectiveness of the proposed method for feature generalization and activity recognition.

The rest of the paper is organized as follows. Section II introduces the related works. Section III provides the details of the proposed method. Section IV presents quantitative experimental results on the four datasets and analyzes the structure of the proposed model with ablation study. Finally, Section V concludes the paper.

II. RELATED WORK

Generally, there are two ways to capture the interpersonal variability: One is to increase the amount of training data from different subjects, and the other is to extract subject-independent features. The former is too expensive and impossible to collect and annotate data from different people. Recently, transfer learning methods have been investigated to solve cross-domain HAR problems. Domain adaptation is the particular branch of transfer learning, that measures data distribution heterogeneity and aligns among data distributions \cite{23}. Deng et al. \cite{24} proposed a cross-person activity recognition method using a reduced kernel extreme learning machine on the source domain, which classifies the target sample and the high-confident samples and applies them to the training dataset. Zhao et al. \cite{25} introduced a transfer learning embedded decision tree algorithm that integrates a decision tree and the k-means clustering algorithm to recognize mobile phone-based different personalized activities by model adaptation. Wang et al. \cite{26} proposed a stratified transfer learning method that adopted the pseudo-leveling concept on the unlabeled target data by measure MMD between the feature spaces for the source domain data and the pseudo-labeled target data. Khan et al. \cite{27} proposed a heterogeneous deep convolutional neural network (HDCNN) that used a feature matching approach to adapt the pre-trained network, trained with the supervised source domain dataset, to an unlabeled target dataset collected from the smartwatch through the minimization of the discrepancy between two datasets after every convolutional and fully connected layer. They used Kullback-Leibler (KL) divergence as a distance measure between the pre-trained network and the target domain feature extractor network. Faridee et al. \cite{28} proposed an AugToAct framework which is directly aligned data distributions between source and target domains by combining augmentation transformations with deep semi-supervised learning to infer complex activities with the minimal labels in both source and target domains. AugToAct similarly performed domain adaptation as HDCNN but employed Jensen–Shannon (JS) divergence to minimize the discrepancy among two different domains instead of KL divergence. Akbari and Jafari \cite{29} extracted stochastic features by training variational auto-encoder instead of deterministic feature extraction and employed the same network architecture of HDCNN to apply the feature matching approach to adapt the model to a target environment. Zhao et al. \cite{30} a local
domain adaptation method for cross-domain HAR, which aligns the distributions of source and target domains by using the MMD regularization. They first classified the activities into abstract clusters and mapped the original features into a low-dimensional subspace where the MMD between two clusters with the same label from different domains were minimized. The above domain adaptation approaches consider only a single source domain for domain adaptation task.

Several studies have researched multiple source domain adaptation for sensor-based activity recognition. Some approaches focus on explicitly identifying the most relevant source domain among the multiple source domains with the target domain based on similarity measurement such as cosine similarity. Wang et al. [51] proposed a transfer neural network to perform knowledge transfer for activity recognition (TNNAR), which captures both the time and spatial relationship between activities. They considered explicitly selecting the most relevant domain from the multiple source domains based on the cosine similarity and applied the selected domain for domain adaptation to the target domain. Another group of approaches combines all the available source domains data and projects into lower-dimensional space, which is further processed by the classifier. Jeyakumar et al. [32] proposed a SenseHAR, which is a sensor fusion model for each device that mapped the raw sensor values to a shared low dimensional latent space. They mitigated the heterogeneous data distribution and assigned labels to the unlabeled data. However, the above-mentioned approaches did not consider multiple source domain data simultaneously, and the approaches cannot capture the uncertainty within the classification tasks.

Recently, Multi-task and generative adversarial learning (GAN) [33]-based methods have been introduced to solve the different data distribution problems. Chen et al. [10] proposed a deep multi-task learning-based activity and user recognition (METIER) model, which combines activity recognition and user recognition with a multi-task model. The model shares parameters between the activity recognition module and the user recognition module, and the activity recognition performance can be improved by the user recognition module employing a mutual attention mechanism. Sheng et al. [11] proposed a weakly supervised multi-task representation learning, which used Siamese networks to exploit a temporal convolutional network as a backbone model. Bai et al. [12] introduced a discriminative adversarial multi-view network, which extracts multi-view features from temporal, spatial, and Spatio-temporal views using CNN, and generalizes the multi-view features by employing WGAN and Siamese network architecture to decrease the variants between the extracted features from different subjects.

III. PROPOSED METHOD

A. Problem Formulation

In this section, we introduce an adversarial subject-independent feature extraction method based on the encoder-decoder structure and GAN scheme for human activity recognition. Specifically, the task is to use data collected by sensor at different positions on the human body to predict one of $n_a$ activity labels. Let $X = [x_1, ..., x_n]$ be the time-series sensor data obtained by applying a sliding window of size $n_w$ of the $n_c$ available sensor channels with $x_i \in \mathbb{R}^{n_c \times n_w}$ consisting of the sensor data for that window and $Y = [y_1, ..., y_n]$ the corresponding activity label set of $X$, and $S = [s_1, ..., s_n]$
the corresponding subject label set of \( X \). We assume our training data \( \{ X_{src}, Y_{src}, S_{src} \} \) shares the same \( n_a \) activities and sensor types with the test data \( \{ X_{tgt}, Y_{tgt}, S_{tgt} \} \) with unseen subjects in the training data. The goal of the proposed method is to generalize extracted features from the \( S_{src} \) source subjects to the target subjects \( S_{tgt} \) and improve the performance of the overall activity classification.

### B. Network Architecture

The proposed neural network architecture is composed of four independent networks:

1) a feature extractor that acts as encoder of the encoder-decoder network structure and its role is to create our user-independent embedding features for activity recognition.

2) a reconstructor that acts as a decoder in our encoder-decoder network structure and its role is to recompute the original signal from the embedding features so that they preserves the characteristics of the input signals.

3) an activity classifier that predicts labels using the embedding features.

4) a subject discriminator whose task is to distinguish the subject label from which the embedding features originated. It is used in an adversarial learning framework with the feature extractor, which tries to fool it by providing features that cannot be discriminated between subjects.

Fig. 1 presents the overall network architecture of the proposed framework with the four independent networks.

The encoder aims to map the input space \( \mathcal{X} \) to a common embedding feature space \( \mathcal{E} \), and the decoder reconstructs from the embedding feature space to its original input space. In this work, we denote the encoder as the feature extractor \( Q : \mathcal{X} \rightarrow \mathcal{E} \) and the decoder as the reconstructor \( P : \mathcal{E} \rightarrow \mathcal{X} \). The embedding feature space \( \mathcal{E} \) from the feature extractor preserves the characteristics of the input signals so that the reconstructor can reconstruct the original signal. The feature extractor is composed of four encoding blocks, each including two convolution layers and a batch normalization respectively, that extract increasingly abstract representation of the input signal and max-pool downsampling layers to encode the input signal into the embedding feature representations at multiple different levels. The structure of the reconstructor is similar to that of the feature extractor. The reconstructor is equipped with three decoding blocks, each including two convolution layers and a batch normalization respectively, and upsampling layers.

The activity classifier \( C \) predicts the activity labels using the embedding features \( C : \mathcal{E} \rightarrow \mathcal{Y} \), where \( \mathcal{Y} \) denotes the activity label space. The network of the activity classifier can be designed with long short-term memory (LSTM) [35], ResNet50 [36], self-attention [37], and so on. In this paper, the activity classifier is designed with a max-pool downsampling layer, a convolution layer, and two fully connected layers. The activity classifier’s loss will also influence the feature extractor, as they are both trained to minimize the supervised classification.

The subject discriminator distinguishes the subject label from which the embedding feature. The goal of the proposed method is to extract subject-invariant features from multiple domains. In other words, the feature extractor generates a common embedding feature space for multiple subjects. Though the training procedure with the supervised activity classification encourages learning the data distribution of the activities, the extracted embedding features still contain subject-specific information. By adopting an adversarial manner between the subject discriminator and the feature extractor, the subject discriminator is trained to distinguish the subject label from the embedding features and the feature extractor is trained to fool the subject discriminator. A strong subject discriminator can train the feature extractor to generate embedding features that generalize across data from different subjects. The subject discriminator is composed of three discriminator blocks, each including a convolution layer, batch normalization, and a dropout respectively, and two fully connected layers. To align the distributions among the \( N + 1 \) source and target subjects and further generalize the embedding feature representation, we use the MMD [15], [16] regularization.

### C. MMD-Regularized Adversarial Learning for Multi-Subject Generalization

As shown in Fig. 1, we define four loss functions to train the four independent networks: 1) a reconstruction loss \( L_{rec} \), 2) a classification loss \( L_{cls} \), 3) a domain loss \( L_D \), and 4) a MMD loss \( L_{MMD} \). Let \( P, Q, C \), and \( D \) denote the reconstructor, the feature extractor, the activity classifier, and the subject discriminator, respectively. The reconstruction loss is defined to minimize the difference between the original signal and the reconstructed signal as follows.

\[
L_{rec}(X) = \|P(Q(X)) - X\|_2^2, \tag{1}
\]

where \( X \) denotes the original sensor data and \( P(Q(X)) \) denotes the reconstructed signal.

In the proposed network architecture, the feature extractor and activity classifier are trained by supervised learning with given activity labels. The classification loss for the feature extractor and activity classifier is expressed as follows:

\[
L_{cls}(X, Y) = -\sum_{i=1}^{n} y_i \log C(Q(x_i)), \tag{2}
\]

which is the cross-entropy classification loss.

The goal of the subject discriminator is to distinguish which subject generated the embedding features. The subject discriminator is thus trained to minimize the domain loss:

\[
L_D(X, S) = -\sum_{i=1}^{n} s_i \log D(Q(x_i)), \tag{3}
\]

Here, we address the MMD regularization to align the distributions among different subjects and to further improve the generalization of embedding features extracted by the feature extractor.
Fig. 2: Training procedure, representing the steps described in Section III-D. Solid lines indicate that the network is being trained, dashed lines indicate that the parameters of the network are fixed.

The MMD is one of the most commonly used non-parametric methods to measure the distance of the distribution between two different domain datasets. The feature extractor represents the embedding features from the input signals \( Q : \mathcal{X} \rightarrow \mathcal{E} \), and we let \( Q(X_s) = E_s = [e_{s,1}, e_{s,2}, \ldots, e_{s,M}] \) and \( Q(X_t) = E_t = [e_{t,1}, e_{t,2}, \ldots, e_{t,N}] \) represent the embedding feature sets of two different subjects (domains). A mapping operation \( \phi(\cdot) \) projects the features of two different domains onto the reproducing kernel Hilbert space (RKHS) \( \mathcal{H} \), and calculates the mean distance between the two domains in RKHS. The MMD between two subjects can be calculated by using the function \( \phi(\cdot) \) as follows:

\[
MMD(E_s, E_t)^2 = \left\| \frac{1}{M} \sum_{i=1}^{M} \phi(e_{s,i}) - \frac{1}{N} \sum_{j=1}^{N} \phi(e_{t,j}) \right\|^2_{\mathcal{H}} \tag{4}
\]

The key to calculate the MMD is to find the appropriate \( \phi(\cdot) \) as a mapping function to map the two domains to RKHS \( \mathcal{H} \). Thus, the mean difference between the two data distributions after the mapping is calculated as their difference. \( \phi(\cdot) \) represents a characteristic kernel function as \( k(e_{s,i}, e_{t,j}) = \langle \phi(e_{s,i}), \phi(e_{t,j}) \rangle \), and the MMD can be rewritten as follows:

\[
MMD(E_s, E_t)^2 = \frac{1}{M} \sum_{i=1}^{M} \sum_{j=1}^{M} k(e_{s,i}, e_{s,i}) \\
+ \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} k(e_{t,i}, e_{t,i}) - \frac{2}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} k(e_{s,i}, e_{t,j}) \tag{5}
\]

Generally, the Gaussian kernel function \( k(e_{s,i}, e_{t,j}) = \exp(-\frac{\sigma^2}{\|e_{s,i} - e_{t,j}\|^2}) \) is used as the kernel function in the MMD algorithm, which maps data to infinite-dimensional space. This MMD method is based on a single kernel transformation. In this work, we adopt the multi-kernel MMD (MK-MMD) \[16\], which is an extension of the MMD and the optimal kernel can be obtained by linear combination of multiple kernels. The kernel function is defined as the convex combination of \( m \) positive semi-definite (PSD) kernels \( k_u \). The total kernel \( k \) is defined as follows.

\[
K \triangleq \left\{ k = \sum_{u=1}^{m} \beta_u k_u : \sum_{u=1}^{m} \beta_u = 1, \beta_u \geq 0, \forall u \right\} \tag{6}
\]

where \( k \) is weighted by different kernel \( k_u \), \( \{\beta_u\} \) is the coefficient, which is the weight of \( K \), to ensure that the generated multi-kernel \( k \) is characteristic.

Unlike the general domain adaptation, the goal of the proposed method is to generalize the features from multiple subject domains from either only the \( N \) source subjects or both \( N+1 \) source and target subjects. Thus, the overall MMD regularization loss \( L_{MMD} \) is described as follows.

\[
\mathbb{I}_{MMD}(E_1, \ldots, E_{N+1}) = \frac{1}{(N+1)^2} \sum_{1 \leq i,j \leq N+1} MMD(E_i, E_j) \tag{7}
\]

The goal of the feature extractor is to extract the generalized feature among different subject domains, preserve the characteristics of the original data, and learn a class-discriminative feature representation. In other words, the feature extractor is
trained to jointly minimize the losses of the reconstruction, classification, and MMD, and maximize the domain loss for the adversarial learning, simultaneously, whereas the reconstructor, the activity classifier, and the subject discriminator are trained to minimize the losses of the reconstruction, classification, and domain, respectively. Finally, The objective functions of the proposed method are defined as follows:

$$\min_{C,Q,P} \max_{D} \mathbb{L}_{obj}(X,Y,S)$$  
(8)

where $\mathbb{L}_{obj}$ is

$$\lambda_{cls} L_{cls}(X,Y) + \lambda_{rec} L_{rec}(X) + \lambda_{MMD} L_{MMD}(X) - \lambda_{D} L_{D}(X,S)$$  
(9)

where $\lambda_{cls}, \lambda_{rec}$ controls the relative importance of different loss terms, and $\lambda_{MMD}$ and $\lambda_{D}$ are hyperparameters that control the effect of domain generalization. In summary, the reconstruction loss $L_{rec}$ is computed to preserve the content information of the embedding features, the classification loss $L_{cls}$ is used to improve the performance of the activity recognition, the MMD regularization term $L_{MMD}$ helps to measure and align the distribution distance among different subjects, and the domain loss $L_{D}$ hinders extracting subject domain-specific information from the feature extractor by the adversarial learning between the feature extractor and subject discriminator.

D. Training Procedure

The training procedure for the proposed adversarial subject-independent feature extraction method is based on three different steps in order to train the four independent neural networks to accomplish our intent. Fig. 2 presents the training procedure with the detailed steps. Before training all the proposed networks, a pre-training step is done where we train the feature extractor and reconstructor only. This step helps improve the stability of the training afterwards by learning the content information of the original input first. Second, we train all four networks by supervised learning without adversarial learning and MMD regularization. In this step, we jointly minimize the losses of reconstruction and classification to capture the data distribution of each activity with the source data and train the subject discriminator first to prevent making it too easy to fool the subject discriminator in the adversarial learning process afterward. Finally, we can train a subject-invariant feature extractor by adversarial learning and MMD regularization. In this step, we freeze the reconstructor so that the feature extractor can now solely focus on classification and generalization. The training details for the proposed adversarial feature extraction method are summarized in Algorithm 1.

Algorithm 1 Training procedure for adversarial generalized feature extraction using MMD regularization. We use default values of $\lambda_{cls} = 5, \lambda_{rec} = 5, \lambda_{MMD} = 1, \lambda_{D} = 1$

Require: Batch size $m$, Adam hyperparameters $\eta$, hyperparameter for $\lambda_{rec}, \lambda_{cls}, \lambda_{D}, \lambda_{MMD}$.

1: Input: $X, Y, S, X_t, Y_t, S_t$
2: for number of training iterations for step 1 do
3: Sample a batch $x$ from the training dataset $X$.
4: $\theta_P \leftarrow \theta_P - \eta P \nabla_{\theta_P} L_{rec}(x; \theta_P)$.
5: $\theta_Q \leftarrow \theta_Q - \eta Q \nabla_{\theta_Q} L_{rec}(x; \theta_Q)$  
\hspace{1cm} $\triangleright$ Eq. (1)
6: for number of training iteration for step 2 do
7: Sample a batch $(x, y, s)$ from the training dataset $X$, corresponding activity label $Y$, and domain label $S$.
8: $\theta_D \leftarrow \theta_D - \eta D \nabla_{\theta_D} L_{D}(x, s; \theta_D)$  
\hspace{1cm} $\triangleright$ Eq. (3)
9: $\theta_P \leftarrow \theta_P - \eta P \nabla_{\theta_P} L_{step2}(x; \theta_P)$.
10: $\theta_C \leftarrow \theta_C - \eta C \nabla_{\theta_C} L_{step2}(x, y; \theta_C)$.
11: $\theta_Q \leftarrow \theta_Q - \eta Q \nabla_{\theta_Q} L_{step2}(x, y; \theta_Q)$  
\hspace{1cm} $\triangleright$ Eqs. (1) and (2)
12: for number of training iteration for step 3 do
13: Sample a batch $(x, y, s)$ from the training dataset $X$, corresponding activity label $Y$, and domain label $S$.
14: $\theta_D \leftarrow \theta_D - \eta D \nabla_{\theta_D} L_{D}(x, s; \theta_D)$  
\hspace{1cm} $\triangleright$ Eq. (3)
15: $\theta_C \leftarrow \theta_C - \eta C \nabla_{\theta_C} L_{obj}(x, y; \theta_C)$.
16: $\theta_Q \leftarrow \theta_Q - \eta Q \nabla_{\theta_Q} L_{obj}(x, y, s; \theta_Q)$  
\hspace{1cm} $\triangleright$ Eq. (8)
17: Sample a batch $(x_t, s_t)$ from the target dataset $X_t$, and corresponding domain label $S_t$.
18: $(x', s') \leftarrow (concat(x, x_t), concat(s, s_t))$
19: $\theta_D \leftarrow \theta_D - \eta D \nabla_{\theta_D} L_{D}(x', s'; \theta_D)$  
\hspace{1cm} $\triangleright$ Eq. (3)
20: $\theta_Q \leftarrow \theta_Q - \eta Q \nabla_{\theta_Q} L_{tgt}(x', s'; \theta_Q)$  
\hspace{1cm} $\triangleright$ Eqs. (3) and (7)

IV. EXPERIMENTAL RESULTS

A. Datasets and Evaluation Metrics

To evaluate the effectiveness of the proposed method for human activity recognition, four types of popular datasets were used, Opportunity [19], PAMAP2 [20], MHEALTH [21] and MoCapaci [22], that contain continuous sensor data of various sensors and different human activities by different participants. Regarding preprocessing for each dataset:

- Opportunity: has three types of sensors: body-worn sensors with 145 channels, object sensors with 60 channels, and ambient sensors with 37 channels. In this paper, we selected a dimension of 113 channels taking into account only the body-worn sensors including the IMUs and accelerometers, following the setup of [19]. We preprocessed all channels of sensor data to fill in missing values using linear interpolation and to normalize the data values per channel to interval $[0, 1]$ with manually set minimum and maximum values per channel as in [4]. We used a sliding window size of 64 with a sliding step of 16, which is close to two seconds of the sliding window and a 0.5-second step size. We use two types of annotations from the dataset. One is modes of locomotion and postures, such as Stand, Walk, Sit, and Lie is annotated with five classes. Another is 18 mid-level gestures such as Open Door, Close Door, and Clean Table.
- PAMAP2: has 52 channels, containing a channel of heart rate, 17 channels per IMU. The full IMU sensory data is composed of 6 channels of acceleration data, 3 channels of gyroscope data, 3 channels of magnetometer data, and 3 channels of orientation. In this work, we selected a total dimension of 36 channels by removing a channel of
TABLE I: Comparison results with the state-of-the-arts on OPPORTUNITY, PAMAP2, MHEALTH, and MoCapaci datasets. The numbers are expressed in percent and represented as mean ± std.

| Dataset   | Task   | Method                | acc      | $F_w$     | $F_m$     |
|-----------|--------|-----------------------|----------|-----------|-----------|
| Locomotion| Gestures| MC-CNN                | 69.19 ± 6.77 | 68.12 ± 6.65 | 69.37 ± 6.35 |
|           |        | DeepConvLSTM          | 72.52 ± 5.34 | 77.62 ± 5.26 | 70.08 ± 10.49 |
|           |        | Transformer-like      | 70.18 ± 15.44 | 68.77 ± 18.37 | 67.68 ± 18.41 |
|           |        | Proposed              | 76.72 ± 1.62 | 76.84 ± 1.45 | 79.16 ± 2.18 |
| Opportunity| Gestures| MC-CNN                | 72.80 ± 5.06 | 69.38 ± 4.36 | 28.94 ± 8.92  |
|           |        | DeepConvLSTM          | 68.27 ± 6.61 | 70.07 ± 5.00 | 37.29 ± 7.13  |
|           |        | Transformer-like      | 77.62 ± 3.17 | 72.55 ± 5.44 | 33.77 ± 13.65 |
|           |        | Proposed              | 78.58 ± 2.35 | 79.52 ± 2.04 | 56.28 ± 2.88  |
| PAMAP2    | Gestures| MC-CNN                | 79.77 ± 14.55 | 79.16 ± 15.92 | 72.72 ± 15.32 |
|           |        | DeepConvLSTM          | 76.23 ± 16.34 | 75.21 ± 17.45 | 67.54 ± 16.00 |
|           |        | Transformer-like      | 82.88 ± 14.82 | 82.37 ± 15.80 | 74.84 ± 15.70 |
|           |        | Proposed              | 85.69 ± 10.76 | 85.85 ± 11.26 | 77.84 ± 11.69 |
| MHEALTH   | Gestures| MC-CNN                | 89.69 ± 8.93 | 87.91 ± 10.41 | 87.42 ± 10.72 |
|           |        | DeepConvLSTM          | 89.24 ± 6.69 | 86.99 ± 8.41 | 87.17 ± 8.08  |
|           |        | Transformer-like      | 87.44 ± 8.10 | 85.45 ± 9.06 | 85.13 ± 9.71  |
|           |        | Proposed              | 96.72 ± 3.61 | 96.37 ± 4.31 | 96.47 ± 4.04  |
| MoCapaci  | Gestures| MC-CNN                | 85.42 ± 6.42 | -          | -          |
|           |        | DeepConvLSTM          | 85.42 ± 5.84 | -          | -          |
|           |        | Transformer-like      | 70.00 ± 11.73 | -          | -          |
|           |        | Proposed              | 87.77 ± 4.65 | -          | -          |

heart rate, a channel of temperature per IMU, 4 channels of orientation per IMU, since the orientation of IMUs is mentioned as invalid in the data collection. Additionally, we remove six activities classified "Optional" in the dataset and the ninth subject since the "Optional" activities were collected by only one subject and the ninth subject executed only one activity. Thus, a total of 12 activities named "protocol" in the dataset from 8 subjects are used in this work. We preprocessed all channels of selected sensor data to fill in NaN values using linear interpolation. All samples were normalized to zero mean and unit variance per user. The IMU data was collected under the sampling frequency of 100 Hz and we used a sliding window length of 200 (2 seconds) with a sliding step of 50 (0.5 second).

- **MHEALTH**: provides a sampling rate for all sensing modalities of 50 Hz. To evaluate the proposed method with the iterative leave-one-subject-out cross-validation procedure, we augmented the dataset with a sliding window length of 200 (4 seconds) and a step size of 50 (1 second), unlike other methods [11, 38] used a sliding window length of 5 seconds and a step size of 2.5 seconds.

- **MoCapaci**: contains a total of 4 channels of capacitive data sampled at 100 Hz per channel. The data of each gesture instance was filtered by a fourth-order Butterworth bandpass filtered from 1 Hz to 10 Hz, and normalized by subtracting the average of the first and last values of the gesture. The length of the signal was resampled to 400 and we use the length of the signal as a sliding window length.

To evaluate not only the performance of the proposed model but also how much performance varies depending on the subject, we adopt the leave-one-subject-out cross-validation procedure that all data from a subject is used as test set while all data from other subjects are used as a training dataset. The evaluation was repeated two times on each test set.

To evaluate and compare the performance of the proposed method with others, we adopted three evaluation metrics, which are used in various human activity recognition studies [4, 12, 39]: accuracy $acc$, weighted F1-score $F_w$, and macro F1-score $F_m$.

### B. Implementation Details

The experiments were all implemented using Python scripts in the PyTorch framework. Training procedures were conducted in the Linux system with four NVIDIA Quadro RTX 8000 GPUs. The hyperparameters for Eq. (7) were $\lambda_{rec} = 5$, $\lambda_{cls} = 5$, $\lambda_{MMD} = 1$, and $\lambda_D = 1$. Through various testing, it is observed that the parameters mentioned in the paper yield the best performance. We chose the Adam optimizer [40] with a learning rate of $\eta_C = \eta_Q = 5 \times 10^{-5}$, $\eta_P = 1 \times 10^{-4}$, $\eta_D = 1 \times 10^{-3}$, $\beta_1 = 0.9$, and $\beta_2 = 0.99$. The batch size was 500 for the Opportunity dataset, 200 for the PAMAP2 dataset, and 128 for the MoCapaci dataset, respectively. For the MK-MMD, the Gaussian kernel is applied in the MK-MMD, and its number is set to 5.

### C. Comparison Results

The proposed method was evaluated on the Opportunity, PAMAP2, MHEALTH, and MoCapaci datasets. The three evaluation metrics were used to evaluate and compare the proposed method to deep-learning-based state-of-the-art methods including multi-channel time-series convolutional neural networks (MC-CNN) [3], DeepConvLSTM [4], and Transformer-like activity recognition method [5]. MC-CNN is a CNN-based model consisting of three convolutional layers, two pooling layers, and two fully connected layers. DeepConvLSTM is a combined model of CNN and LSTM for activity recognition, that comprises four convolutional layers and two LSTM layers to learn both spatial and temporal correlations.
The transformer-like activity recognition method introduced a self-attention mechanism to improve the performance of the human activity recognition based on wearable sensors. For the fair comparison study, we set up the same experimental conditions, such as splitting the training and test datasets, data preprocessing, the window size, and step size, as we addressed in the previous section.

The Opportunity dataset is normally evaluated using two of its label types: the modes of locomotion recognition task and the gesture recognition task. We conducted the comparison experiment and introduce the experimental results on the two tasks separately.

Table 4 shows the quantitative evaluation results on the Opportunity, PAMAP2, MHEALTH, and MoCapaci datasets. Because the Opportunity dataset has 18 types of activities and is severely imbalanced, the results in terms of $F_m$ are relatively lower and have a larger standard deviation than the results in terms of $acc$ and $F_w$. The results show that the proposed method achieves significantly higher performance on the Opportunity dataset for both locomotion and gesture recognition tasks in terms of all three of the measurements. Furthermore, the proposed method provides high-performance results with small inter-subject variation, whereas the state-of-the-arts give high standard deviation results relatively. Additionally, the performance variance on the PAMAP2 dataset is much larger than on the Opportunity dataset, because of the diversity between different subjects and the data quality. Nevertheless, the proposed method outperforms all the state-of-the-arts and achieves lowest standard deviation results among the state-of-the-arts.

The proposed method outperforms all the state-of-the-art methods on the MHEALTH datasets in terms of all three metrics. The proposed method achieves 7.03, 8.46, 9.05 percent points improvements over the best state-of-the-art method in terms of $acc$, $F_w$, and $F_m$, respectively. Additionally, the standard deviation of the performance by the proposed method is much smaller than that of the state-of-the-art methods. The comparison results demonstrate the superiority of the proposed model.

Unlike other datasets, the MoCapaci dataset is perfectly class-balanced and subject-balanced. Thus, we evaluate the performance on the MoCapaci dataset only in terms of $acc$. The proposed method outperforms other methods and the variance is also smaller than the state-of-the-art methods.

In Fig. 3 we analyze the results of the proposed method and the stat-of-the-arts in the box-and-whisker plots in terms of $acc$, $F_w$, and $F_m$. The proposed method not only provides significantly better performance but also gives small performance variances on both tasks than the state-of-the-arts.

**D. Ablation Study**

To evaluate the effectiveness of the proposed adversarial feature extraction network architecture with MMD regularization, we conducted the ablation study.

1) **Effect of the proposed adversarial learning network architecture:** To show the effect of the proposed adversarial
learning network architecture, we evaluate the proposed network architecture by changing the network architecture and loss functions for optimization. **NoAdv** is the proposed activity classifier with the encoder-decoder architecture without the discriminator and adversarial learning to show the advantage of adversarial learning. **OnlySupervised** is the proposed adversarial feature extraction architecture and training procedure without the unsupervised learning for the target dataset to show the performance difference between with and without the unsupervised learning. **NoMMD** is to show the impact of the MK-MMD regularization by implementing the proposed adversarial learning without the MMD regularization. We denote **1Stage** as the proposed network architecture trained by only one stage training procedure, unlike the proposed method trained by three stages training procedure.

Table II shows the evaluation results of the ablation study for the proposed adversarial learning network architecture on OPPORTUNITY and PAMAP2 datasets. The numbers are represented as mean ± std.

| Dataset | Task      | Method  | acc     | $F_w$    | $F_m$    |
|---------|-----------|---------|---------|----------|----------|
| Opportunity | Locomotion | NoAdv   | 72.08 ± 3.30 | 72.26 ± 2.99 | 72.03 ± 6.43 |
|         |           | OnlySupervised | 74.05 ± 2.66 | 74.26 ± 2.25 | 76.40 ± 2.72 |
|         |           | NoMMD   | 76.15 ± 4.11 | 76.45 ± 3.52 | 77.74 ± 5.99 |
|         |           | 1Stage  | 74.32 ± 1.92 | 74.41 ± 2.22 | 75.52 ± 2.99 |
|         |           | Proposed | 76.72 ± 1.62 | 76.84 ± 1.45 | 79.16 ± 2.18 |
|         | Gestures  | NoAdv   | 73.28 ± 2.28 | 74.20 ± 1.98 | 43.67 ± 4.29 |
|         |           | OnlySupervised | 77.25 ± 2.31 | 77.30 ± 2.18 | 49.05 ± 6.16 |
|         |           | NoMMD   | 76.55 ± 2.10 | 77.39 ± 1.91 | 50.28 ± 3.65 |
|         |           | 1Stage  | 76.31 ± 2.75 | 77.13 ± 2.52 | 50.93 ± 4.27 |
|         |           | Proposed | 78.58 ± 2.35 | 79.52 ± 2.04 | 56.28 ± 2.88 |
| PAMAP2  | Locomotion | NoAdv   | 81.92 ± 14.35 | 81.99 ± 15.34 | 74.14 ± 15.35 |
|         |           | OnlySupervised | 83.48 ± 11.36 | 83.60 ± 11.90 | 76.48 ± 13.33 |
|         |           | NoMMD   | 84.46 ± 13.86 | 84.61 ± 14.44 | 76.51 ± 14.51 |
|         |           | 1Stage  | 85.27 ± 9.48 | 85.75 ± 9.74 | 77.92 ± 12.05 |
|         |           | Proposed | 85.69 ± 10.76 | 85.85 ± 11.26 | 77.84 ± 11.69 |

Fig. 5: Performance on OPPORTUNITY and PAMAP2 datasets by changing hyperparameter $\lambda_{MMD}$.
does not significantly affect the performance of the proposed model if the hyperparameter values are changed in the range of the scales.

V. CONCLUSION

In this study, we have proposed an adversarial feature extraction method with MMD regularization. The main idea of the proposed model is to learn a feature representation by joint optimization an encoder-decoder network structure regularized by the MK-MMD distance, an activity classifier, and a subject discriminator in an adversarial training manner. The encoder-decoder network structure for the feature extractor and reconstructor is designed to learn an embedding feature space to preserve the characteristics of the original signal, and the adversarial learning procedure between the feature extractor and subject discriminator learns the distributions of multiple domain data and extracts subject-invariant generalized features for activity recognition. The MK-MMD based regularization method helps enhance the generalization ability by aligning the feature distributions among different subject domains. The experimental results indicated that the proposed method can capture the important information for activity recognition and generalize the feature among different subject domains. Additionally, the proposed method outperformed the state-of-the-art methods and the ablation study showed that the advantage of the proposed model and objective loss function.

For future work, we plan to extend the proposed method to the sensor-invariant feature extraction for human activity recognition. We found that the datasets we have tested used different types and numbers of sensors on different positions of the body. Recognizing the importance of each sensor or generalizing the features from different sensors can optimize their number and placement on the body and enable learning across datasets, domains and modalities. We look forward to reducing the labor-intensive data collection and annotation processes by utilizing the various datasets for different tasks.

REFERENCES

[1] O. D. Lara and M. A. Labrador, “A survey on human activity recognition using wearable sensors,” IEEE communications surveys & tutorials, vol. 15, no. 3, pp. 1192–1209, 2012.
[2] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, “Deep learning for sensor-based activity recognition: A survey,” Pattern Recognition Letters, vol. 119, pp. 3–11, 2019.
[3] J. Yang, M. N. Nguyen, P. P. San, X. Li, and S. Krishnaswamy, “Deep convolutional neural networks on multichannel time series for human activity recognition,” in Twenty-fourth international joint conference on artificial intelligence, 2015.
[4] F. J. Ordóñez and D. Roggen, “Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition,” Sensors, vol. 16, no. 1, p. 115, 2016.
[5] S. Mahmud, M. Tommoy, K. K. Bhauimik, A. Rahman, M. A. Amin, M. Shoyaib, M. A. H. Khan, and A. A. Ali, “Human activity recognition from wearable sensor data using self-attention,” arXiv preprint arXiv:2003.09008, 2020.
[6] J. E. Cutting and L. T. Kozlowski, “Recognizing friends by their walk: Gait perception without familiarity cues,” Bulletin of the psychonomic society, vol. 9, no. 5, pp. 353–356, 1977.
[7] M. S. Singh, V. Pondeenkandath, B. Zhou, P. Lukowicz, and M. Liwickit, “Transforming sensor data to the image domain for deep learning — an application to footstep detection,” in 2017 International Joint Conference on Neural Networks (IJCNN), 2017, pp. 2665–2672.
[8] T. R. D. Saputri, A. M. Khan, and S.-W. Lee, “User-independent activity recognition via three-stage ga-based feature selection,” International Journal of Distributed Sensor Networks, vol. 10, no. 3, p. 706267, 2014.
[9] J.-H. Hong, J. Ramos, and A. K. Dey, “Toward personalized activity recognition systems with a semipopulation approach,” IEEE Transactions on Human-Machine Systems, vol. 46, no. 1, pp. 101–112, 2016.
[10] L. Chen, Y. Zhang, and L. Peng, “Metier: A deep multi-task learning based activity and user recognition model using wearable sensors,” Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 4, no. 1, pp. 1–18, 2020.
[11] T. Sheng and M. Huber, “Weakly supervised multi-task representation learning for human activity analysis using wearables,” Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 4, no. 2, pp. 1–22, 2020.
[12] L. Bai, L. Yao, X. Wang, S. S. Kanhere, B. Guo, and Z. Yu, “Adversarial multi-view networks for activity recognition,” Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 4, no. 2, pp. 1–22, 2020.
[13] M. Arjovsky, S. Chintala, and L. Bottou, “Wasserstein generative adversarial networks,” in International Conference on Machine Learning, 2017, pp. 214–223.
[14] Y. Iwasawa, K. Nakayama, I. Yairi, and Y. Matsuo, “Privacy issues regarding the application of dnns to activity-recognition using wearables and its countermeasures by use of adversarial training,” in UCI, 2017, pp. 1930–1936.
[15] A. Gretton, K. Borgwardt, M. Rasch, B. Schölkopf, and A. Smola, “A kernel method for the two-sample-problem,” Advances in neural information processing systems, vol. 19, pp. 513–520, 2006.
[16] M. Long, Y. Cao, J. Wang, and M. Jordan, “Learning transferable features with deep adaptation networks,” in International conference on machine learning. PMLR, 2015, pp. 97–105.
[17] M. Zeng, T. Yu, X. Wang, L. T. Nguyen, O. J. Mengshoel, and I. Lane, “Semi-supervised convolutional neural networks for human activity recognition,” in 2017 IEEE International Conference on Big Data (Big Data). IEEE, 2017, pp. 522–529.
[18] A. A. Varamin, E. Abbasnejad, Q. Shi, D. C. Ranasinghe, and H. Rezatofighi, “Deep auto-set: A deep auto-encoder-set network for activity recognition using wearables,” in Proceedings of the 15th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, 2018, pp. 246–253.
[19] R. Chavarriaga, H. Sagha, A. Calatroni, S. T. Digumarti, G. Tröster, J. d. R. Millán, and D. Roggen, “The opportunity challenge: A benchmark database for on-body sensor-based activity recognition,” Pattern Recognition Letters, vol. 34, no. 15, pp. 2033–2042, 2013.
[20] A. Reiss and D. Stricker, “Introducing a new benchmarked dataset for activity monitoring,” in 2012 16th international symposium on wearable computers. IEEE, 2012, pp. 108–109.
[21] O. Banos, R. Garcia, J. Á. Holgado-Terriza, M. Damas, H. Pomares, I. Rojas, A. Saiz, and C. Villalonga, “mhealthbirdroid: a novel framework for agile development of mobile health applications,” in International workshop on ambient assisted living. Springer, 2014, pp. 91–98.
[22] H. Bello, B. Zhou, S. Suh, and P. Lukowicz, “Mocapci: Posture and gesture detection in loose garments using textile cables as capacitive antennas,” in 2021 International Symposium on Wearable Computers, 2021, pp. 78–83.
[23] D. Cook, K. D. Feuz, and N. C. Krishnan, “Transfer learning for activity recognition: A survey,” Knowledge and information systems, vol. 36, no. 3, pp. 537–556, 2013.
[24] W.-Y. Deng, Q.-H. Zheng, and Z.-M. Wang, “Cross-person activity recognition using reduced kernel extreme learning machine,” Neural Networks, vol. 53, pp. 1–7, 2014.
[25] Z. Zhao, Y. Chen, J. Liu, Z. Shen, and M. Liu, “Cross-people mobile-phone based activity recognition,” in Twenty-second international joint conference on artificial intelligence, 2011.
[26] J. Wang, Y. Chen, L. Hu, X. Peng, and S. Y. Philip, “Stratified transfer learning for cross-domain activity recognition,” in 2018 IEEE international conference on pervasive computing and communications (PerCom). IEEE, 2018, pp. 1–10.
[27] M. A. H. Khan, N. Roy, and A. Misra, “Scaling human activity recognition via deep learning-based domain adaptation,” in 2018 IEEE international conference on pervasive computing and communications (PerCom). IEEE, 2018, pp. 1–9.
[28] A. Z. M. Fariede, M. A. H. Khan, N. Pathak, and N. Roy, “Aug-toact: Scaling complex human activity recognition with few labels,” in
[29] A. Akbari and R. Jafari, “Transferring activity recognition models for new wearable sensors with deep generative domain adaptation,” in Proceedings of the 18th International Conference on Information Processing in Sensor Networks, 2019, pp. 85–96.

[30] J. Zhao, F. Deng, H. He, and J. Chen, “Local domain adaptation for cross-domain activity recognition,” IEEE Transactions on Human-Machine Systems, vol. 51, no. 1, pp. 12–21, 2020.

[31] J. Wang, V. W. Zheng, Y. Chen, and M. Huang, “Deep transfer learning for cross-domain activity recognition,” in Proceedings of the 3rd International Conference on Crowd Science and Engineering, 2018, pp. 1–8.

[32] J. V. Jeyakumar, L. Lai, N. Suda, and M. Srivastava, “Sensehar: a robust virtual activity sensor for smartphones and wearables,” in Proceedings of the 17th Conference on Embedded Networked Sensor Systems, 2019, pp. 15–28.

[33] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” in Advances in neural information processing systems, 2014, pp. 2672–2680.

[34] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” in International conference on machine learning. Lille, France: PMLR, 2015, pp. 448–456.

[35] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[36] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[37] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in Advances in neural information processing systems, 2017, pp. 5998–6008.

[38] L. T. Nguyen, M. Zeng, P. Tague, and J. Zhang, “Recognizing new activities with limited training data,” in Proceedings of the 2015 ACM International Symposium on Wearable Computers, 2015, pp. 67–74.

[39] H. Ma, W. Li, X. Zhang, S. Gao, and S. Lu, “Attnsense: Multi-level attention mechanism for multimodal human activity recognition.” in IJCAI, 2019, pp. 3109–3115.

[40] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.