MetaGanFi: Cross-Domain Unseen Individual Identification Using WiFi Signals

JIN ZHANG, Shenzhen University, China
ZHUANGZHUANG CHEN, Shenzhen University, China
CHENGWEN LUO*, Shenzhen University, China
BO WEI, Lancaster University, United Kingdom
SALIL S. KANHERE, University of New South Wales, Australia
JIANQIANG LI, Shenzhen University, China

Human has an unique gait and prior works show increasing potentials in using WiFi signals to capture the unique signature of individuals' gait. However, existing WiFi-based human identification (HI) systems have not been ready for real-world deployment due to various strong assumptions including identification of known users and sufficient training data captured in predefined domains such as fixed walking trajectory/orientation, WiFi layout (receivers locations) and multipath environment (deployment time and site). In this paper, we propose a WiFi-based HI system, MetaGanFi, which is able to accurately identify unseen individuals in uncontrolled domain with only one or few samples. To achieve this, the MetaGanFi proposes a domain unification model, CCG-GAN that utilizes a conditional cycle generative adversarial networks to filter out irrelevant perturbations incurred by interfering domains. Moreover, the MetaGanFi proposes a domain-agnostic meta learning model, DA-Meta that could quickly adapt from one/few data samples to accurately recognize unseen individuals. The comprehensive evaluation applied on a real-world dataset show that the MetaGanFi can identify unseen individuals with average accuracies of 87.25% and 93.50% for 1 and 5 available data samples (shot) cases, captured in varying trajectory and multipath environment, 86.84% and 91.25% for 1 and 5-shot cases in varying WiFi layout scenarios, while the overall inference process of domain unification and identification takes about 0.1 second per sample.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing systems and tools**.

Additional Key Words and Phrases: WiFi sensing, CSI, mobile deep learning

*Corresponding author.

Authors' addresses: Jin Zhang, jin.zhang@szu.edu.cn, National Engineering Laboratory for Big Data System Computing Technology, College of Computer Science and Software Engineering, Shenzhen University, Shenzhen, China; Zhuangzhuang Chen, chenzhuangzhuang2016@email.szu.edu.cn, National Engineering Laboratory for Big Data System Computing Technology, College of Computer Science and Software Engineering, Shenzhen University, Shenzhen, China; Chengwen Luo, chengwen@szu.edu.cn, National Engineering Laboratory for Big Data System Computing Technology, College of Computer Science and Software Engineering, Shenzhen University, Shenzhen, China; Bo Wei, School of Computing and Communications, Lancaster University, Lancaster, United Kingdom, bo.wei@lancaster.ac.uk; Salil S. Kanhere, School of Computer Science and Engineering, University of New South Wales, Sydney, Australia, salil.kanhere@unsw.edu.au; Jianqiang Li, National Engineering Laboratory for Big Data System Computing Technology, College of Computer Science and Software Engineering, Shenzhen University, Shenzhen, China, lijq@szu.edu.cn.

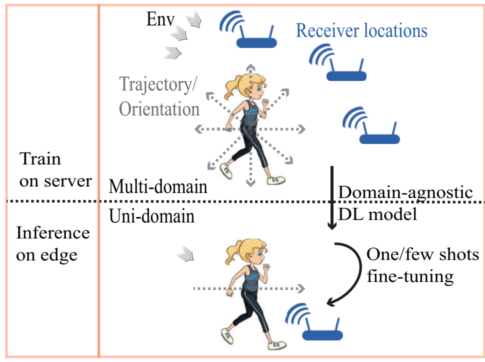

Fig. 1. A typical operation scenario.

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1 INTRODUCTION

The personalized automatic space such as smart homes, offices, cars get much attention by giant company and various intelligent products like Google Home, Amazon Echo are introduced to provide customized services like TV channel selection according to personalized preference. Human identification (HI) is a key enabler for these personalization applications, which mainly employs cameras, microphones or biometrics to realize identification. However, these approaches have strong restrictions. Camera-based systems require a frontal facial pose and sufficient ambient light. Both visual and audio systems commonly raise serious public privacy concerns as well. Thus, WiFi-based solutions as device-free and non-intrusive HI systems become increasingly promising to evolve traditional smart devices.

The WiFi devices like routers and smart lamps invisibly fill the air with radio frequency (RF) signals as a WiFi spectrum during communication. When in this RF space, a person's body reflects and diffracts signals and creates perturbations that could be captured for daily activity recognition [28] [29] and even breathing monitoring [30]. Many existing works show potentials in using WiFi for HI tasks by monitoring gait, since everyone's natural walking style (i.e., gait) is unique. For example, WiFi-ID [26] first tried to use hand-crafted features to capture signature of individuals' gait in WiFi. GateWay [20] and Gate-ID [27] explored the signal processing and deep learning approaches to recognize identities.

Generally, the existing WiFi-based HI systems need to collect large amount of data samples of individuals that are being monitored and involve two operational phases - training a recognition model to realize sensing applications and testing it on site. However, there are several strong assumptions that inhibit their applications in real-world deployment. First, prior works assume that both operational phases are executed in exactly the same conditions. For instance, WiFi-ID [26] and WiWho [24] require individuals to walk along a fixed trajectory that is either perpendicular or parallel to line of sight between transmitter and receiver. WiFiU [17] and GaitSense [34] extract WiFi CSI's Doppler as environment-independent velocity profile of gait, but they assume one or multiple WiFi receivers are fixed in same location so that the Doppler features of a individual's body motion remain consistent in both phases. Unfortunately, these assumptions are impractical because walking trajectory, WiFi layout, multipath environment, (which we refer to as domains), often change in realistic scenarios. The trained-once recognition model of prior works may overfit to specific domains and cannot adapt to other environments during testing. Second, prior works have to collect sufficient training samples of each class and need re-train the recognition model every time a new user is added to the set of users who need to be identified. Moreover, the training data for these new users must be collected in same domain as prior classes stored in the training dataset. The aforementioned issues impede real-world deployment of WiFi-based HI systems.

There is thus a need for a WiFi-based HI system that support cross-domain one/few shot unseen individual identification. A practical and scalable system would be similar to fingerprint biometric system, where only a small number of training samples are collected in uncontrolled domains for any unseen individual, and the recognition model could be fine-tuned using these samples to neutralize domain impact and accurately identify the new joined individuals. These user-friendly characteristics would greatly foster the WiFi-based HI system's wide applications.

In this paper, we present MetaGanFi, a cross-domain WiFi-based unseen human identification (HI) system, which is resilient various domain changes in terms of walking trajectory/orientation, WiFi layout (receiver locations) and multipath environment (deployment time and site). As shown in Fig. 1, the MetaGanFi is in a form of edge computing architecture. Initially, users only need to collect one or few samples (shot) for each new unseen individuals to be identified, and acknowledge the trajectory or layout of WiFi devices to server. Then, the server would treat the on-site conditions at edge as target domain, and train a domain unification model, CCG-GAN and a meta learning based identification model, DA-Meta for the user. Finally, the edge obtains the trained CCG-GAN model from server to neutralize the negative impact of domain variations and fine-tune the trained DA-Meta model from the server by using one or few samples to accurately identify these new joined individuals in cross-domain situations. The data samples and labels of unseen individuals are not sent to server during domain unification and classification process. The ability of fast domain adaption and privacy protection of MetaGanFi would significantly increase WiFi-based HI system convenience and scalability. There are several challenges to be solved to realize our approach.

The first challenge is to remove the negative impact of multiple domains without losing the uniqueness of human gait in WiFi signals. The MetaGanFi theoretically analyzes the reflection effect on gait and demonstrates certain strong mapping relations exist in between different walking trajectory/orientation and WiFi receiver placement, and weak mappings in between versatile multipath environment. It would be too complex to use modeling methods to eliminate domain impacts. Thus, the MetaGanFi proposes a learning based model, CCG-GAN to learn the strong mappings that is able to transfer multiple domains into a certain single domain, for example transforming multiple trajectories or WiFi receiver locations into a single trajectory and location, while, maintain the uniqueness of a person's gait. To achieve this, CCG-GAN designs cycle consistence loss, identity mapping loss and gait classification cycle loss as supervisory conditions to eliminate gait-irrelevant factors and keep discriminative patterns of gait in the transformed samples. Few prior works exploit Generative Adversarial Networks (GAN) to generate virtual samples for each deployed site, which is cumbersome and hardly handle impacts of walking trajectory, WiFi layout and deployed time. In contrast, our proposed novel CCG-GAN model delivered from server to edge would operate as a domain filter to efficiently remove the influence of external factors while keep identities unchanged.

The second challenge is to recognize unseen individuals with one or few samples, which incur no extensive data collection and training overhead, and train a domain-agnostic classification model to mitigate the impact of multipath environment. It is essentially a few-shot learning problem that the model learn prior knowledge from training dataset and only need few data samples to be fine-tuned to adapt to specific domain and identify unseen individuals. The MetaGanFi proposes a customized meta learning framework DA-Meta to achieve few-shot learning for WiFi-based HI system. Specifically, first, DA-Meta applies a data generator (part of the prior trained CCG-GAN model) on all meta dataset as a domain filter to ensure WiFi CSI data at server and edge share the same domain and neutralize impact of trajectory or layout. Then, DA-Meta augments training meta set by time stretching and orientation reversal methods to further mitigate influence of walking speed and orientation.

Finally, DA-Meta conducts pretraining and meta-training to separately update a classifier and a feature extractor as a domain-agnostic DL model. As such, the representation of the model's feature extractor could adapt to unseen individuals in cross-domain situations, specially stochastic multipath environment changes incurred by relocation in new room or electromagnetic variations at different monitoring time. In all, two modules CCG-GAN and DA-Meta of MetaGanFi are designed to eliminate the interfering domains with strong and weak mappings, respectively, and achieve cross-domain one/few shot unseen human identification.

We suppose the training phase of CCG-GAN and DA-Meta are carried out once in a server and the inference phase for domain unification and identification are efficient enough to be done at the edge device, as shown in Fig. 1. We evaluate the MetaGanFi through extensive experiments on a real-world human gait dataset that involves nearly 4k gait samples in different deployment time, environment, trajectories/orientations, collected by 6 WiFi receivers spread in 6 different locations. The general problem of uniquely identifying an individual in any physical domain is inarguably very challenging. To make the problem more tractable, in experiments, we change trajectories/orientations while keeping a WiFi receiver's location the same or vice versa. Subsequently, multipath environment is versatile for each data sample. This is a representative of a smart home or office for example where a person walks in varying trajectories next to a fixed WiFi receiver, or walks along a fixed trajectory next to a WiFi receiver deployed in unknown locations. The results demonstrate the MetaGanFi accurately identify 4 of new individuals in varying trajectories/orientations settings with average accuracies of 87.25%, 90.50%, 93.50% and 93.75% for 1, 3, 5 and 7 samples (shot) cases, and achieve average accuracies of 86.84%, 90.16%, 91.25% and 93.42% for 1, 3, 5 and 7-shot cases in varying WiFi layout situations. In summary, our contributions are as follows:

- Design and implement MetaGanFi, a first-of-its-kind domain-agnostic DL framework for WiFi-based unseen individual identification that mitigates the impact of walking trajectory/orientation, WiFi layout (receivers locations) and multipath environment (deployment time and site).
- Design a novel conditional cycle generative adversarial network, CCG-GAN to transfer multiple domains into a certain single domain and eliminate cross-domain impacts inasmuch as retaining inherent patterns of human gait.
- Propose a domain-agnostic meta-learning network, DA-Meta to identify unseen individuals with one or few gait samples in cross-domain scenarios.
- Extensive evaluations on a real-world gait dataset demonstrate the effectiveness of the MetaGanFi in achieving domain adaption and unseen individual identification simultaneously.

Through this work we present an alternative solution for WiFi-based domain-agnostic human sensing system. In a real-world scenario, users would put WiFi devices in a random place at home or office and may relocate occasionally to recognize unseen individuals like new family members. Prior works employ complex theoretical model-based methods to extract environment-independent features. However, the WiFi device relocation or surrounding electromagnetic variations may lead to data collection again and retraining for model-based solutions. In this paper, we establish a new state-of-the-art learning-based solution for cross-domain one/few-shot WiFi-based unseen human identification.

The remaining paper is organized as follows. Section 2 explains our design logic. Section 3 presents the whole MetaGanFi architecture. Section 4 comprehensively evaluates the system. Section 5 presents related works. Section 6 discusses the limitation and future works. Section 7 concludes the paper.

2 MOTIVATION

2.1 Problem Definition

Existing works have explored the model-based and learning-based approaches to enable WiFi-based human identification system to adapt to different domains. The model-based approaches try to extract environment-independent features e.g. Doppler shifts and the learning-based ones typically rely on adversarial training or losses. However, these prior works still hold strong assumptions, such as, WiFi devices always fixed in certain location for consistent patterns incurred by Doppler effect, and extensive training data more than 10 of samples of each person to be recognized for each domain need to be captured, which are not realistic in real-world scenario.

A typical biometric authentication system i.e., fingerprint, iris normally only need enroll one/few data samples of new unseen individuals as biometric template in database, which is crucial for these systems' fast and wide deployment in real-world scenarios. As for WiFi-based authentication system, from user-centered perspective, the gait samples during enrollment could be seldom identical, since numerous domains negatively affect the consistence of gait samples in WiFi. For example, the walking trajectories, WiFi device placement and surrounding environment could be stochastic and ubiquitous, especially when new users obtain the device and join in the system. Thus, the objective and assumption of our paper are defined as follow,

- The **objective** is to enable WiFi-based gait sensing system to be *domain-agnostic* and *adapt to unseen individuals through one/few samples (shot)*, simultaneously.
- An **assumption** is we assume the service provider of the system has a training dataset of a group of people with multiple labels including person's ID and domain types. The training dataset only needs to be collected by the service provider for once and stored in server. The unseen individual dataset collected by users at edge side has no overlapping classes with the training dataset. Users do not need upload their own gait samples and labels to server thus no privacy concern. Users only have a single pair of WiFi devices i.e., a transmitter and a receiver.

2.2 Human Gait in Different Domains

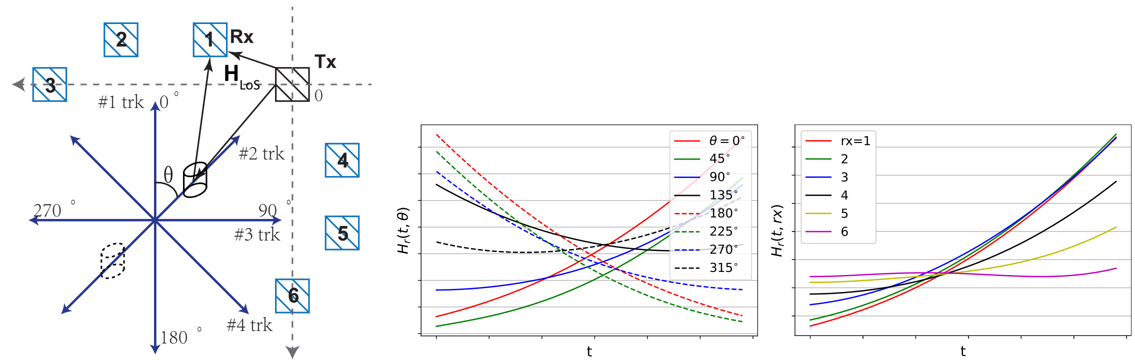
It is important to theoretically understand the inner essence of different existing domains and its impact on gait. As a person in WiFi spectrum, the human body is a strong reflector for electromagnetic waves and could be modeled as a conducting circular cylinder [7]. The presence of moving human body would interfere signal propagations between WiFi devices and cause signal fluctuations that manifested as multiple radio phenomena, i.e., reflection, diffraction, scattering, absorption. The trajectories/orientation and device location domains have distinct propagation paths and incur these radio effects in varying extent. On the other hand, the physical and electromagnetic surroundings e.g., furniture, oven, constitute the multipath environment domain and such indoor surroundings change randomly at different time and space where the HI system deployed.

The location of human body relative to line of sight (LoS) of transceivers determines the extent of prior radio effect [7]. Reflection occurs when human body is 0.5 meters away from LoS and diffraction also termed as shadowing mostly occurs when block or close to LoS, since the dimension of human body is larger than WiFi wavelength significantly. Scattering spread out WiFi energy in all directions and absorption occurs only when human body is close to the transmitter. For gait-based identification tasks, a person normally keeps certain distance away from WiFi devices, thus we assume reflection effect is a key factor in determining WiFi signal perturbations incurred by gait. As such, the WiFi CSI amplitude stream h can be expressed as follows,

$$h = H_{LoS} + H_r + H_n, \tag{1}$$

where H_{LoS} is a constant value since LoS is not blocked in our scenario. In varying trajectories or WiFi layout, the projection area of a person's silhouette[3], i.e, body height and width, towards WiFi receiver could slightly change that affect the prior radio effects such as high absorption rate if a person faces to receiver. Thus, H_n involves both such inconsistency and electromagnetic background noises. The power of WiFi rays reflected by human body dissipate as the radio signal propagates in space. We employ the following path loss model [37] to simulate the reflection radio paths H_r,

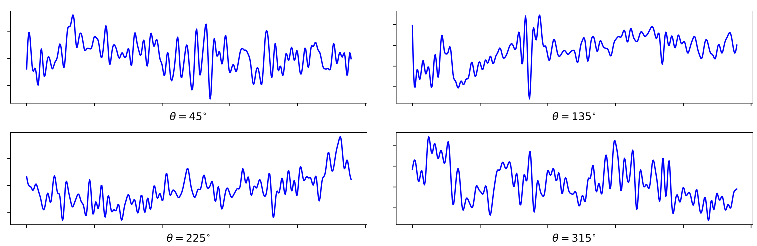
$$H_r = \frac{P_r}{P_t} = \frac{\lambda^2}{16\pi^2 d^2} \cdot \frac{f_{max} - f_{min}}{B} \cdot G_{tx} \cdot G_{rx}, \tag{2}$$



(a) WiFi propagation model in a real deployment that involves 6 WiFi receivers and 4 trajectories.

(b) The simulation of reflection channels in different trajectories at 1st receiver.

(c) The simulation of reflection channels in a trajectory ($\theta = 0$) at 6 different receivers.



(d) A person's gait in trajectories of 45 and 225 degree at 1st receiver.

(e) A person's gait in trajectories of 135 and 315 degree at 1st receiver.

Fig. 2. WiFi signal of a person's gait, modeling and experimental deployment.

where P_r and P_t is received and transmit power, respectively; λ is light wavelength; B is WiFi bandwidth; f_{max} and f_{min} are the maximum and minimum frequency of WiFi signals; G_{tx} and G_{rx} are transmit and receive antenna gains, respectively. The prior parameters are all constants, therefore the attenuation of radio signals is a function of propagation distances d. Thus, the fluctuations of WiFi CSI streams h largely depend on d reflected by human body.

To model human gait captured in WiFi, a set of WiFi transceivers spread in a square area and a person is asked to walk along 4 trajectories in both back and forth orientations as depicted in Fig. 2(a). The person is modeled as a conducting circular cylinder c, a transmitter denoted as tx and 6 receivers denoted as rx are deployed. We assume reflection has no power loss and phase shift, thus H_r can be simplified as follows,

$$H_r = \phi \cdot \frac{1}{(d_{txc} + d_{rxc})^2}, \tag{3}$$

where d_{txc} and d_{rxc} denote the path distance of tx-to-c and c-to-rx channel, respectively; ϕ represents the multiplication of constant values mentioned in Eq. (2). The angle of trajectory denoted as θ increase clockwise and the vertical one from bottom to top is set as 0 degree. The coordinate of tx is (0, 0), and the person is at (x_0, y_0) initially and moves to ($x_0 + v \cdot t \cdot \sin\theta$, $x_0 + v \cdot t \cdot \cos\theta$) after t seconds in a velocity of v. The initial coordinates of trajectories and receiver locations are detailed in an open access dataset [33]. Assume a person walks for t = 3 seconds in v = 1.5 m/s. We are able to exploit these coordinates to calculate d_{txc}, d_{rxc} and model the reflection effect. Fig. 2(b) simulates power changes of reflected WiFi signals in different θ trajectories at the 1st receiver. Fig. 2(c) simulates power changes of a $\theta = 0$ trajectory at 6 of receivers. Fig. 2(d) and Fig. 2(e) display filtered WiFi signals of a person's gait along 2nd and 4th trajectories in back and forth orientation recorded at the 1st WiFi receiver.

We observe in the modeling and real CSI data that a person's gait captured in WiFi signal is not always unique and has inconsistent patterns under different domains, i.e., trajectories/orientations and WiFi receiver locations. Fig. 2(b) shows in modeling each trajectory/orientation cause different reflection effect. Especially, trajectories in opposite orientation has mirrorlike fluctuation patterns. For instance the trajectories at $\theta = 45$ and $\theta = 225$ have opposite trend in modeling shown in Fig. 2(b), which also happen in real signals displayed in Fig. 2(d) and Fig. 2(e). Fig. 2(c) demonstrates WiFi layout cause similar impact as trajectories, whereas, the characteristics of two domains' reflection channels are not same. Therefore, it is important to eliminate interfering domains' influence and preserve unique gait patterns for WiFi-based HI system.

The prior analysis of Eq. (3) simply considers the impact of a person's torso (modeled as a cylinder), while a person's arm and leg also bring similar effect in prior domains on WiFI signals. It is complex to precisely model each part of human body and convert their impact in between domains, especially hard for traditional model-based approaches, thus, a learning-based method CCG-GAN is proposed in this paper. In essence, the aforementioned reflection channel H_r incurred by a walking individual follow the same model Eq. (3) in a function of t, θ and rx (WiFi receiver locations). There might exist certain strong mapping relations between walking trajectories/orientations and receiver locations. CCG-GAN estimates the distribution of CSI dataset and learns a mapping that translate domains with each other. Thereby, multiple interfering domains would be transformed into a single domain. On the other hand, multipath environment at certain date or room when monitoring a person is entirely random thus we assume this domain has weak mapping relations with each other. To resolve its influence, we take advantage of a meta learning framework, DA-Meta that learn domain info from one/few data samples of unseen individuals recorded in the deployed site of the system, then update and fine-tune a DL model to adapt to on-site multipath environment, meanwhile, obtain the ability of recognizing these new joined individuals. In all, MetaGanFi categorizes interfering domains as two types one with strong or weak mappings, and proposes CCG-GAN and DA-Meta to tackle with them accordingly so as to achieve one/few shot cross-domain unseen human identification.

3 SYSTEM DESIGN

The MetaGanFi framework consists of two conceptual devices: the server and the edge. The server provided by service provider is to train the both CCG-GAN model and DA-Meta model. The WiFi-integrated edge device such as a WiFi router, a smart TV, a laptop, is to exploit the trained models to accurately identify gait during inference.

Fig. 3 depicts the architecture of MetaGanFi. In the training phase, the MetaGanFi uses the CCG-GAN model to transfer multiple trajectories or WiFi layout (referred to as multi-domain) to the same domain (referred to as uni-domain), and train domain-agnostic DA-Meta model to recognize unseen individuals in sequence at server. In the inferencing phase, the MetaGanFi firstly neutralizes the negative impact of domain variations and fine-tune the trained DA-Meta model by using one/few shot samples to realize accurate prediction at edge.

3.1 Domain Unification

As prior discussions certain domains including walking trajectory/orientation and transceiver layout have strong mapping relations between them. It is often too complex and versatile for model-based methods to calculate feature irrespective of these domains variations in real-world scenarios. The MetaGanFi proposes the learning-based domain unification method to remove the impact of multiple interfering domains. The idea behind is a conditional cycle consistent gait GAN model is proposed to learn mappings between multiple domains at server

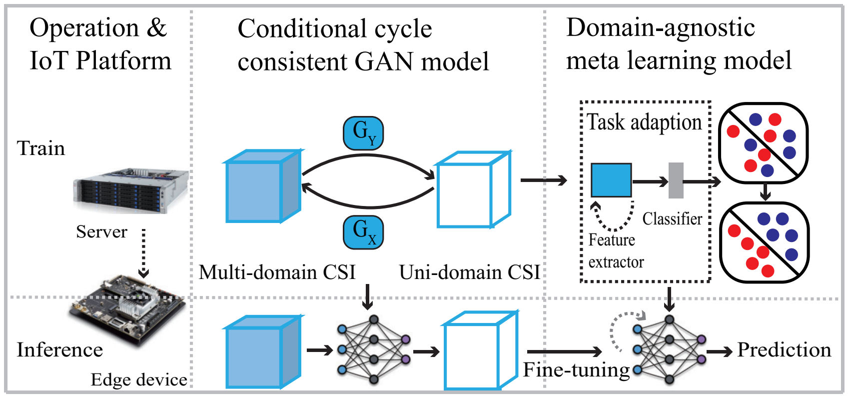
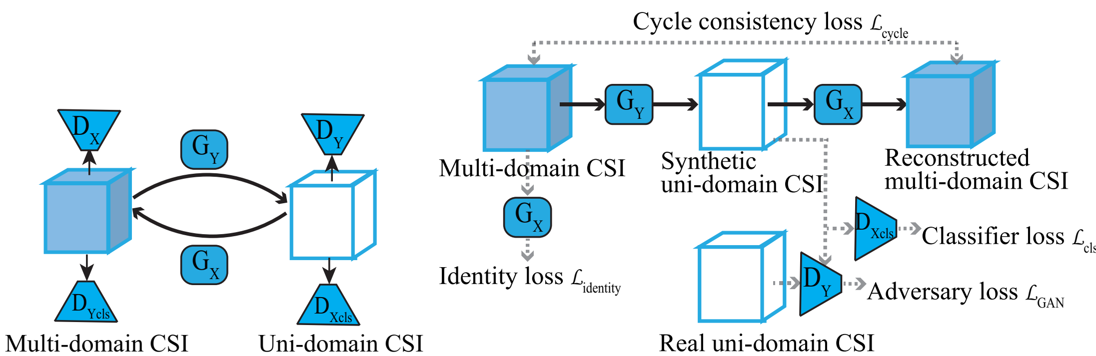


Fig. 3. Overview of the MetaGanFi framework.



(a) The brief overview of the CCG-GAN model.

(b) The detailed architecture of the CCG-GAN model.

Fig. 4. The CCG-GAN model.

and then behaves as a domain filter that transforms multi-domain CSI to uni-domain CSI at edge, while no information loss of inherent gait in WiFi, explained in the following.

3.1.1 Conditional Cycle-consistent Gait GAN Model. Our goal is to learn prior mapping functions and retain inherent gait patterns in WiFi CSI, so that the multi-domain CSI could be transformed to specific uni-domain CSI. Recently, the cycle-consistent adversarial network (CycleGAN) [38] is designed to learn one-to-one mapping and translate image styles between two different domains. In our scenario, since each domain also involves multiple individuals' identities, CycleGAN could incorrectly mix multiple samples' patterns during domain conversion resulting in the loss of uniqueness of human gait captured in WiFi. To resolve this, we propose a Conditional Cycle-consistent Gait GAN (CCG-GAN) model shown in Fig. 4(a). CCG-GAN designs two gait classifiers to minimize the loss of gait uniqueness in the transformed WiFI CSI, and exploits a set of adversarial losses including cycle consistency loss and identity mapping loss to learn mapping relations between domains. CCG-GAN is not designed to augment data but behaves as a domain filter that detailed in the following.

The CCG-GAN utilizes a pair of GANs involving two generators (G_X and G_Y) and two discriminators (D_X and D_Y) as adversarial losses to supervise the gait conversion between domains. For the mapping from source X to target Y domain, the objective function of the adversarial loss is defined as follow:

$$\mathcal{L}_{GAN}(G_Y, D_Y) = \mathbb{E}_y[logD_Y(y)]+ \\ \mathbb{E}_x[log(1 - D_Y(G_Y(x)))], \tag{4}$$

where the generator G_Y takes x in source domain X as input and generate $G_Y(x)$ that looks similar with data in target domain Y and deceives the discriminator D_Y, while, D_Y as a binary classifier is trained to decide whether the input is the real data y in target domain or the fake ones $G_Y(x)$, shown in the middle of Fig. 4(b). For the mapping from target to source domain, similarly, the adversarial loss is $\mathcal{L}_{GAN}(G_X, D_X)$. The CCG-GAN also utilizes the cycle consistency loss as follow:

$$\mathcal{L}_{cycle}(G_X, G_Y) = \mathcal{L}_{cycle}(G_X) + \mathcal{L}_{cycle}(G_Y) \\ = \mathbb{E}_x[\|G_X(G_Y(x)) - x\|] + \mathbb{E}_y[\|G_Y(G_X(y)) - y\|]. \tag{5}$$

The cyclic conversion brings the transformed data in target domain back to original input data in source domain, which keeps semantic content in CSI unchanged during conversion.

The CCG-GAN applies the identity mapping loss that ensure the generator should not modify target samples when it is fed into the generator as the input. The identity mapping loss is defined as follows:

$$\mathcal{L}_{identity}(G_X, G_Y) = \mathcal{L}_{identity}(G_X) + \mathcal{L}_{identity}(G_Y) \\ = \mathbb{E}_x[\|(G_X(x)) - x\|] + \mathbb{E}_y[\|(G_Y(y)) - y\|]. \tag{6}$$

Therefore, the characteristics of generators are twofold: first, transforming samples from source to target domain i.e., $G_Y(x) \rightarrow Y$; second, keeping CSI samples unchanged if the input are originally in target domain, i.e., $G_Y(y) \rightarrow y$. Such domain conversion can be achieved, without prior knowledge of input data samples' domain labels. In our scenario, every unseen individuals may choose a random trajectory or WiFi layout, thus it is impossible to acquire domain labels for each CSI gait sample when the system is deployed at edge. Therefore, the identity mapping loss is essential to realize our domain unification.

The gait dataset in either source or target domain has inherent unique patterns of different individuals. To ensure the persistence of such unique patterns during domain conversion, the CCG-GAN designs another two discriminators D_{Xcls} and D_{Ycls} and construct the gait classification cycle loss to guide gait transition. The classifiers calculate losses that summarize difference between predicted labels of the transformed gait samples and the actual original samples' labels. Such classification loss reflect the possibilities of unique gait patterns still persist in the transformed gait data between domains that evaluated in Section 4.2. The gait classification cycle loss is defined as follows:

$$\mathcal{L}_{cls}(G_Y, D_{Xcls}) = \mathbb{E}_x[\|D_{Xcls}(G_Y(x))\|] \\ = -\mathbb{E}_x[\| \textstyle\sum_{c=1}^{C} \mathbf{1}_{[l_x=c]} log\sigma(G_Y(x))\|], \tag{7}$$

where $\mathcal{L}_{cls}$ uses cross-entropy loss, l_x is samples' label, σ is softmax, C is gait categories. The adverse direction is similar.

Considering the above all conditional adversarial losses shown in Fig. 4(b), the objective function of CCG-GAN can be summarized as follow:

$$\mathcal{L}_{CCG-GAN}(G, D) = \mathcal{L}_{GAN}(G_X, D_X) + \mathcal{L}_{GAN}(G_Y, D_Y)+ \\ \lambda_0\mathcal{L}_{cycle}(G_X, G_Y) + \lambda_1\mathcal{L}_{identity}(G_X, G_Y)+ \\ \lambda_2(\mathcal{L}_{cls}(G_Y, D_{Xcls}) + \mathcal{L}_{cls}(G_X, D_{Ycls})), \tag{8}$$

where λ_0, λ_1 and λ_2 are the weights of cycle consistency, identity mapping and classification cycle loss, respectively. Theoretically, a high λ_1 of $\mathcal{L}_{identity}$ could make the generator of CCG-GAN generate target samples entirely identical with source samples and lose domain conversion ability, whereas, a low λ_1 may let the generator excessively change samples if the input are originally in target domain, resulting in the loss of unique patten of gait in WiFi CSI. Similarly, a low λ_2 of $\mathcal{L}_{cls}$ may cause the synthetic gait samples fall into wrong individuals' identities. A high λ_2 constrains the ability of domain conversion that cause the generated samples to be identical with original data. In all, appropriate hyperparameters are needed to mitigate the impact of trajectory and WiFI layout meanwhile retain the unique pattern of every person's gait in WiFi samples, which would be evaluated in Section 4.2.

In the training phase, certain trajectories in both directions or certain receivers in specific locations are chosen as the target domain and the others are set as the source domain. We train the CCG-GAN model on the training dataset at server to obtain the generator G_X and G_Y. With the help of the three adversary training losses, the trained generator are able to learn mapping functions between domains and reserve unique gait patterns, simultaneously. In the inference phase, the generators are transferred to the edge device and employed to convert data at the server and the edge to target domains, without prior knowledge of data samples' domain labels. This conversion process is considered as a preprocessing step and the synthetic dataset would be used in the following meta learning method explained in Section 3.2.

In implementation, the generators incorporate 4-layer ResNet model and 1-layer self-attention [13] stacked in sequence to effectively capture features in WiFi CSI. The discriminators employ 4-layer convolutional neural networks (CNN). The CCG-GAN uses spectral normalization [11] in addition with the batch normalization to stabilize the GAN model's training process. The batch size is set as 10, learning rate is set as 5e-4 and the training epoch is set as 500. Each WiFi CSI data sample is a three dimensional matrix (i.e., $N_a \times N_s \times N_l$). N_a (=3) is the number of WiFI transceiver antenna pair, N_s (=30) is the number of subcarriers, N_l is equal to the WiFi sampling rate multiplied by monitoring duration. In experiments, the sampling rate is downsampled to 160Hz, the duration is about 3s. The CCG-GAN model uses raw CSI data without any complex signal processing methods.

Fig. 5 shows an original and a transformed CSI example and corresponding spectrograms. Fig. 5(c) demonstrates the synthetic CSI has much pronounced periodical patterns incurred by gait compared with the original CSI as shown in Fig. 5(a). In frequency domain, the synthetic CSI has much clear and consistent patterns of gait cycle (steps) in a frequency band between 0-40Hz marked in the dashed area of Fig. 5(d) compared with the original CSI's spectrogram shown in Fig. 5(b), which verify CCG-GAN helps mitigate the negative impact of interfering domain and retain inherent gait patterns captured in WiFi CSI.

3.2 Domain Adaptive Meta Learning

To be a qualified biometric authentication method, WiFi-base HI system should be able to recognize new unseen individuals with only one or few enrolled data samples. In addition, in real-world scenarios, the unseen individuals commonly locate in new multipath environment which is hardly replicated in the system training phase by service providers. To solve these two challenges that fast adaption to different domains with one/few data samples of unseen individuals, the MetaGanFi proposes a deep learning based domain adaptive meta learning DA-Meta model. The DA-Meta is designed to find a good initial parameters of a feature extractor model that can be adapted with a few steps of gradient descent to novel classification tasks. Specifically, DA-Meta applies the generator of CCG-GAN to obtain the uni-domain data which is considered as a task preprocessing phase and propose task augmentation methods to mitigate the impact of walking speed variations and opposite orientation discussed in Section 3.2.2. Then, instead of training a whole DL model at once, DA-Meta separately updates a classifier network and a feature extractor network to obtain a domain-agnostic DL model detailed in Section 3.2.3.

3.2.1 *Few-shot Learning Problem Definition.*

The DA-Meta that adapting models to new classification tasks with limited data samples is essentially to solve few-shot learning problem termed in DL context. In our WiFi-based HI scenarios, we formulate gait identification as the N-way K-shot classification tasks in which a WiFi gait dataset contains N classes (i.e., individuals' identities), each with K samples. To ensure well generalization, the DA-Meta utilizes the inductive learning method that divide the tasks into a training meta-set S^{tr}, validation meta-set S^{val},

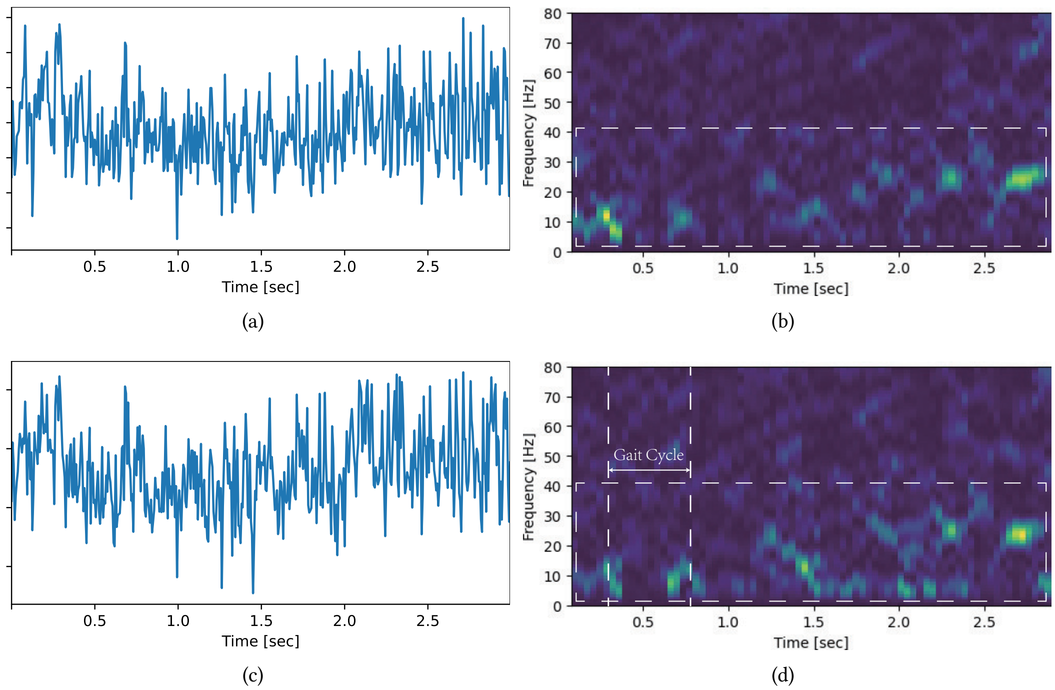


Fig. 5. Comparison of an original and the corresponding transformed CSI sample generated by the CCG-GAN model in temporal and frequency domain. Fig. 5(a) is a certain subcarrier's original CSI stream and its spectrogram is shown in Fig. 5(b). Fig. 5(c) is the domain neutralized CSI stream generated by CCG-GAN and its spectrogram is shown in Fig. 5(d). The domain filtered CSIs have much pronounced periodical patterns incurred by human gait.

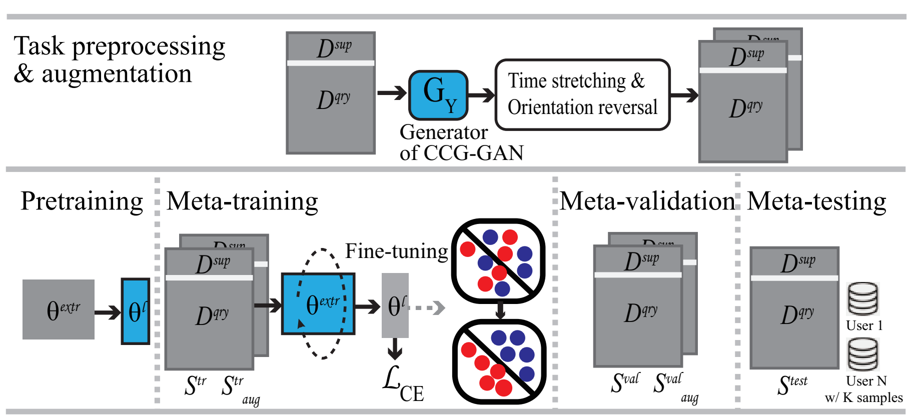


Fig. 6. The DA-Meta model.

and testing meta-set S^{test}, each with a disjoint set of classes. S^{val} is used for model selection and S^{test} is used for final evaluation. In other words, an individual seen during testing at edge devices would not be seen during training at server.

Each task instance is composed of a support set D^{sup} and a query set D^{qry} and contains N classes and K samples that randomly selected from each meta-sets. Thus each support set $D^{sup} = \{(x_n^k, y_n^k) \| k = 1 \dots K; n = 1 \dots N\}$ contains $K \times N$ samples. Each query set has a number of samples from the same class with the corresponding support set. A typical few-shot problem would have only 1 to 7 ($= K$) support samples which means users only have to enroll such few amount of data samples into our WiFi HI system. Common supervised learning approaches would easily overfit and fail to solve such few-shot problems because of the scarcity of labeled data. The proposed meta learning approach DA-Meta instead tries to learn an internal presentation from a batch of support and query sets that broadly suitable to many tasks, then fine-tunes the parameter slightly to fit and improve performance on the unseen tasks, i.e., new individuals.

3.2.2 Task Preprocessing and Augmentation. The MetaGanFi is in a typical edge computing architecture as mentioned above. The training and validation meta-set are prepared by service providers stored at server while the testing meta-set are collected by users after the system deployment at certain time and site. The multipath environment at edge is inevitably different with conditions at server. The proposed DA-Meta itself could quickly adapt with such domain variations with weak mapping relations. For walking trajectory/orientation and transceiver layout changes, the CCG-GAN's generator mentioned in Section 3.1.1 are to be used to eliminate these domain variations that treated as a preprocessing step, depicted at the top of Fig. 6. The generator with capability of domain transition is applied on training and validation meta-set at server and also on testing meta-set collected by users at edge to filter out interfering domain impact. As a task preprocessing phase, the inference time of the CCG-GAN's generator model is fast enough to support real-time applications at edge that evaluated in Section 4.6.

Even though the MetaGanFi considers a set of potential domains, an individual naturally walks in varying speed at different time and situation that leads to inconsistency in gait captured by WiFi CSI. Moreover, in realistic in-door scenario, this person would walk back and forth in opposite orientations along a trajectory. Thus, the DA-Meta generate an additional augmented training and validation meta-set S_{aug}^{tr}, S_{aug}^{val} to mitigate the prior factors' influence. The DA-Meta use two approaches - (1) *time stretching* and (2) *orientation reversal* for task augmentation. First, to slow down or speed up the CSI streams, the DA-Meta exploits the linear interpolation to horizontally stretch CSI. The stretching rate is α, the percentage of the duration of the original CSI streams. α is set as 20%, empirically. The synthetic CSI are to be extended or cropped to keep their original duration. Second, the CSI streams are to be flipped along the time dimension to simulate the impact of opposite orientations, because the experiment and theoretic analysis demonstrate the incurred mirrorlike patterns mentioned in Section 2.2. Finally, the purified and augmented meta-sets are used to train the following proposed meta learning model.

3.2.3 Meta Learning Model. To address the few shot learning problem, the DA-Meta adopts an optimization-based meta-learning approach that aim to find a set of model parameters to adapt to unseen tasks with a few steps of gradient descent. Model-agnostic meta-learning (MAML) [5] is a typical representative optimization-based meta-learning algorithm that train a base DL model comprised of a feature extractor network and a classifier network together but lack of sufficient abilities of domain adaption in between training and testing meta-sets. To ensure well model generalization on versatile multipath environment, DA-Meta exploits the representation change strategy [12] that explicitly update and fine-tune the feature extractor network instead of the classifier corresponding to unseen tasks, so that the feature extractor has well cross-domain adaption ability, detailed in the following.

The DA-Meta consists of a backbone deep learning network f_θ, parameterized by θ, and a meta-learning model $\mathcal{G}$. f_θ that composed of a feature extractor f_θ^{extr} and a classifier f_θ^{l} is to extract features from CSI signals and predict its identities. $\mathcal{G}$ aims to learn a set of parameters θ from S^{tr} and S_{aug}^{tr} which can be adapted to any unseen tasks in S^{test} with few gradient descent. For a particular task $T_i = (D_i^{sup}, D_i^{qry})$ in S^{test}, the adaption form can be summarized as the following:

$$\theta^{'} = \mathcal{G}(\theta, D^{sup}), \tag{9}$$

where $\theta^{'}$ is the adapted model parameters to the specific task T_i.

The DA-Meta framework has four operation phases, depicted at bottom of Fig. 6, including pretraining, meta-training, meta-validation, and meta-testing and involves two optimization loops including inner and outer optimization loops. During the pretraining phase we sample several tasks from S^{tr} and learn parameters of classifier f_θ^l that are to be fixed for the following operation phases. The initial f_θ^l has basic classification ability and the extractor f_θ^{extr} is not stored at this stage. During meta-training, the DA-Meta has the inner and outer (finetunning) loop. In the inner loop, the DA-Meta instantiate f_θ^{extr} combined with prior f_θ^l as the meta-initialized θ. Then we sample a batch of tasks from both S^{tr} and S_{aug}^{tr} and use the support set to update θ to task-specific parameters $\theta_{D_i^{sup}}$ with few steps of gradient descent using cross entropy loss $\mathcal{L}_{D_i^{sup}}^{tr}$, as follows:

$$\theta_{T_i}^{extr} = \theta^{extr} - \alpha \nabla_\theta^{extr} \mathcal{L}_{D_i^{sup}}^{tr}(f_\theta), \tag{10}$$

where α is the inner loop learning rate set as 1e-2. The inner loops keep fixing the parameters of classifier f_θ^l, meanwhile force and change the parameters of feature extractor f_θ^{extr} to adapt to specific tasks, so that the stacked neural layers in the feature extractor could be resilient with domain changes, i.e., multipath environment variations, which is the key difference compared with MAML. In the outer loop, the model is trained on the query set D_i^{qry}, and the meta training loss $\mathcal{L}_{D_i^{qry}}^{tr}$ is obtained based on each inner updated parameter. Then, the model parameters θ are updated by back-propagation using the meta-loss of each meta-batch denoted as B, as follows:

$$\theta^{'} = \theta - \beta \nabla_\theta^{extr} \sum_{i=1}^{B} \mathcal{L}_{D_i^{qry}}^{tr}(f_{\theta_{T_i}^{extr}}), \tag{11}$$

where β is the outer loop learning rate set as 1e-3.

Next, the meta-validation is performed to evaluate the generalization of the trained $\theta^{'}$ on both S^{val} and S_{aug}^{val} meta sets. Finally, the meta-testing choose the model with highest accuracy during meta-validation and obtain the final performance on S^{test}. In the meta-validation and meta-testing, the inner loop is the same as in meta-training that used for learning task-specific knowledge. The outer loop calculates the prediction accuracy of query sets on corresponding tasks, whereas does not update the model parameters. In implementation, we choose 3 layers of ResNet as the backbone network of the DA-Meta that comprehensively evaluated in Section 4.3. The inner and outer loop update step is set as 5 and 25, respectively. The DA-Meta framework uses raw WiFI CSI data samples same as CCG-GAN with no extra signal processing methods.

4 EVALUATION

In this section we present a comprehensive evaluation of the system. Section 4.1 outlines the experimental setup and explains the interfering domains existed in WiFi-based human sensing. Section 4.2 and Section 4.3 evaluate the impact of hyperparameters and backbone of the CCG-GAN and DA-Meta models. Section 4.4 conducts the ablation study and compare it with baselines. Section 4.5 evaluates the effectiveness of our proposed framework on performing one/few shot unseen human identification with domain adaption.

4.1 Experiment Setup

As described in Section 2 and depicted in Fig. 2, the MetaGanFi considers two types of external domains existed in WiFi-based human sensing, the first type is with strong mapping relations - walking trajectory/orientation and WiFi layout (receiver location), second is with weak mapping relations - deployment time and site (when and where) to monitor subjects. To experiment these varying domains, the MetaGanFi utilizes an open access dataset [33] that incorporates one WiFi transmitter and six WiFi receivers deployed in six different locations as the layout depicted in Fig. 2(a). The individual to be monitored walk in four linear trajectories in both forward and backward directions that indexed in clockwise depicted in Fig. 2(a). The WiFi CSI gait of 11 individuals are collected on 7 different day in 2 different rooms. These recruited individuals were asked to walk normally at varying speed along each of trajectory and orientation and each collected CSI data sample contains about 5 steps. In our experiment, we separate 4 of 11 subjects as unseen individuals in the testing meta-set. Since each subject's dataset cover a wide range of domains, the training and validation meta-set in source domains are selected for model training, the testing meta-set in target domains are selected for final testing. The experiments are programmed with PyTorch and run on NVIDIA Tesla Titan with 12GB memory. The true detection rate (accuracy), inference time cost, model size are used to evaluate our system performance and estimate the feasibility to tackle domain adaption for one/few shot HI applications deployed in a collaborative edge-server architecture.

4.2 Effect of Different Loss Weights of CCG-GAN

As mentioned in Section 3.1.1, the CCG-GAN employs a set of conditional adversarial losses including GAN loss $\mathcal{L}_{GAN}$, cycle consistency loss $\mathcal{L}_{cycle}$, identity mapping loss $\mathcal{L}_{identity}$ and classification cycle loss $\mathcal{L}_{cls}$ to supervise domain conversion process. The λ_0, λ_1 and λ_2 are the corresponding importance weights of the prior losses in the objective function of CCG-GAN Eq. (8). To determine them, we empirically set λ_0 of $\mathcal{L}_{cycle}$ as 10 and experiment varying λ_1 and λ_2, as shown in Fig. 7. In this experiment, assume users at edge select 1st track as target domain. Then, we train a generator of CCG-GAN that converts the 2nd and the 4th track into the 1st and the 3rd track and transforms dataset at server into a proper uni-domain gait dataset adaptable to situations at edge. Next, we selects the filtered gait samples of the 1st track as testing meta-set and the rest of tracks from 2-4 as training and validation meta-set. The performance of DA-Meta on the prior meta-sets are used to evaluate the impact of different loss weights.

As shown in Fig. 7, it is obvious when $\lambda_1 = 5$ and $\lambda_2 = 5$ the uni-domain gait meta-set filtered by CCG-GAN has average accuracies of 89.5%, 92.0%, 95.0%, 95.0% for 1, 3, 5 and 7-shot cases. This setting consistently helps DA-Meta to achieve the best performance across varying number of shots. In contrast, the extreme low or high settings of λ_1 and λ_2 tend to have low accuracy and high variance, for instance, the accuracy of DA-Meta drop to 82.0% if $\lambda_1 = \lambda_2 = 1$ for the 1-shot case. It demonstrates a proper setting of prior loss weights helps find a balance in between domain unification and maintenance of uniqueness of individuals' gait captured in WiFi which is essential as discussed in Section 3.1.1. Therefore, we set $\lambda_1 = \lambda_2 = 5$ as the default in the following experiments if without explicit mentions.

In addition, Fig. 8 displays a log of prior adversarial losses of CCG-GAN during training. As mentioned in Eq. (4), $D_Y(y)$ and $D_Y(G_Y(x))$ represents the discriminator D_Y's loss for the original gait sample and the synthetic gait sample. It is obvious that the values of $D_Y(y)$ and $D_Y(G_Y(x))$ oscillate around 0.5 which show $\mathcal{L}_{GAN}$ and $\mathcal{L}_{cycle}$ effectively enable generators and discriminators of CCG-GAN compete with each other while training so as to generate realistic WiFi CSI gait sample. In Fig. 8, $\mathcal{L}_{identity}(G_X)$ and $\mathcal{L}_{identity}(G_Y)$ are close to 0 which means the trained CCG-GAN can keep the target domain's samples unchanged and only transform the source domain's ones without prior domain labels as mentioned in Section 3.1.1. In Fig. 8, $\mathcal{L}_{cls}(G_X, D_{Ycls})$ and $\mathcal{L}_{cls}(G_Y, D_{Xcls})$ are close to 0 and drop rapidly as training. It demonstrates that the trained CCG-GAN accurately recognizes the transformed CSI samples by using their original individual identities' labels, as discussed in Section 3.1.1. In other words, the uniqueness of gait in WiFi CSI is effectively retained after domain unification.

4.3 Comparison of Different Backbones of DA-Meta

Recall that in Section 3.2 the DA-Meta framework employ the three meta sets to obtain an optimized network that can be adapted with a few steps of gradient descent to recognize unseen individuals. Therefore, this network

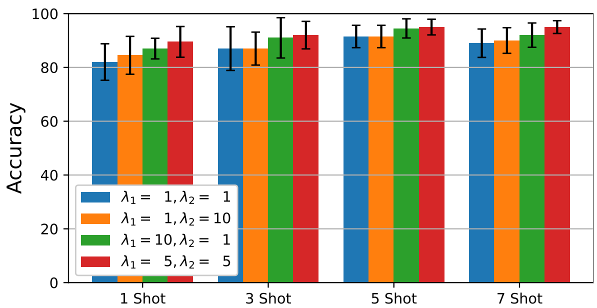


Fig. 7. Impact of loss weights of CCG-GAN.

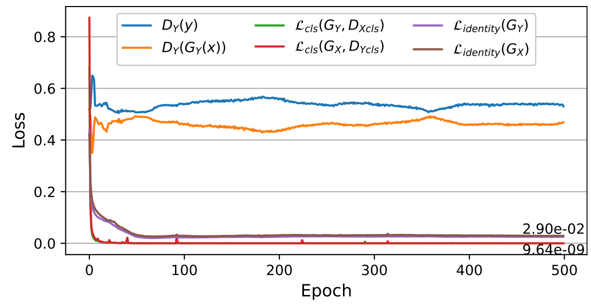


Fig. 8. A log of adversarial losses of CCG-GAN during training in an experiment.

as the backbone of the DA-Meta plays an important role in the meta learning framework. As shown in Fig. 9, we experiment a set of typical deep learning models with varying stacked layers: cnn-1, cnn-3, resnet-1, resnet-2, resnet-3, resnet-4 and resnet-3 combined with 1-layer self-attention (transformer) [13] which has been widely employed in prior works [10] [23]. Herein, we reuse the 1-shot trajectory adaption experiments explained in the prior Section 4.2 and choose $\lambda_1 = \lambda_2 = 1$ to highlight the behavior of the DA-Meta framework. In Fig. 9, the baselines including cnn-1, cnn-3, resnet-1, resnet-2 have average accuracy of 55.0%, 60.0%, 71.5% and 76.5%, respectively. It is obvious that the simple convolutional neural networks do not have enough representation ability to learn unique features of human gait from few WiFi CSI samples. In contrast, the 3 stacked layers of ResNet models achieve the best performance, with an average accuracy of 82.0%, in recognizing unseen individuals.

Interestingly, we find the deeper or complex backbone network are not necessarily beneficial for the DA-Meta. As shown in Fig. 9, the deeper model 'resnet-4' and the self-attention model 'resnet-3 + attention-1' have average accuracy of 78.5% and 73.5% respectively lower than the 3 layers ResNet model. Conventionally, the deep network and the attention mechanism help focus on specific area of feature maps to extract representative features, however, they could easily overfit to meta-training dataset and have incompetent generalization ability, which is essential towards domain independent in terms of trajectory, WiFi layout and multipath environment as discussed in Section 2.2. Therefore, we choose the 3 layers of ResNet as the default backbone of our DA-Meta model.

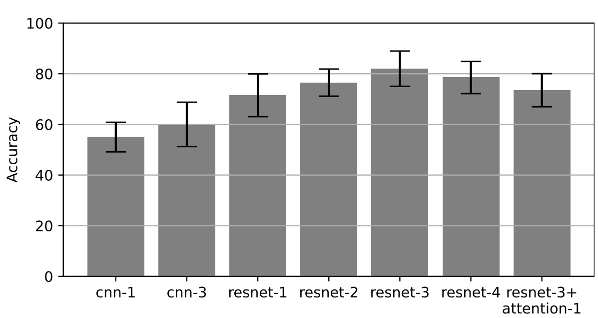


Fig. 9. Impact of different backbones of DA-Meta.

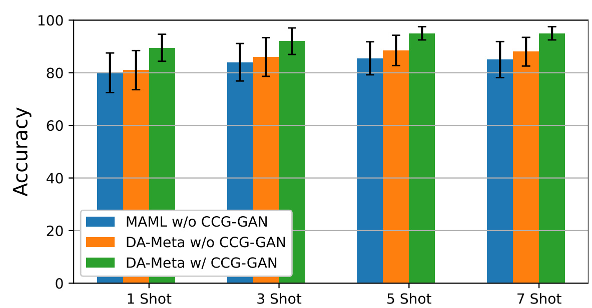


Fig. 10. Comparison of MAML, DA-Meta w/o and w/ CCG-GAN.

4.4 Ablation Study

In this section, we compare DA-Meta with domain adaption realized by CCG-GAN short as 'DA-Meta w/ CCG-GAN', DA-Meta without CCG-Meta, short as 'DA-Meta w/o CCG-GAN'and the baseline model MAML short as 'MAML w/o CCG-GAN' to study the impact of each proposed module, as shown in Fig. 10. Note, this MAML model has been tailored in terms of the backbone network and hyperparameters to suit our gait recognition CSI dataset. In this experiment, we also employ the trajectory adaption scenarios similar with the prior Section 4.2 and select the 1st track as testing meta-set and repeat experiments 5 times for each model. In Fig. 10, we observe DA-Meta without domain unification from CCG-GAN still consistently outperforms the original MAML baseline by 2.25% of accuracy with less deviation, increasing from 80.0% to 81.0%, 84.0% to 86.0%, 85.5% to 88.5%, 85.0% to 88.0% for 1, 3, 5 and 7-shot cases, respectively. Moreover, DA-Meta combined with CCG-GAN has significant performance improvement that increase around 7.8% and 10.1% of accuracy on average compared with the DA-Meta w/o CCG-GAN and the baseline MAML, respectively. The DA-Meta w/ CCG-GAN achieves the average accuracies of 89.5%, 92.0%, 95.0% and 95.0% for 1, 3, 5 and 7-shot cases, respectively, that consistent with the result in Fig. 7. It demonstrates the prominent characteristics of domain unification and generalization brought from CCG-GAN and DA-Meta framework of MetaGanFi in one/few shot unseen individual identification.

4.5 Cross-Domain Performance

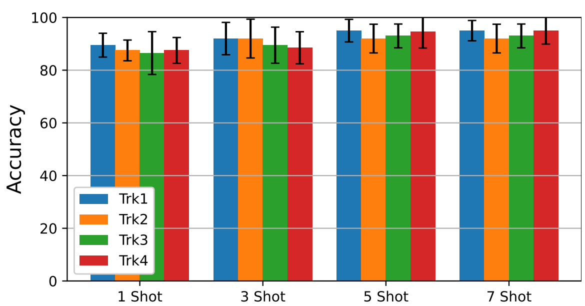


Fig. 11. Recognition accuracy on unseen individuals in different walking trajectories in both direction.

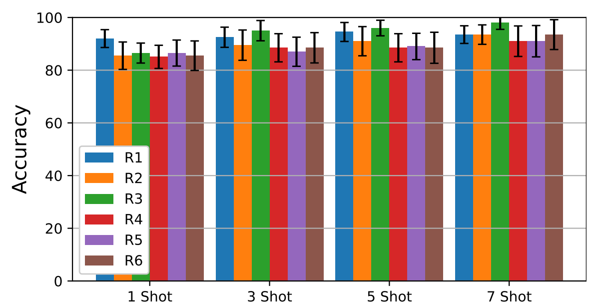


Fig. 12. Recognition accuracy on unseen individuals captured by different WiFi receivers.

As the discussion in Section 2, WiFi CSI could be easily affected by the surrounding domains including the walking trajectories/orientations and WiFi device layout, or multipath environment. The MetaGanFi proposes the CCG-GAN model to transform domains with strong mapping relations (i.e., track and receiver locations) and utilize the DA-Meta model to handle the implicit domain variations such as varying monitoring time and deployment. To evaluate the effectiveness of the proposed approaches, we separately apply the proposed models on track adaption and WiFi receiver adaption scenarios, because the inherent models of wireless channel in these two domains are not the same as discussed in Section 2.2. It is important to mention that first, the testing meta set are captured in a different deployment site compared with the training and validation meta-set; second, every recruited individual in the WiFi CSI gait dataset is mostly captured at different date (time). Therefore, the track and receiver adaption experiments discussed in this experiment section have naturally counteracted the versatile domains caused by multipath environment variations. In the following, we separately experiment cross-domain performance in terms of trajectory/orientation (track) and WiFi layout (receiver location) changes.

4.5.1 Track Adaption. As shown in Fig. 2(a), a person could walk along 4 trajectories in back and forth orientations in a typical indoor area. In Section 2.2, the theoretical model reveals that there exist certain strong mapping

Table 1. Time cost of the DA-Meta during inference per query sample.

Shots	1	3	5	7
Time (s)	0.078	0.094	0.118	0.157
Deviation (s)	0.004	0.005	0.006	0.005

relations as shown in Fig. 2(b) in WiFi signals across different trajectories and orientations. Thus, the proposed CCG-GAN model is exploited to learn such mappings then unify such domain variations. To do this, we choose the 1st and 3rd track as source domain and the 2nd and 4th as target domain to train the CCG-GAN. To eliminate negative impact of WiFi layout, this experiment only uses the 1st receiver's CSI data. When users select a specific track as target domain, a corresponding trained generator of the CCG-GAN is applied to filter all three meta-set for domain unification. For instance, if #1 track is the target, the generator that transforming #2 and #4 tracks to #1 and #3 tracks will be used for domain conversion. Then, the DA-Meta would only select data samples in the source tracks (#2-#4) from training and validation meta-set to train the backbone model and select data samples in the target track (#1) from testing meta-set to evaluate the identification performance. In experiments, *we separately consider each track as target domain and Fig. 11 shows average accuracies of 87.25%, 90.50%, 93.50% and 93.75% for 1, 3, 5 and 7-shot cases.* It demonstrates the well generalization ability of the proposed model on cross-domain unseen individuals.

4.5.2 Receiver Adaption. As shown in Fig. 2(a), a WiFi transmitter is deployed at top right place and 6 receivers spread evenly next to the transmitter. The layout of WiFi devices also brings domain variations similar with various trajectories and orientations scenarios, and the theoretical model as shown in Fig. 2(c) verifies strong mappings do exist in between different receivers. To unify such domain variations, we choose the 1st, 3rd and 5th receiver as source domain and the 2nd, 4th and 6th receiver as target domain to train the CCG-GAN. To eliminate negative impact of trajectory/orientation, this experiment only uses CSI data in the 1st track. Similar with the prior track adaption, if a specific receiver is selected as target domain, the DA-Meta applies a corresponding generator for domain unification. For instance, take the 1st receiver as the target. Then, the DA-Meta chooses data samples in source domain (#2 – #6 receiver) from training and validation meta-set to train the backbone network and select the 1st receiver's data samples from testing meta-set for evaluation. *In Fig. 12, the comprehensive experiments show average accuracies of 86.84%, 90.16%, 91.25% and 93.42% for 1, 3, 5 and 7-shot cases with less deviations.*

In these experiments, the data samples and labels in testing meta-set are only used for final evaluations, not participated in any training process. Moreover, the data samples of all three meta-sets only has one single receiver's CSI data. In real-world, a pair of WiFi device i.e., a single receiver deployed at random corners of a living room is the most common scenario. As presented in these experiments, The MetaGanFi could handle these challenging cross-domain scenarios and accurately identify unseen individuals with one/few shots which is user-friendly in real-world environment.

4.6 Inference Overhead

The MetaGanFi consists of two conceptual layer which is the server and the edge. The server is responsible for the heavy computation workload including training phases of both CCG-GAN and DA-Meta models. The edge obtain the two trained model files and perform inference process. In this experiment, we consider the inference overhead in terms of model file size and time cost to evaluate the system. First, the file size of the CCG-GAN and DA-Meta model is 85 KB and 104 KB, respectively. Therefore, the communication cost and delay for transferring models between the server and the edge is low. Second, the time cost of the CCG-GAN model's generator is only 0.00012s per sample which is negligible. The time cost of the DA-Meta depends on the number of shots as shown in Table 1, since the DA-Meta need firstly train on a number of support samples and then test query samples. Some prior works mentioned in Section 5.1 design complex novel signal processing algorithms to extract environment independent features such as Doppler profile of human motions to realize cross-domain identification. However, these model-based methods are not only computationally intensive and but also sensitive to WiFi receiver relocation. In contrast, our proposed system does not have such heavy computation tasks and directly works on raw WiFi CSI signals. Thus, the efficient inference around 0.1s shown in Table 1 is achievable, and important for human identification applications deployed in real-world environment.

5 RELATED WORK

5.1 WiFi-based Human Identification

We have witnessed a growing interest in exploiting WiFi signals for human identification and gait recognition. Initially, researchers explore traditional machine learning approaches to extract patterns of gait from WiFi signals for identification. WiFi-ID [26] and WiWho [24] first tried to use hand-crafted features to calculate various patterns of gait cycles (steps) for recognizing human identities. WifiU [17] analyzed WiFi spectrogram to estimate the torso and leg speeds and find the inherent unique patterns. These exploring prior works often restrict experimental environment for instance individuals need walk in a fixed trajectory which is unrealistic in real-world. In the next stage, researchers attempt to solve cross-domain scenarios and improve system's adaption and reliability. The evolved techniques at this stage can be divided into the deep learning based and the model based system. Gate-ID [27] explored to accurately recognize individuals in different walking orientations. CrossSense [25] and TransferSense [1] proposed to use transfer learning in achieving gait recognition across different monitoring sites. In contrast, WiDIGR [31] fused multiple receivers' spectrograms as direction-independent features to realize WiFi-based HI system. GaitSense [35] exploited Doppler effect to calculate domain independent features as body-coordinate velocity profile and also adopted DL based model to realize identification that resilient with environment and trajectory change. The similar model-based methods [36] [32] [21] [6] have also been used to achieve WiFi-based cross-domain gesture recognition. [18] discussed WiFi layout affect sensing coverage in gait monitoring scenarios. However, these systems have several types of limitations. First, the layout of WiFi devices might change regularly which could negatively affect the uniqueness of features of human gait generated by the model-based methods. Second, current systems face extensive data collection and training overhead to identify unseen individuals. In this paper, we solve these problems with a combination of a GAN variant model and a meta learning framework.

5.2 GAN-based WiFi Sensing Techniques

To our best knowledge, in literature, only some few works exploit GAN models on WiFi-based activity recognition. CsiGAN [22] introduced a semi-supervised GAN netwwork to generate complement fake data samples and improve activity recognition accuracy when performed by new users. WiGAN [9] focused on the expansion of WiFi data capacity and diversity as well. DMNet [19] and GNG [15] also utilized GAN to produce additional samples and facilitate activity recognition. A recent work [39] explored GAN to learn domain independent features for activity recognition. These prior works in essence exploit the data generation ability of GAN model to synthesize virtual samples in target domains and facilitate domain adaption. However, this approach needs to generate an additional dataset for each specific target domain resulting in cumbersome training procedures, even impractical to be deployed in realistic environment. In contrast, the generator of our proposed CCG-GAN operates as a domain filter that would remove external factors if the filtered samples in interfering domains or keep them unchanged if originally in target domain. Thus, CCG-GAN is able to effectively eliminate impact of various interfering domains at edge such as WiFi layout or trajectories.

5.3 Meta Learning Based WiFi Sensing Techniques

The fast learning and adapting from few data samples while avoid overfitting to new data becomes important for applications of the learning-based systems. It is essentially the few-shot learning problem and recent proposed meta learning approaches have superior generalization ability on unseen class training. Some few works have tried to apply meta learning to recognize unseen activity or gesture using WiFi signals. RF-Net [4] adopted a metric-based meta learning method similar with Matching Network to achieve one-shot human activity recognition. WiONE [8] also used a metric-based method Prototypical Network to realize user authentication by monitoring a person's typing motions. These prior works mostly try to solve the few-shot problem and do not consider domain-adaption issues. MatNet-eCSI [14] designed a signal processing method to extract activity-related features and exploited Matching Network to achieve cross environment activity recognition. OneFi [23] also employed the model-based method to extract domain independent features combined with meta learning to realize unseen gesture recognition and cross-domain ability. However, the prior proposed model-based methods could be negatively affected by WiFi layout changes and require multiple WiFi receivers deployed on sites calculate predetermined domain independent features. To our best knowledge, the MetaGanFi is the first to achieve cross-domain WiFi-based unseen individual identification, irrespective of various domain variations including trajectory/orientation, WiFi layout (receiver location), and multipath environment (deployment time and site) in one/few shot scenarios through a single pair of WiFi devices.

6 DISCUSSION

All-in-One Cross-Domain Adaption. Section 4.5 shows MetaGanFi is able to separately neutralize impact of various trajectories/orientations or WiFi layout in different multipath environment. The reason behind is mapping relations of reflection channels in different trajectory or receiver locations are not the same as discussed in Section 2.2. For instance, the mappings transforming a trajectory at $\theta = 0$ to certain other trajectory or WiFi receiver location are inconsistent as displayed in Fig. 2(b) and Fig. 2(c). The CCG-GAN module of MetaGanFi can only learn a mapping of either tracks or layout and keep the other factor unchanged. The DA-Meta module tries to tackle with other domain impacts such as varying walking speed, mirrorlike orientations, and multipath environment. To obtain the all-in-one domain adaption, extra efforts are required, for instance, applying multi-domain translation method, StarGAN [2] on WiFi CSI to learn a general mappings between aforementioned WiFi domains.

Irregular Trajectory Domain Adaption. As shown in Fig. 2(a), MetaGanFi considers individuals only walk in straight lines and the experiments are conducted on just one suitable dataset that involves 4 trajectories and each with two orientations. This assumption is still far from realistic environment and quite stringent in a typical indoor area, e.g, a person would walks around freely in a living room or an office. To further support irregular trajectory domain adaption, we could extend the CCG-GAN method. An irregular trajectory such as a curving or zigzag course can be treated as a combination of multiple trajectories with varying orientations. Therefore, we could segment such irregular trajectory's WiFi CSI and exploit the CCG-GAN method to recursively convert each segment of WiFi CSI into a certain domain. Thus, the future work is to collect such diversified human gait dataset in WiFi that involve multiple types of irregular trajectories and orientations and evaluate the proposed system on it. A potential technical extension is to combine the framework of Temporal Segment Networks [16] with CCG-GAN to eliminate the irregular trajectory's influence. This will further improve the robustness of future WiFi-based HI system deployed in realistic environment.

7 CONCLUSION

In this paper, we propose MetaGanFi, a one/few shot WiFi-based human identification system to identify unseen individuals in varying interfering domains. Our theoretical analysis shows the potential domain existed in gait monitoring could have strong and weak mapping relations. To eliminate impact of the domains with strong mappings, we propose the CCG-GAN model as a filter to transform WiFi CSI from multi-domain to uni-domain. Besides, we propose the DA-Meta model, a one/few shot framework, to handle the domain with weak mappings and achieve unseen individual identification. Extensive experiments show the MetaGanFi achieves satisfactory performance in various cross-domain scenarios. Combined with the designed edge-server structure, MetaGanFi is a fast, efficient and robust WiFi-based human identification system. Even though the proposed methods still have several prior limitations, MetaGanFi brings significant improvement towards wide applications in future WiFi human sensing areas.

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REFERENCES

[1] Qirong Bu, Xingxia Ming, Jingzhao Hu, Tuo Zhang, Jun Feng, and Jing Zhang. 2021. TransferSense: towards environment independent and one-shot wifi sensing. *Personal and Ubiquitous Computing* (2021), 1–19.

[2] Yunjey Choi, Youngjung Uh, Jaejun Yoo, and Jung-Woo Ha. 2020. Stargan v2: Diverse image synthesis for multiple domains. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 8188–8197.

[3] Robert T Collins, Ralph Gross, and Jianbo Shi. 2002. Silhouette-based human identification from body shape and gait. In *Proceedings of fifth IEEE international conference on automatic face gesture recognition*. IEEE, 366–371.

[4] Shuya Ding, Zhe Chen, Tianyue Zheng, and Jun Luo. 2020. RF-net: A unified meta-learning framework for RF-enabled one-shot human activity recognition. In *Proceedings of the 18th Conference on Embedded Networked Sensor Systems*. 517–530.

[5] Chelsea Finn, Pieter Abbeel, and Sergey Levine. 2017. Model-agnostic meta-learning for fast adaptation of deep networks. In *International conference on machine learning*. PMLR, 1126–1135.

[6] Ruiyang Gao, Wenwei Li, Yaxiong Xie, Enze Yi, Leye Wang, Dan Wu, and Daqing Zhang. 2022. Towards Robust Gesture Recognition by Characterizing the Sensing Quality of WiFi Signals. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 6, 1 (2022), 1–26.

[7] Mohamad Ghaddar et al. 2007. A conducting cylinder for modeling human body presence in indoor propagation channel. *IEEE Transactions on Antennas and Propagation* 55, 11 (2007), 3099–3103.

[8] Yu Gu, Huan Yan, Mianxiong Dong, Meng Wang, Xiang Zhang, Zhi Liu, and Fuji Ren. 2021. WiONE: One-Shot Learning for Environment-Robust Device-Free User Authentication via Commodity Wi-Fi in Man–Machine System. *IEEE Transactions on Computational Social Systems* 8, 3 (2021), 630–642.

[9] Dehao Jiang, Mingqi Li, and Chunling Xu. 2020. Wigan: A wifi based gesture recognition system with gans. *Sensors* 20, 17 (2020), 4757.

[10] Bing Li, Wei Cui, Wei Wang, Le Zhang, Zhenghua Chen, and Min Wu. 2021. Two-stream convolution augmented transformer for human activity recognition. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 35. 286–293.

[11] Takeru Miyato, Toshiki Kataoka, Masanori Koyama, and Yuichi Yoshida. 2018. Spectral normalization for generative adversarial networks. *arXiv preprint arXiv:1802.05957* (2018).

[12] Jaehoon Oh, Hyungjun Yoo, ChangHwan Kim, and Se-Young Yun. 2020. Boil: Towards representation change for few-shot learning. *arXiv preprint arXiv:2008.08882* (2020).

[13] Zhuoran Shen, Mingyuan Zhang, Haiyu Zhao, Shuai Yi, and Hongsheng Li. 2021. Efficient Attention: Attention with Linear Complexities. In *WACV*.

[14] Zhenguo Shi, Jian Andrew Zhang, Yi Da Richard Xu, and Qingqing Cheng. 2020. Environment-robust device-free human activity recognition with channel-state-information enhancement and one-shot learning. *IEEE Transactions on Mobile Computing* (2020).

[15] Shelly Vishwakarma, Chong Tang, Wenda Li, Karl Woodbridge, Raviraj Adve, and Kevin Chetty. 2021. Gan based noise generation to aid activity recognition when augmenting measured wifi radar data with simulations. In *2021 IEEE International Conference on Communications Workshops (ICC Workshops)*. IEEE, 1–6.

[16] Limin Wang, Yuanjun Xiong, Zhe Wang, Yu Qiao, Dahua Lin, Xiaoou Tang, and Luc Van Gool. 2018. Temporal segment networks for action recognition in videos. *IEEE transactions on pattern analysis and machine intelligence* 41, 11 (2018), 2740–2755.

[17] Wei Wang, Alex X Liu, and Muhammad Shahzad. 2016. Gait recognition using wifi signals. In *Proceedings of International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 363–373.

[18] Xuanzhi Wang, Kai Niu, Jie Xiong, Bochong Qian, Zhiyun Yao, Tairong Lou, and Daqing Zhang. 2022. Placement Matters: Understanding the Effects of Device Placement for WiFi Sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 6, 1 (2022), 1–25.

[19] Lijian Wei, Jun Feng, Yufei Liu, Tuo Zhang, Qirong Bu, and Baoying Liu. 2021. A Dense Margin Network for Human Activity Recognition Based on Augmented Channel State Information. In *2021 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/IOP/SCI)*. IEEE, 67–74.

[20] Chenshu Wu, Feng Zhang, Yuqian Hu, and KJ Ray Liu. 2020. GaitWay: Monitoring and Recognizing Gait Speed Through the Walls. *IEEE Transactions on Mobile Computing* (2020).

[21] Dan Wu, Youwei Zeng, Ruiyang Gao, Shengjie Li, Yang Li, Rahul C Shah, Hong Lu, and Daqing Zhang. 2021. WiTraj: Robust Indoor Motion Tracking with WiFi Signals. *IEEE Transactions on Mobile Computing* (2021).

[22] Chunjing Xiao, Daojun Han, Yongsen Ma, and Zhiguang Qin. 2019. CsiGAN: Robust channel state information-based activity recognition with GANs. *IEEE Internet of Things Journal* 6, 6 (2019), 10191–10204.

[23] Rui Xiao, Jianwei Liu, Jinsong Han, and Kui Ren. 2021. OneFi: One-Shot Recognition for Unseen Gesture via COTS WiFi. In *Proceedings of the 19th ACM Conference on Embedded Networked Sensor Systems*. 206–219.

[24] Yunze Zeng, Parth H Pathak, and Prasant Mohapatra. 2016. WiWho: wifi-based person identification in smart spaces. In *Proceedings of the 15th International Conference on Information Processing in Sensor Networks*. IEEE, 4.

[25] Jie Zhang, Zhanyong Tang, Meng Li, Dingyi Fang, Petteri Nurmi, and Zheng Wang. 2018. CrossSense: Towards cross-site and large-scale WiFi sensing. In *Proceedings of the 24th Annual International Conference on Mobile Computing and Networking*. 305–320.

[26] Jin Zhang, Bo Wei, Wen Hu, and Salil S Kanhere. 2016. Wifi-id: Human identification using wifi signal. In *International Conference on Distributed Computing in Sensor Systems (DCOSS)*. IEEE, 75–82.

[27] Jin Zhang, Bo Wei, Fuxiang Wu, Limeng Dong, Wen Hu, Salil S Kanhere, Chengwen Luo, Shui Yu, and Jun Cheng. 2020. Gate-ID: WiFi-based Human Identification Irrespective of Walking Directions in Smart Home. *IEEE Internet of Things Journal* (2020).

[28] J. Zhang, F. Wu, W. Hu, Q. Zhang, W. Xu, and J. Cheng. 2019. WiEnhance: Towards Data Augmentation in Human Activity Recognition Using WiFi Signal. In *Proceedings of International Conference on Mobile Ad-Hoc and Sensor Networks (MSN)*. IEEE, 309–314.

[29] Jin Zhang, Fuxiang Wu, Bo Wei, Qieshi Zhang, Hui Huang, Syed W Shah, and Jun Cheng. 2020. Data augmentation and dense-lstm for human activity recognition using wifi signal. *IEEE Internet of Things Journal* (2020).

[30] Jin Zhang, Weitao Xu, Wen Hu, and Salil S Kanhere. 2017. Wicare: Towards in-situ breath monitoring. In *Proceedings of the 14th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*. 126–135.

[31] Lei Zhang, Cong Wang, Maode Ma, and Daqing Zhang. 2019. WiDIGR: Direction-independent gait recognition system using commercial Wi-Fi devices. *IEEE Internet of Things Journal* 7, 2 (2019), 1178–1191.

[32] Yi Zhang, Yue Zheng, Kun Qian, Guidong Zhang, Yunhao Liu, Chenshu Wu, and Zheng Yang. 2021. Widar3. 0: Zero-Effort Cross-Domain Gesture Recognition with Wi-Fi. *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2021).

[33] Yi Zhang, Yue Zheng, Guidong Zhang, Kun Qian, Chen Qian, and Zheng Yang. 2020. GaitID: Robust Wi-Fi Based Gait Recognition. In *Wireless Algorithms, Systems, and Applications*, Dongxiao Yu, Falko Dressler, and Jiguo Yu (Eds.). Springer International Publishing, Cham, 730–742.

[34] Yi Zhang, Yue Zheng, Guidong Zhang, Kun Qian, Chen Qian, and Zheng Yang. 2021. GaitSense: Towards Ubiquitous Gait-Based Human Identification with Wi-Fi. *ACM Transaction on Senor Network* 18, 1, Article 1 (oct 2021), 24 pages. https://doi.org/10.1145/3466638

[35] Yi Zhang, Yue Zheng, Guidong Zhang, Kun Qian, Chen Qian, and Zheng Yang. 2021. GaitSense: Towards Ubiquitous Gait-Based Human Identification with Wi-Fi. *ACM Transactions on Sensor Networks (TOSN)* 18, 1 (2021), 1–24.

[36] Yue Zheng, Yi Zhang, Kun Qian, Guidong Zhang, Yunhao Liu, Chenshu Wu, and Zheng Yang. 2019. Zero-effort cross-domain gesture recognition with Wi-Fi. In *Proceedings of the 17th Annual International Conference on Mobile Systems, Applications, and Services*. 313–325.

[37] Qianbin Chen Zhi Ren, Guangyu Wang and Hongbin Li. 2011. Modelling and simulation of Rayleigh fading, path loss, and shadowing fading for wireless mobile networks. *Simulation Modelling Practice and Theory* 19, 2 (2011), 626 – 637.

[38] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision*. 2223–2232.

[39] Augustinas Zinys, Bram van Berlo, and Nirvana Meratnia. 2021. A Domain-Independent Generative Adversarial Network for Activity Recognition Using WiFi CSI Data. *Sensors* 21, 23 (2021), 7852.