# freeGait: Liberalizing Wireless-based Gait Recognition to Mitigate Non-gait Human Behaviors

Dawei Yan[1], Panlong Yang[2 *], Fei Shang[1], Feiyu Han[1], Yubo Yan[1 *] and Xiang-Yang Li[1]
[1]University of Science and Technology of China
[2]Nanjing University of Information Science and Technology

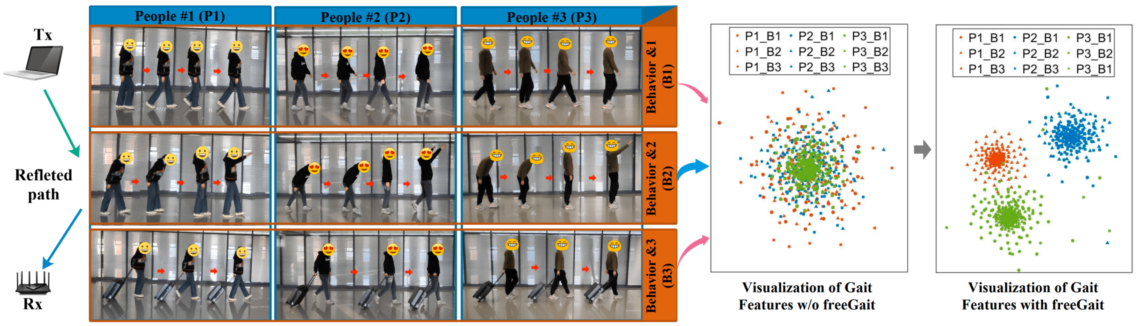


**Figure 1: Users are often accompanied by various gait or non-gait human behaviors when walking, *e.g.*, normal continuous walking (B1), bending or waving (B2), carrying luggage (B3). WiFi propagation signals under different non-gait human behaviors are different, which leads to inconsistency in user gait patterns based on WiFi, thus making the gait recognition system ineffective. *freeGait* can accurately extract the users' gait features despite their accompanying various non-gait behaviors.**

## ABSTRACT

Recently, WiFi-based gait recognition technologies have been widely studied. However, most of them work on a strong assumption that users need to walk continuously and periodically under a constant body posture. Thus, a significant challenge arises when users engage in non-periodic or discontinuous behaviors (*e.g.*, stopping and going, turning around during walking). This is because variations of non-gait behaviors interfere with the extraction of gait-related features, resulting in recognition performance degradation. To solve this problem, we propose *freeGait*, which aims to mitigate the user's non-gait behaviors of WiFi-based gait recognition system. Specifically, we model this problem as domain adaptation, by learning domain-independent representations to extract behavior-independent gait features. We consider human behaviors with labels of users as source domains, and human behaviors without labels of users as target domains. However, directly applying domain adaptation to our specific problem is challenging, because the classification boundaries of the unknown target domains are unclear for WiFi signals. We align the posterior distributions of the source and target domains, and constrain the conditional distribution of the target domains to optimize the gait classification accuracy. To obtain enough source domains data, we build a data augmentation module to generate data similar to the labeled data, and use supervised learning to make the data different between users. We conduct experiments with 20 people and 3 different scenarios, and the results show that accurate predictions of a total of 15 domains data can be achieved by only collecting and labeling a small amount of data from 6 source domains, and user classification accuracy can be improved by up to 45% compared to other existing techniques.

* Panlong Yang and Yubo Yan are the corresponding authors.


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## CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**.

## KEYWORDS

WiFi-based Sensing; Gait Recognition; Domain Adaptation; Data Augmentation.

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## 1 INTRODUCTION

WiFi-based gait recognition has been widely studied due to its advantages of ubiquity, non-contact and non-invasion [33, 40, 42, 44, 45]. The basic principle is that person's movements while walking disturb WiFi signals such as *channel state information* (CSI), and each person's natural walking pattern is unique. This difference in limb movement patterns and speed has been shown to be used as a signature of an individual's gait, thereby identifying the user. Although previous WiFi-based gait recognition systems have provided certain conveniences for human identification, their real-world deployment still faces significant problems.

In particular, the current WiFi-based gait recognition systems are studied based on the assumption that the walking patterns of users are periodic. However, we observe that in real-world scenarios, users not only move their legs when walking, but may also be accompanied by various other non-periodic human behaviors (*e.g.*, turning around, bending, and carrying luggage), as shown in Fig. 1. What's more, in many cases, people do not walk normally and continuously, but may stop and go. Such non-periodicity and discontinuity are challenging for scenarios that require long-term human recognition, because the unique gait-related features cannot be comprehensively extracted, resulting in system failure.

Most of WiFi-based gait recognition schemes utilize CSI to extract gait-related features. Since CSI represents the fine-grained channel characteristics, it is susceptible to human behaviors. As shown in Fig. 1, we give an example. It can be seen that the reflection paths between the laptop (*i.e.*, Tx) and the WiFi router (*i.e.*, Rx) change due to differences in human behaviors, resulting in the inability to accurately separate gait features even if the same people walks along the same path, and ultimately making different users' gait features are mingled together. It indicates that human non-gait patterns extremely interfere with the distribution of gait features.

Theoretically, if we collect sufficient CSI data from all possible behaviors of each user, we can train a gait recognition model that is robust to human behaviors. However, considering the diversity and richness of human behaviors and the impact of various walking paths on gait patterns, this would be extremely labor-intensive. More importantly, there are many non-gait human behaviors and walking paths that may not be taken into account, so this solution is not practical in real-world scenarios. In addition, combining human behavior identification solutions with gait recognition systems is a feasible solution, but this requires accurately detecting each human behavior and separating it from the mixed CSI to eliminate the impact of human behaviors on gait features. Unfortunately, we still need to collect data on all possible human behaviors, and signal separation is a challenging problem.

Furthermore, although there are some works to eliminate the influence of the walking path by estimating the walking direction, this requires strictly setting up multiple transceivers, and users need to walk normally and continuously in a specific area [2, 34, 45]. However, these setups are onerous for many scenarios and users, hindering the application of gait recognition. In this paper, we aim to achieve accurate gait recognition of users accompanying many different human behaviors using only a pair of WiFi transceiver.

Therefore, to develop such a system, we have three challenges:

- Users are often accompanied by various non-periodic or discontinuous human behaviors when walking, which have different influences on WiFi-based gait patterns. To eliminate these influences, we need to cover all possible human behaviors of the users when collecting gait data that represents the users' identity, but this is difficult.
- Other items also affect the gait patterns of users, such as walking paths and speeds. To eliminate the influence of other items, we still need to cover all other items even for the same human behavior. However, it is impractical to label the data of all other items associated with the user.
- Extracting fine-grained gait patterns from a pair of WiFi transceiver is difficult. When the user is far away from the WiFi transceiver or the user's walking direction is close to parallel to the WiFi transceiver, it may cause CSI noise to flood the gait pattern.

To address the above challenges, we present *freeGait*, a WiFi gait recognition system based on data processing methods and a fine-grained deep learning framework, only by collecting and labeling a small amount of CSI data from one WiFi transceiver.

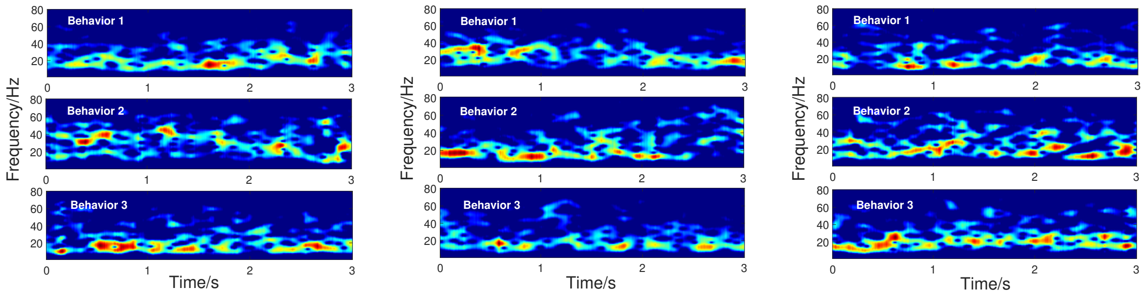
Firstly, we perform a series of processing on the raw CSI and obtain refined spectrograms reflecting the users' gait patterns. Specifically, we observe that using *principal component analysis* (PCA) at the subcarrier-level and extracting the first principal component can better remove environmental noise. Then, to eliminate *automatic gain control* (AGC) noise while retaining the original data characteristics, we use *density-based spatial clustering of applications with noise* (DBSCAN) on the CSI and extract the class with the highest density. These two technologies make it possible to extract dynamic target signals well even when the user is far away from the transceiver. Additionally, we use *short-time Fourier transform* (STFT) to obtain the spectrograms.

Secondly, we model the acquisition of gait features independent of human behaviors and walking paths as the domain adaptation problem. Specifically, *freeGait* considers human behaviors and walking paths in the database with users' IDs as the source domains, and unknown human behaviors and walking paths without users' IDs as the target domains. The network model is then jointly trained using labeled user's ID data in the source domains and unlabeled data in the target domains, and the ultimate goal is to learn common features (gait patterns) of the labeled and unlabeled data, while downplaying the differences between source and target domains (effects of different human behaviors and walking paths). In this way, *freeGait* can predict users from different human behaviors and walking paths without relabeling users' IDs for new data.

Finally, to obtain enough source domains data to eliminate the influence of different human behaviors and other items, we utilize data augmentation technology to generate synthetic data similar to the collected labeled data with users' IDs, allowing us to scale the labeled data to cover a wide range of human behaviors and other items. Specifically, we collect some data for each user walking along different paths (*e.g.*, one-minute data), combine it with human behaviors data in the source domains, and use an *adversarial autoencoder* (AAE) [22], generating similar but different gait data for each user separately. In addition, we also incorporate the idea of supervised learning to avoid generating extremely close sample data among different users. In this way, *freeGait* can predict users' gait under more human behaviors, walking paths.

Overall, the main contributions of this paper are as follows:

- In this paper, we analyze the impact of users' non-periodic or discontinuous behaviors on WiFi-based gait recognition. Then, we propose *freeGait*, a WiFi-based gait recognition system, aim to mitigate users' diverse non-gait behaviors while maintaining accurate gait recognition.
- We design domain adaptation techniques to reduce the coupling of gait patterns with behaviors and paths, and enable




(a) People #1. (b) People #2. (c) People #3.

**Figure 2: Spectrograms of three different people walking with three different human behaviors (behavior 1: normal continuous walking; behavior 2: stop-and-go and bending; behavior 3: individual carrying luggage). Even for the same people, gait patterns are different in different human behaviors.**

*freeGait* to learn behavior- and path-independent gait features. Then, we design data augmentation method so that using only a small amount of labeled data with users' IDs, *freeGait* can perform well in processing a variety of rich gait data of behaviors and paths without user IDs.

- We implement *freeGait* with a pair of WiFi transceiver and conduct extensive experiments. We define 6 different human behaviors, 3 different walking paths and 3 different walking speeds, and recruit twenty volunteers of different heights and weights to participate in the experiment. The results show that accurate predictions for a total of 15 domains can be achieved by collecting and labeling only a small amount of data from 6 source domains, which is at worst 45% improvement over other existing techniques.

## 2 HUMAN BEHAVIORS IMPACT ANALYSIS

When users walk in different time periods accompanied by different human behaviors, the WiFi signals reflected by the human body are different due to complex and variable multipath effects, even for the same person. To verify the impact of different human behaviors on CSI, we perform preliminary tests in an empty space of $12m \times 10m$. Specifically, we invite three volunteers of different heights and weights to participate in the tests. They walk along the same path in a specific area of the space, and are asked to perform three different human behaviors, *i.e.*, normal continuous walking, stop-and-go and bending, and individual carrying luggage as shown in Fig. 1. We build Tx and Rx based on the *industrial personal computer* (IPC) equipped with Intel 5300 *network interface card* (NIC), working at the ISM band 5GHz/HT40-, and we set the packet sending rate to 1000Hz. Then, we collect the CSI of each volunteer while walking under each human behavior, and each condition repeats three times. It is worth noting that we only analyze the impact of human behaviors on gait patterns, so we control the volunteers to walk in the same path each time, and the scenario (including the surrounding environment and transceiver) does not change.

We extract the amplitude of each CSI packet and use the 30 subcarriers of the first antenna of Rx to specifically analyze the gait patterns of different people accompanied by different human behaviors. We perform a series of preprocessing on the raw CSI amplitude, including data denoising and STFT, to obtain the spectrograms under each condition, and the detailed settings can be found in Section 3.2. Fig. 2 shows the gait patterns of three volunteers while walking accompanied by three different human behaviors. It can be seen that even if the same people walk along the same path and direction, the differences in gait patterns can be large when the accompanying human behaviors are different. Furthermore, this variation due to the influence of human behaviors may be greater than the variation between gait patterns of different people. Therefore, gait recognition may be poor when subjects walk accompanied by untrained human behaviors. From the above analysis, we think that the human behaviors that accompany walking do have a significant impact on gait patterns. Next, we illustrate how our proposed techniques and models eliminate this effect, using only a small amount of labeled gait data from human behaviors.

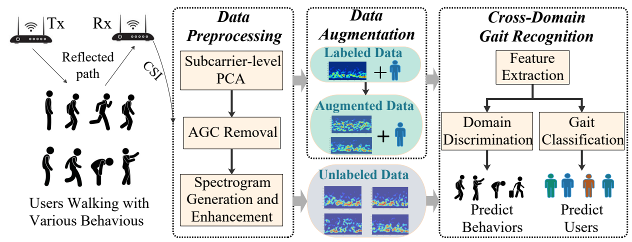



**Figure 3: Overview of *freeGait*: consist of data preprocessing, data augmentation and cross-domain gait recognition.**

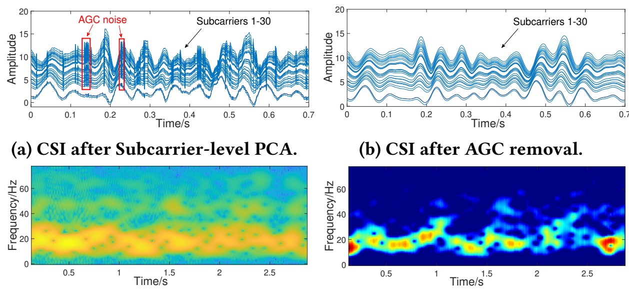
## 3 SYSTEM DESIGN

### 3.1 Overview

As shown in Fig. 3, we place one Tx and one Rx in the physical space to form a WiFi propagation link, so that a gait sensing area can be constructed. Specifically, we collect the CSI of each subject when walking within the sensing area and input them into the data preprocessing module to obtain the spectrograms. Then, A small part of the data (*i.e.*, known behaviors and paths) with users' IDs enters the data augmentation to expand more potential human behaviors and walking paths. Finally, the augmented labeled data (source domains data) and unlabeled data (target domains data) are input the cross-domain gait recognition to learn gait features independent of non-gait human behaviors and walking paths.

### 3.2 Data Preprocessing

**Subcarrier-level PCA.** Raw CSI collected using WiFi NIC contains many noise [14], generally manifested as environmental noise




(a) CSI after Subcarrier-level PCA. (b) CSI after AGC removal.

(c) Raw spectrogram. (d) Enhancement spectrogram.

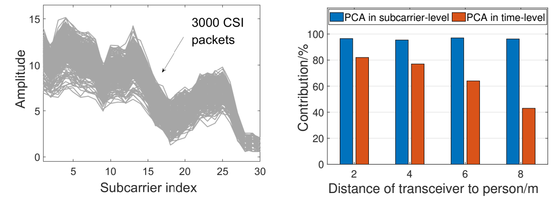
**Figure 4: Data preprocessing.**

and AGC noise [4, 25], and environmental noise obeys Gaussian distribution in the entire space [39]. In our setup, we use one WiFi transceiver and perform continuous gait recognition of the user's entire walking process. When the user is far away from the transceiver or the walking direction is close to parallel to the propagation path, the gait pattern may be overwhelmed by the noise. At this time, traditional denoising methods (*e.g.*, lowpass, wavelet) perform poorly [21]. In addition, the effect of traditional PCA denoising in the time dimension depends on the selection of the number of principal components. Selecting more or fewer components may result in retaining environmental noise or losing important target signals. When a dynamic signal is masked by environmental noise, it loses effectiveness because the principal components do not clearly correspond to the dynamic signal.

Fortunately, we shift the perspective to the subcarrier-level. We transpose the CSI matrix to represent the reflection paths of all subcarriers in the environment over a period of time. As shown in Fig. 5a, in the subcarrier-level, CSI amplitude changes represent changes in reflection paths caused by human motion. Assuming that the static environment remains unchanged, CSI in the subcarrier dimension space show higher correlation. In particular, we employ a covariance method to compute PCA of CSI data collected at different distances and measure the correlation of them [31, 46]. As shown in Fig. 5b, the contribution of the first principal component in the time dimension decreases with increasing distance, while the contribution of the first principal component in the subcarrier dimension remains high at different distances. Therefore, using subcarrier-level PCA, we only need the first principal component to remove environmental noise, and the effect performs well even if the noise overwhelms the gait pattern signal, as shown in Fig. 4a.

**AGC removal.** After removing the environmental noise, we also need to remove the influence of AGC noise. Previous schemes using the ratio of two antennas can effectively remove AGC noise [38]. In this paper, to completely preserve the distribution of CSI data, we do not use the ratio method. According to our observation, the noise caused by AGC is uncertain and sparse points around the dynamic signal in the time dimension [19, 20], so we can filter out the noise caused by AGC according to the sparse density distribution. Specifically, we utilize the DBSCAN spatial clustering method [6] to cluster AGC-related points according to their sparse distribution density and retain only the cluster with the largest number of scatter points [46], and the results are shown in Fig. 4b.

**Spectrogram generation and enhancement.** To represent the gait features of different people while walking, we perform STFT on the CSI processed above to obtain a spectrogram reflecting time and frequency information. Specifically, we first apply a sliding window to slice the time series CSI, each segment contains 3s (*i.e.*, 3000 CSI packets), and the sliding window is 1s (*i.e.*, 1000 CSI packets apart). Then, we perform STFT on each slice. To maintain the balance of time and frequency resolution, we set the FFT size to 1024 and the sliding window step size to 6, which can achieve a frequency resolution of 0.95Hz and a time resolution of 6 ms, which has a better discrimination effect on human gait signals between 10Hz and 70Hz. The spectrogram is shown in Fig. 4c. We only show the image of 0-80Hz, where yellow indicates higher reflected energy.




(a) CSI subcarrier level. (b) PCA contributions in subcarrier and time levels.

**Figure 5: The first component of the subcarrier-level PCA is higher than time-level PCA.**

Furthermore, to reduce the noise of the spectrogram to obtain a refined spectrogram, we used some technologies in WifiU [33] to enhance each spectrogram. Specifically, we add the amplitudes of the corresponding spectrograms of 30 subcarriers to obtain the superimposed spectrogram, and only retain 0-80Hz. We then normalize each FFT block and subtract the mean of the amplitude of the entire spectrogram to remove background noise (anything less than 0 is set to 0). Finally, we apply a two-dimensional Gaussian filter with size=10 and $\delta = 0.4$ to obtain the enhanced spectrogram, and the result is shown in Fig. 4d.

## 3.3 Cross-Domain Gait Recognition

**Feature extraction.** As shown in Fig. 6, we input all labeled and unlabeled data together into the feature extractor to output their feature vectors. We use the widely adopted CNN and LSTM deep learning architectures to extract gait features [8, 13]. Particularly, we use three-layer stacked CNN and three-layer stacked LSTM. At each layer of the CNN, we use convolutional layers with 2D convolution kernels, utilize batch normalization layers to speed up training with the batch size is 256, insert *rectified linear units* (ReLUs) to introduce nonlinearity, and use max pooling layers to reduce the size of the representation. In addition, LSTM has good performance in time series data processing. It is used to learn the temporal dynamic features extracted by CNN. Each LSTM layer has the same number of neurons and the number of each LSTM is 128, and uses the Sigmoid activation function. Therefore, given the input data $\mathbf{S}_i$, we can obtain the features $\mathbf{Z}_i$ through CNN and LSTM:

$$\mathbf{Z}_i = \mathrm{CNN}(\mathbf{S}_i; \Theta_{cnn}) \oplus \mathrm{LSTM}(\mathbf{S}_i; \Theta_{lstm}), \tag{1}$$

where $\Theta_{lstm}$ and $\Theta_{lstm}$ are the parameters of CNN and LSTM, $\oplus$ represents the operation of concatenation.

**Gait classification.** As shown in Fig. 6, after obtaining the feature $\mathbf{Z}_i$, we use three fully connected layers [17] and the activation function ReLU to learn the representation $\mathbf{V}_i$ of $\mathbf{S}_i$, and let

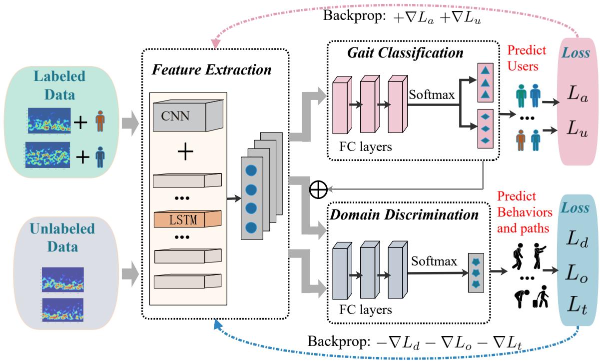



**Figure 6: The framework for learning behavior- and path-independent gait features using domain adaptation is used in *freeGait.***

$\mathbf{V}_i$ through an output layer with an activation function of softmax to obtain the predicted probability vector $\hat{y}_i$ of the gait. It is worth noting that the reason why three fully connected layers are used is to obtain more parameters, and more fully connected layers not improve the performance much. In addition, to improve the accuracy of gait classification, we use a combination of supervised learning and unsupervised learning [11]. Specifically, we predict user labels $\hat{y}_i^a$ and $\hat{y}_i^u$ for labeled and unlabeled data respectively. For all data, we use cross-entropy as the loss function for gait classification:

$$\begin{aligned}\mathcal{L}_a &= -\frac{1}{n_a}\sum_{i=1}^{n_a}\sum_{k=1}^{K} \mathrm{y}_{ik}^a \log\left(\hat{\mathrm{y}}_{ik}^a\right), \\ \mathcal{L}_u &= -\frac{1}{n_u}\sum_{i=1}^{n_u}\sum_{k=1}^{K} \hat{\mathrm{y}}_{ik}^u \log\left(\hat{\mathrm{y}}_{ik}^u\right),\end{aligned} \tag{2}$$

where $n_a$ and $n_u$ are the numbers of labeled and unlabeled data used for training, and $K$ is the total number of users.

**Domain discrimination.** *Domain-adversarial training of neural networks* (DANN) is a special case of transfer learning [26]. We use the idea of DANN to eliminate the effects of human behaviors and walking paths. Specifically, we define different walking paths and human behaviors as different domains, and the domain discriminator is used to identify different walking paths and human behaviors. Our goal is to enable the feature extractor to fool the domain discriminator, thereby producing gait features that are independent of human behaviors and walking paths.

As shown in Fig. 6, we input the output $\mathbf{Z}_i$ of the feature extractor into the domain discriminator and predict the domain label $\hat{d}_i$ through the same process. The domain discriminator is also composed of three fully connected layers with activation function ReLU and an output layer with softmax activation function. We use cross-entropy as the loss function for domain label prediction:

$$\mathcal{L}_d = -\frac{1}{n_d}\sum_{i=1}^{n_d}\sum_{j=1}^{D} \mathrm{d}_{ij} \log\left(\hat{\mathrm{d}}_{ij}\right), \tag{3}$$

where $n_d$ is training data number, $D$ is the number of domains.

However, directly applying DANN to our specific problem of gait recognition does not work well. In fact, for WiFi signals, it is difficult to distinguish the features of different domains and the features of different gaits, which makes the classification of unknown target domains very challenging. To improve the classification performance of the target domains, we adopt two operations to optimize the model. Firstly, we concatenate $\mathbf{Z}_i$ with the predicted label $\hat{y}_i$ of the gait classification, align the posterior distributions of the source and target domains:

$$\mathrm{P}_i = \mathrm{Z}_i \oplus \hat{\mathrm{y}}_i, \tag{4}$$

which together feed into the domain discriminator to predict the domain label $\hat{\mathrm{d}}_{ij}^o$. We use cross-entropy as the loss function:

$$\mathcal{L}_o = -\frac{1}{n_d}\sum_{i=1}^{n_d}\sum_{j=1}^{D} \mathrm{d}_{ij} \log\left(\hat{\mathrm{d}}_{ij}^o\right). \tag{5}$$

Secondly, we add classification constraints to the target domains, and use the conditional entropy as the loss function for target domain classification:

$$\mathcal{L}_t = -\frac{1}{n_t}\sum_{i=1}^{n_t} \hat{\mathrm{d}}_i^t \log\left(\hat{\mathrm{d}}_i\right). \tag{6}$$

where $n_t$ is the number of target domains data, $\hat{\mathrm{d}}_i^t$ is the predict label of target domain. In this way, the domain discriminator attempts to separate target domains data with the same domain label, thereby better obtaining domain-independent gait features.

**Model training.** The overall loss function of our model:

$$\mathcal{L}_{all} = \mathcal{L}_a + \alpha\mathcal{L}_o + \beta\mathcal{L}_d + \gamma\mathcal{L}_o + \lambda\mathcal{L}_t, \tag{7}$$

where $\alpha$, $\beta$ and $\gamma$ are hyperparameters. The goal of model training is to minimize the loss $\mathcal{L}_a + \alpha\mathcal{L}_o$ of gait classification, while maximizing the loss $\beta\mathcal{L}_d + \gamma\mathcal{L}_o + \lambda\mathcal{L}_t$ of the domain discriminator. Note that the loss of the domain discrimination is inverted when backpropagated, while the gait classification is directly backpropagated [7]. We use all labeled and unlabeled data to train the model and iteratively update the parameters during the training process.

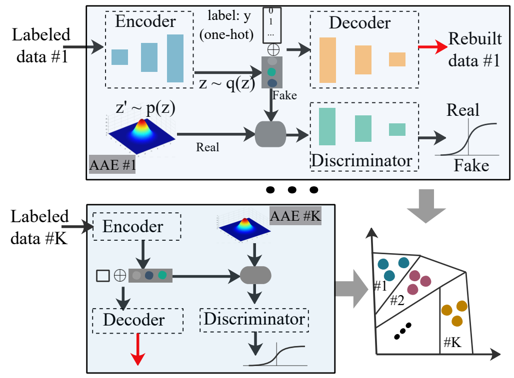



**Figure 7: We train AAE-based data augmentation with different distributions $N(0,k)$ for each user $k$ to generate more data similar to the labeled data.**

## 3.4 Data augmentation

To better eliminate the influence of different walking paths and human behaviors on gait patterns, a feasible solution is to collect as much CSI as possible of different walking paths and human behaviors. However, the time and labor costs of collecting and labeling data from different users are huge. In addition, although there are works to calculate the user's walking direction through two mutually perpendicular WiFi transceiver links [34, 44, 45], this requires strictly accurate prior position knowledge of the transceiver and requires the user to walk normally and continuously in a specific area, so it cannot meet the needs of this paper. Fortunately, data augmentation schemes have been widely used recently, aiming to expand the training data set by generating more equivalent data from limited data [1, 29, 30]. Thus, we use the idea of data augmentation to generate more data on potential behaviors and paths.

Specifically, we design the AAE [22] as shown in Fig. 7, and use a separate AAE for each user's labeled gait data, that is, if $K$ users are need to be identified, we train $K$ AAEs. AAE is a general method that can convert autoencoders into generative models. It combines adversarial ideas, and its typical network architecture consists of a standard *autoencoder* (AE) [24] and a *generative adversarial Network* (GAN) [10]. AAE aims to enable the decoder to generate realistic samples from any sampled data point by encouraging the encoder's output to completely fill the space of the prior distribution. In this paper, we use a small amount of processed spectrogram data accompanying human behavior and different walking paths (*i.e.*, source domain data) for data augmentation, and we input these data $S^k$ into the corresponding AAE #$k$ for training. Firstly, the data $S^k$ of the $kth$ AAE into the encoder of AAE #$k$ to generate the latent vector $z \sim q(z)$ , where $q(z)$ is the aggregate posterior distribution. $z$ is sent to the decoder, and the vector $\hat{S}^k$ is generated to reconstruct the data $S^k$. We define the reconstruction loss $\mathcal{L}_B^k$ using *Mean Square Error* (MSE):

$$\mathcal{L}_B^k = \frac{1}{2n_g^k}\sum_{i=1}^{n_g^k}\left(S_i^k - \hat{S}_i^k\right)^2, \tag{8}$$

where $n_g^k$ is the number of samples.

Secondly, we train the discriminator to normalize the rebuilt data. At this time, the encoder of AE becomes the generator of GAN, and its output $S^k$ is sent to the discriminator together with the vector $z'$ that obeys the prior distribution $p(z)$. Here, we choose the normal distribution $N(0,k)$ as the prior distribution $p(z)$. For the discriminator, the label $l^k$ is 0 when $S^k$ is used as input, and the label $l^k$ is 1 when $z'$ is used as input. Use cross entropy as the loss function $\mathcal{L}_G^k$ of the discriminator:

$$\mathcal{L}_G^k = -\frac{1}{n_g^k}\sum_{i=1}^{n_g^k}\left(l_i^k \log\left(\hat{l}_i^k\right) + \left(1 - l_i^k\right)\log\left(1 - \hat{l}_i^k\right)\right). \tag{9}$$

However, we find that since we use separate AAE for each user for data augmentation, the rebuilt data samples are very likely to be located among different users, which in turn affect the classification accuracy of different users. In order to avoid this situation, as shown in Fig. 7, in addition to the prior distribution $p(z)$ of each AAE being different (the variance of the normal distribution is different), we also feed the user's label $y$ (one-hot form) and the latent vector $z$ into the decoder together to force the decoder generate data that is highly relevant to users. Our goal for the augmented data is that the size of the rebuilt data for the $k$th user is 10 times larger than the size of the original labeled source domain data $S_L$. Finally, we collect all rebuilt data $S_R$ as well as source domain data as labeled augmentation data $S_A = S_R \cup S_L$.

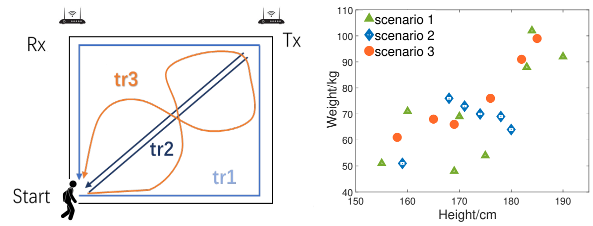
# 4 PLATFORM IMPLEMENTATION

## 4.1 Hardware and environments

We build the hardware platform based on two IPCs equipped with Intel 5300 NICs, one of them used as Tx with one antenna, another used as Rx with three antennas, and fixed on a tripod 0.5m above


(a) Scenario 1. (b) Scenario 2. (c) Scenario 3.

**Figure 8: Three experimental scenarios.**




(a) (b)

**Figure 9: (a) Three different traces and (b) twenty volunteers with different heights and weights.**

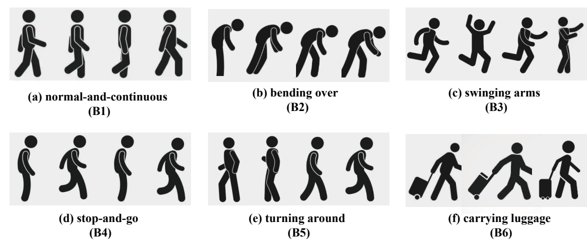
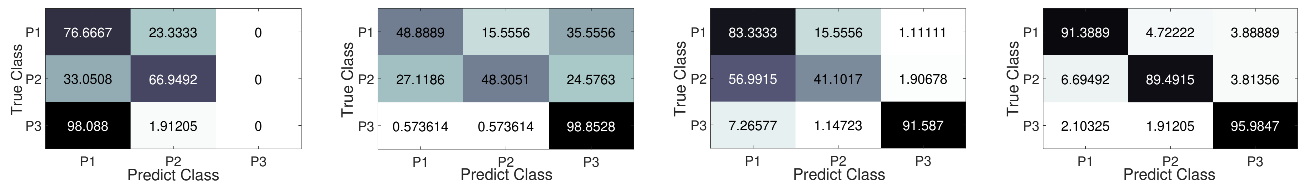



**Figure 10: Six common human behaviors when users walk.**

the ground to better detect human movement. As shown in Fig. 8, we deploy our experiments in three different environments, and the distance between Tx and Rx is 6m. Note that the environments and the positions of WiFi transceiver remain unchanged during all tests. Although changes in the environment also cause changes in CSI, we do not analyze this in the paper. In addition, all data are preprocessed based on Matlab R2020b on a computer with Intel-i5 2.7GHz CPU. The deep learning model training and result prediction are completed on a server with NVIDIA 3090 graphics card based on Python 3.10 with CUDA 11.8 and Pytorch 2.0. We train our model offline with a total of 200 epochs. During training, the Adam optimizer is used with a learning rate of 0.001.

## 4.2 Data collection

To collect CSI of different human behaviors and walking paths, we considered six human behaviors (*i.e.*, B1-B6) as shown in Fig. 10, and three paths (*i.e.*, tr1-tr3) as shown in Fig. 9a. We recruit twenty volunteers of different heights and weights (*i.e.*, P1-P20) to record the CSI of different people in three scenarios as shown in Fig. 8. The allocation detail of scenarios and volunteers is as shown in Fig. 9b. We install the CSI Tool on two IPCs and collect CSI using injection/monitoring mode with the sampling rate set to 1000Hz [12]. We ask each volunteer to walk and collect CSI as follows: *(i)* Each user walks along tr1 at a normal speed according to six different human behaviors, and each human behavior is repeated three times. *(ii)* Each user walks along tr2 at a normal speed according to six different human behaviors, and each human behavior is repeated three times. *(iii)* Each user walks along tr3 according to human




**(a) Basic-CNN.** **(b) AAE-only.** **(c) Domain-adaptation-only.** **(d) *freeGait*.**

**Figure 11: The location prediction confusion matrices obtained after the predicted data of ten locations pass through the basic CNN, AAE-only, domain adaptation-only and *freeGait* respectively.**

**Table 1: Classification results of the four methods.**

| Method | TPR | FPR |
|---|---|---|
| Basic-CNN | 47.87% | 26.06% |
| AAE-only | 65.35% | 17.33% |
| Domain-adaptation-only | 72.01% | 14.00% |
| ***freeGait*** | **92.29%** | **3.86%** |

behavior 1 (*i.e.*, B1) at three different speeds (*i.e.*, slow (S1), normal (S2), fast (S3)) for one minute at each speed.

Then, we follow the method in Section 3.2 to perform data preprocessing and obtain the spectrograms. Specifically, there are $\sum_{i=1}^{N_b} N_i$ sets of spectrogram data for each user ($N_i$ is the number of sliced data in each case, $N_b$ is the total number of cases, *i.e.*, the number of domains), and the size of each group of data is $3 \times 80 \times 458$ (antenna $\times$ frequency $\times$ time). We divide the data into $6+6+3 = 15$ domains based on walking paths and human behaviors, and randomly divide the data in each domain into 50% training data and 50% testing data. Furthermore, for the training data, the source domain data has user labels, while the target domain data does not have user labels. Additionally, all tags are encoded using one-hot.

## 4.3 Baseline methods

- **Basic-CNN** is used as the baseline, *i.e.*, without data augmentation and domain adaptation, labeled and unlabeled data are directly input into CNN and LSTM based feature extractors and gait classifiers to directly predict users' labels. Some previous work is based on this scheme [45].
- **AAE-only** implements only *freeGait*'s AAE and connects them directly to the feature extractor and gait classifier without domain adaptation.
- **Domain-adaptation-only** implements only the domain adaptation network of *freeGait*, *i.e.*, directly feeds labeled and unlabeled data into the feature extractor, gait classifier and domain discriminator without AAEs.

# 5 EVALUATION

## 5.1 Basic performance of *freeGait*

To evaluate the basic performance of *freeGait*, we first classify the gait data of three volunteers in Scenario 1. We select 6 of the 15 combinations of human behaviors, traces and speeds of these three volunteers in the training data as source domains data (B1_tr1, B4_tr1, B6_tr1, B5_tr2, S1_tr3, S3_tr3), *i.e.*, with user labels, and the remaining training data is used as target domains data, *i.e.*, without user labels, and all training data contains domain labels. During the training process, both Domain-adaptation-only and *freeGait* are able to train their respective models using data with user labels and data without user labels, but Basic-CNN and AAE-only just use data with user labels to train their models. We then compare *freeGait* with the above baseline methods.

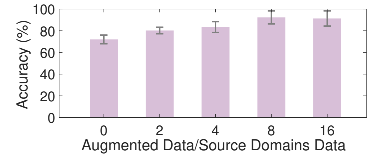



**Figure 12: Impact of augmented data amount.**

We use True Positive Rate (TPR) and False Positive Rate (FPR) to evaluate classification performance, where $TPR = \frac{TP}{TP+FN}$, and $FPR = \frac{FP}{TN+FP}$, TP, TN, FP, and FN represent the number of true positives, true negatives, false positives and false negatives. Tab. 1 shows the classification results of four methods. As can be seen, the accuracy of the Base-CNN is extremely low because it only uses less labeled data for training. AAE-only and Domain-adaption-only improve some accuracy through data augmentation and domain adaptation respectively, but there is still a lot of room for improvement. Compared with these techniques, *freeGait* can improve accuracy by at least 20% and in the worst case 45%.

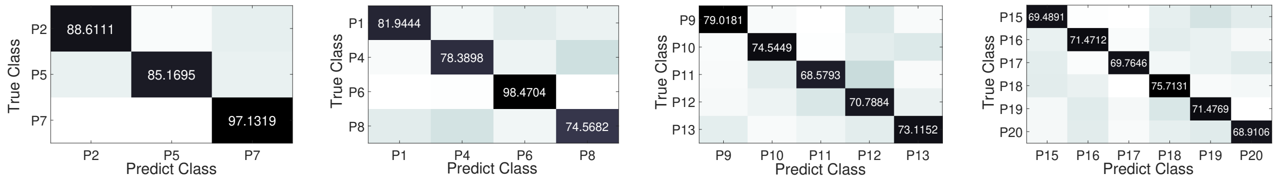
To more intuitively show the comparison results of *freeGait* with other methods, we also provide the gait classification confusion matrix, and the results are shown in Fig. 11. From the results, compared to other schemes that cannot accurately distinguish multiple users, *freeGait* can achieve high classification accuracy for all users.

## 5.2 Impact of augmented data amount

We already know that augmented data can improve the performance of *freeGait*. To analyze in detail the effect of the amount of augmented data on the users' gait classification effect, we select three users in Scenario 1 for verification. Specifically, we use pre-trained AAE-based data augmentation models to generate augmented data that are 0 times, 2 times, 4 times, 8 times, and 16 times the amount of source domains data, respectively. Then, we use these data to train *freeGait* respectively, and the accuracy of users gait classification is shown in Fig. 12. The results show that the classification accuracy increases as the amount of augmented data increases. However, when there is too much augmented data (16 times), the classification accuracy decreases slightly. This may be caused by excessive enhancement that makes the sample distribution uneven.

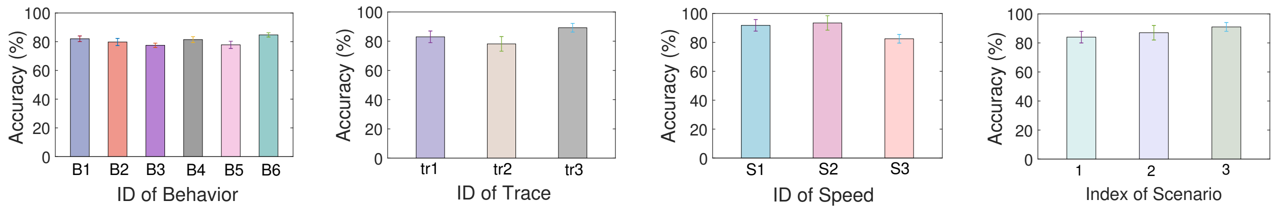
## 5.3 Impact of people's number

The increase in the number of users and different user affect the classification accuracy of gait features. To further examine the performance of *freeGait*, we test *freeGait* on different users and a larger number of users. Specifically, we divide 20 volunteers into




(a) **Three people.** (b) **Four people.** (c) **Five people.** (d) **Six people.**

**Figure 13: Classification results for different people and different numbers of people.**




(a) **Different behaviors.** (b) **Different traces.** (c) **Different speeds.** (d) **Different environments.**

**Figure 14: Classification accuracy for different behaviors, traces, speeds, and environments.**

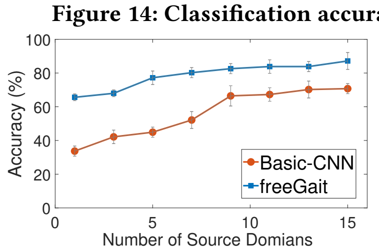
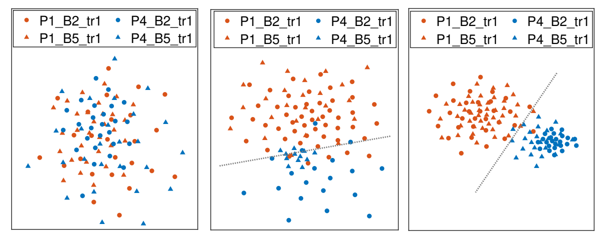



**Figure 15: Impact of source domains' number.**




(a) **Basic-CNN.** (b) **DANN-only.** (c) ***freeGait.***

**Figure 16: Visualization results of gait features after going through Basic-CNN, DANN-only and *freeGait*.**

four different group sizes of 3, 4, 5, and 6 people. The confusion matrix for classification is shown in Fig. 13. It can be seen that as the number of people increases, *freeGait* can still achieve 70% classification accuracy for each user, but the overall classification accuracy decreases slightly, because the features of domains are also gradually increasing. We plan to optimize our model in future work to be able to predict more diverse users.

## 5.4 Impact of different behaviors, traces and speeds

Different human behaviors, walking paths and walking speeds all affect gait patterns. In order to evaluate the robustness of *freeGait* to these influencing factors, we divide the users' gait data into 15 groups according to domain categories, and predict users' IDs respectively (the source domain data for training is the same as Section 5.1), the accuracy is shown in Fig. 14. The results show that for the six (behavior, speed, trace) including the source domains, the users gait classification accuracy is above 81%, while for the nine (behavior, speed, trace) that are all in the target domains, the users gait classification accuracy still higher than 72%, although it has declined. Therefore, *freeGait* remains robust to different human behaviors, walking paths and walking speeds.

## 5.5 Impact of different environments

Different environments affect the collected CSI data. In order to evaluate the robustness of *freeGait* to different environments, we divide the data into three groups according to the three scenarios as shown in Fig. 8, and predict users' IDs respectively (the source domain data for training is the same as Section 5.1). The results in Fig. 14d show that for the three scenarios, the users gait classification accuracy is above 83%, thus *freeGait* remains robust to different environments. It is worth noting that we evaluate *freeGait* in three scenarios separately without predicting users' IDs across environments, which is beyond the scope of this paper.

## 5.6 Impact of source domains' number

Intuitively, the amount of source domains used for training affects the model's accuracy. To analyze the impact in detail, we pre-train the deep learning model of *freeGait* and predict users' IDs with the number of source domains ranging from 1 to 15. The result is shown in Fig. 15, the users' gait classification accuracy increases as the number of source domains increases, and the classification accuracy of *freeGait* is always higher than Basic-CNN with the same number of source domains. In real-world applications, users can choose an appropriate number of source domains by considering the balance between accuracy and training data collection cost.

## 5.7 Visualization of gait feature

Our model aims to learn representations of gait features that are independent of discontinuous human behaviors and walking paths. To verify that the model has learned the representation, we use t-SNE [32] to reduce the dimensionality and display it in 2D space. Specifically, we select the data of two human behaviors of two users from the data in the target domain that does not carry user tags, *i.e.*, four domain-user pairs. Then, we randomly select several samples for each domain-user pair and draw the learned representations of these samples through Basic-CNN, DANN-only (*i.e.*, Domain-adaptation-only) and *freeGait* respectively. The results are shown in Fig. 16, where different colors (orange and blue) represent different users, and different shapes (circles and triangles) represent different human behaviors. When Basic-CNN is used to extract gait features, the gait features of two users overlap. Although DANN-only can distinguish the gait features of two users, these features are scattered and not concentrated into two clusters. In addition, the gait features extracted by *freeGait* are concentrated in two clusters, while there is almost no overlap between different users. This proves that the proposed model learns the target features.

# 6 DISCUSSIONS AND FUTURE WORK

**Diverse real-world non-gait behaviors.** In the real world, human non-gait behaviors are very diverse and complex beyond the six behaviors we defined. Specifically, there are many similar or unpredictable behaviors, such as falling, lying down, jumping and etc. Verifying these richer behaviors is essential for the promotion of *freeGait*. Specifically, we plan to use an iterative model training approach in future work to update the non-gait behavior library and continuously enhance the adaptability of *freeGait* to more unseen human behaviors. Additionally, we aim to conduct a detailed analysis of various human behaviors and explore metrics that can evaluate non-gait behaviors, to further demonstrate the impact of different non-gait behaviors on gait recognition systems.

**Cross-environment gait recognition.** In this paper, we do not migrate the same user in different environments, because this paper focuses on the impact of human behaviors on the gait recognition system. In practice, due to the complexity of the real world, cross-environment gait recognition is indeed an important research problem. We plan to explore the possibility of cross-environment gait recognition in future work. Specifically, we can accurately identify different environments or even similar environments, and regard the environment as domain, so that cross-domain technology can also be applied to realize cross-environment gait recognition. In addition, we plan to implement a WiFi-based gait recognition system that simultaneously considers influencing factors such as behaviors, trajectories and environments, to promote the deployment of such solutions in the real world.

# 7 RELATED WORK

## 7.1 WiFi-based gait recognition systems

Compared with vision-based [3], acoustic signal-based [36], and wearable device-based [23] gait recognition technologies, WiFi has been widely studied recently due to its advantages of ubiquity, non-contact, and non-privacy invasion. Many systems that accurately recognize human gait based on commercial WiFi devices. However, most systems require subjects to walk along specific paths [33, 37, 40–43], and a few systems combine the use of daily activity features to improve accuracy [15, 27]. These either have severe restrictions on users' behaviors or require the collection of large amounts of data. Recently, there have been works studying gait recognition schemes that are independent of walking direction and path, but they require the collection of data from multiple WiFi transceivers and the subject walking normally and continuously in a specific area [44, 45, 47]. Compared with the above solutions, we have considered a variety of discontinuous behaviors that may be accompanied by the user's walking. *freeGait* can accurately identify the user's gait by only collecting a small amount of data from a pair of randomly placed WiFi transceivers, and at the same time liberalizing the user's walking requirements.

## 7.2 Domain adaptation for WiFi sensing

WiFi signals are extremely sensitive to the surrounding environment. Changes in the environment, different people, and different actions all lead to changes in reflected information, which affects the performance of WiFi-based sensing systems. Collecting enough data is expensive and impractical. To solve this problem, domain adaptive learning improves the learning performance of the data-poor target domain by minimizing the data distribution difference between the source domains and the target domains [7]. Therefore, it is gradually applied in WiFi sensing systems, such as fingerprint localization [5, 18], object recognition [9], activity recognition [16, 28, 48], gesture recognition [35] and human identification [40]. In this paper, we combine the idea of domain adaptation with data augmentation to collect a small amount of data to adapt to the various non-periodic or discontinuous behaviors accompanying users' walking, so that the WiFi-based gait recognition system remains accurate while facing users' non-gait behaviors.

# 8 CONCLUSION

In this paper, we propose *freeGait*, a WiFi-based gait recognition system that is not affected by non-periodic and discontinuous users' behaviors and walking paths. Specifically, *freeGait* utilizes a new perspective to remove CSI noise to obtain fine-grained spectrograms, and uses a deep learning framework combined with data augmentation and domain adaptation to solve the problem of inconsistent gait patterns caused by users' multiple behaviors and paths. In order that domain adaptation can solve our specific problem, we align the posterior distributions of the source and target domains, and constrain the conditional distribution of the target domains to optimize the domain adaptation model. To address the aliasing of reconstructed samples in data augmentation, we employ supervised learning to force the decoder to generate data that is highly relevant to the user. By leveraging a large amount of unlabeled data from a pair of WiFi transceiver, *freeGait* enables the model to learn user gait features independent of human behaviors and paths with only a small amount of labeled data. Our experiments on 20 volunteers in three real-world scenarios show that *freeGait* outperforms existing techniques in handling rich unlabeled human behaviors and walking paths, thereby mitigating non-gait behaviors of the users, which has the potential to facilitate the practical deployment of WiFi-based gait recognition systems.

# ACKNOWLEDGMENTS

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