

Poster: Deep Gait Recognition via Millimeter Wave

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Abstract

The key to personalizable behavior in smart spaces is knowing where and who a particular person is. However, concerns arise around potential leakage of face/video information, and many people do not accept cameras in their homes or workplaces. With the aid of a deep recurrent network, we propose a human recognition system that identifies gaits based on millimeter wave (MMwave). By a commercial, off-the-shelf radar, our system first obtains sparse point clouds from the reflection profiles of people walking. A deep neural network is then used to extract gait information from sequential point clouds and identify different people. Preliminary results demonstrate that MMwave is a very promising modality for gait recognition.

1 Introduction

Knowing ‘who is where’ in smart spaces is a key requirement for emerging applications and services. However, current people identification methods are mainly based on cameras, which relies on lights-in-sights and has potential risk of video information leakage. As a disruptive technology, millimeter wave (MMWave) gains increasing popularity in a variety of applications, such as 5G communications[2], driving safety[3], etc. As a type of RF signal, MMwave does not rely on optics and has a high precision in sensing. These properties potentially enable it supplement many identification scenarios when optical sensors (e.g., cameras) fail. However, to our best knowledge, using MMWave for human identification is still a blank space.

In this work, we introduce a system that identifies people by the unique characteristics of both their body shape and how they walk, with sparse point clouds generated by a MMWave radar, operating in the 77-81 GHz band. MMWave radar provides highly precise ranging with the RF signals reflected by obstacles in the environment, such as humans. It

has a number of interesting properties, such as the ability to not only measure the range to an object, but also its relative radial velocity with high accuracy. Exploiting these characteristics, we developed our gait recognition pipeline based on a commercial-off-the-shelf MMWave Radar. This is the first work using the point cloud generated by commercial MMWave Radar to track and identify people while they are walking, where gait features are implicitly included.

2 Proposed System

2.1 Overview

Our tracking and identification system exploits the unique properties of MMWave radar. It operates by transmitting an RF signal and recording its reflections off objects. By analyzing these reflection profiles, it then infers the people’s trajectories and identifies them from the database of legitimate users. The system consists of four modules that operate in a pipeline fashion, as shown in Fig. 1:

1. *Point Cloud Generation.* In this module, a FMCW radar transmits MMWave and records the reflections off the environment in the view. It then computes the sparse point clouds and removes those points corresponding to static objects.
2. *Clustering.* In this module, potential human objects are detected by merging the points into large clusters with DBScan algorithm.
3. *Tracking.* In this module, our system associates the same human object in consecutive frames and uses a multiple object tracking algorithm to maintain trajectories of different people. We use Hungarian Algorithm to associate point clusters between frames and Kalman Filter to predict and correct tracks.
4. *Identification.* In this module, a recurrent neural network is used to recognize user identities from different point-cloud trajectories.

2.2 Deep Gait Recognition

After the points corresponding to human objects are determined, we can use tracklets to recognize their identities. Specifically, at each frame in the trajectory, we use a fixed-size bounding box to enclose the points of potential human objects, and voxelize it to an occupancy grid. Note that, the occupancy grids inherently encapsulate body shape information, which is known as gait features. For instance, tall people tend to have higher center of mass. By feeding the se-

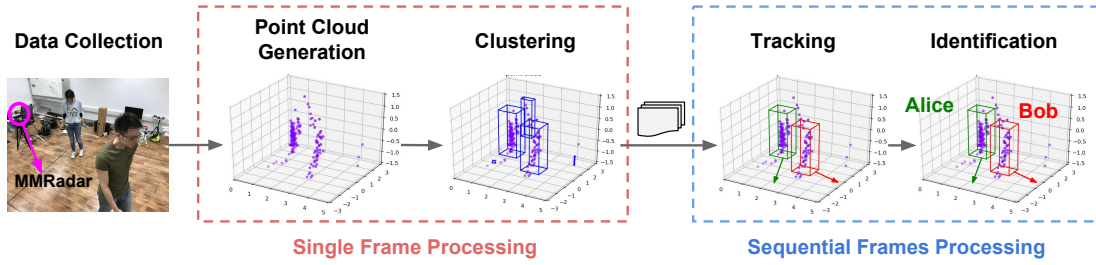


Figure 1. System Overview

quential occupancy grids to a classifier, the ID of a tracklet is recognized based on gait. The tracklet used in the system is segmented with the sliding window method. A window contains consecutive occupancy grids for 2 seconds, at 75% overlapping ratio with the previous window. Extracting useful features directly from the occupancy grids is difficult, as most feature engineering methods are not effective for point cloud classification tasks [1]. The 3D data is first flattened then each frame is converted into a feature vector, then passed into a bi-directional LSTM network. Lastly, a softmax layer is used to output the final classification result.

3 Evaluation

3.1 Setup

Our system is developed on top of a commercial, off-the-shelf MMWave radar, IWR1443Boost¹. The sensor was configured to use all the three transmitter and four receiver antennas in order to generate 3D point cloud data. Start frequency and end frequency were set to 77GHz and 81GHz respectively, so the bandwidth was 4GHz. We implemented the deep neural network classifier with Keras library. Each frame of the input data was first flattened to 16000 dimensional vector. Bi-directional LSTM with size 256 and hidden size of 128 was used. We set the dropout ratio to 0.5 and used Adam optimizer. We used a balanced dataset where training/test sample ratio was set to 11:1. To avoid overfitting, we further augmented the training data to 8 times the original size, by shifting the data in X and Y axis respectively for 1 voxel, and rotating each frame by 90°, 180° and 270°.

3.2 Results

We examine our system by an identification task with 12 participants². These participants aged from 22 to 35, and 3 of them are female. The heights of the participants range from 155cm to 188cm, and the weights of the participants range from 55kg to 80kg. To mimic the real-world complexity, we asked participants to walk in their most-comfortable way randomly in our testbed for 10 minutes. The collected data was then cut into chunks with length of 2 seconds and overlap of 75%. Overall, our system is able to reach the accuracy of 89%, out of 12 people. Note that, such performance is non-trivial, considering that the original point clouds are very sparse. The confusion matrix is shown in Fig. 2.

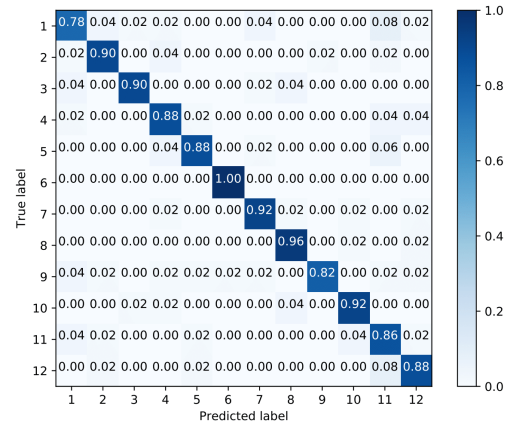


Figure 2. Confusion Matrix of 12 Users.

4 Conclusions

In this paper, we propose an gait identification system based on MMWave radar. With the aid of IWR1443Boost, a commercial-off-the-shelf MMWave FMCW radar, we first obtain sparse point clouds which is highly precise and contains speed data of each detected point. Then, we extract the point clouds representing human objects and associate them to their past trajectories. Based on the tracklets, a recurrent neural network is used to recognize their identities. Extensive experimental results show that our system achieves an overall recognition accuracy of 89% with 12 people in identification. A video demo that showcases our system can found here³. We envision gait recognition with MMWave radar as a promising step towards human identification and tracking in smart buildings and smart homes.

5 References

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¹<http://www.ti.com/tool/IWR1443BOOST>

²The study has received ethical approval SSD/CUREC1A CS.C1A.18.024

³https://youtu.be/3m84xZo6E_A