mmWave Based User Identification using Gait Signatures

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***Abstract*—In this work, we present *milliGait* , a user identification using gait patterns captured by millimeter wave (mmWave) radar technology. *milliGait* takes into account the unique movement signatures of individuals to enable privacy secured accurate user identification. Using a Commercial-Off-the-self (COTS) mmWave radar we have collected mmWave features, particularly the range information and range-doppler profile features, extracted from the raw I/Q samples. To categorize people according to their leg movement patterns, we developed a Convolutional Neural Network (CNN) model using the mmWave features. The two features namely the range information and the range-doppler profile is fed into two concurrent CNN models (1D and 2D CNN models respectively). Finally a fully-connecyed classifier is employed to identify the subjects. We have evaluated *milliGait* with 3 different subjects with an authentication accuracy of over 80%.**

***Index Terms*—Gait Signatures, User Identification, mmWave Sensing.**

I. Introduction

Gait recognition is a biometric method that uses each person's distinct walking patterns to identify them. Gait recognition is perfect for real-time applications since it doesn't require the active cooperation of the user, unlike conventional biometric techniques like fingerprint recognition, video monitoring, or facial identification. Numerous fields have taken a keen interest in this technology, especially in **security** and **surveillance** systems, where it allows for continuous and contactless monitoring without violating privacy [1], [2], [3], [4]. Compared to video-based authentication approach, one of the main benefits of mmWave-based gait recognition is its capacity to **preserve privacy**. While motion data without clear visual features is used for mmWave radar-based gait detection, video footage can collect identifiable visual information, which raises privacy concerns. This solves privacy issues that frequently accompany video surveillance by guaranteeing that people may be tracked or recognized without disclosing private or sensitive visual information.

In **healthcare**, gait recognition can be instrumental in diagnosing and monitoring conditions affecting mobility, such as Parkinson's disease or arthritis. It allows for continuous, non-invasive tracking of a patient's movement patterns, providing valuable insights into their physical health over time. Additionally, in **personalized user experiences**, gait recognition enables smart environments that can adapt based on the specific individual present. For instance, homes or workplaces equipped with this technology could adjust lighting, temperature, or security settings based on who is identified. Although there exists several works that uses mmWave-based sensing for human gait based authentication [1], [2] however most of these methods uses complex signal processing approach to render human lower limb features [4].

Instead of heading for a complex signal-based feature extraction, *milliGait* uses simple Convolutional Neural Networks (CNNs) which take raw human body reflected mmWave signals and capture gait features for user identification. The CNN model leverages the rich motion information from the mmWave radar to recognize and differentiate between individuals effectively. *milliGait* achieves 80% authentication accuracy in correctly identifying subjects purely on mmWave based raw features.

II. Related Works

In recent years, the field of device-free human identification and activity recognition using mmWave radar has gained substantial attention [5], [6], [7], [8]. Several methods have been proposed to improve the accuracy and robustness of these systems, particularly for applications in activity classification [5], [8]. In this section, we discuss four key works that leverage mmWave signals for human identification and activity recognition, and contrast them with our approach.

In [2], the authors present a method for robustly identifying individuals through gait recognition in complex indoor environments. The approach processes radar range-Doppler heatmaps by filtering out the background and isolating dense regions, which are then grouped into clusters corresponding to actual subjects or potential ghost targets. A target tracking algorithm is employed to associate these clusters across multiple frames, allowing for the construction of each target's trajectory. Finally, an LSTM-based attention network is used to assign different weights to the frames, enhancing the accuracy of subject identification.

In [1] authors design a multi-person identification and intruder detection using gait micro-doppler signatures using mmWave radar. In multi-person scenarios, the system detects and tracks each subject separately in the range-doppler space, extracting their unique gait signatures frame by frame. An open-set identification network is then trained using a large-margin Gaussian mixture loss to learn highly discriminative features, ensuring that the learned features of the training data follow a Gaussian mixture distribution, with each component representing a registered user. Similarly in [3] the authors propose a path-independent, device-free gait recognition system that can identify an individual regardless of the path they take while walking. The system uses location data and Doppler spectrograms to generate a corrected velocity spectrogram that approximates the actual velocity. It also employs an energy normalization technique to mitigate the impact of the walking path on the spectrogram's energy, ensuring the recognition process is path-independent. Using this path-independent gait spectrogram, a convolutional neural network is applied to extract deep features and perform the gait recognition task.

Another work MU-ID [4] utilizes range-doppler maps to examine the users' lower limb movements and captures unique gait patterns, which vary in terms of step length, duration, instantaneous lower limb velocity, and inter-lower limb distance. Additionally, the system proposes an effective spatial-temporal silhouette analysis to segment each user's walking steps. These steps are then identified using a CNN classifier, which further enables user identification within the area of interest.

Unlike previous works that primarily rely on doppler signatures and complex signal processing techniques to extract features for user classification, this work takes a different approach by leveraging both the range and range-doppler heatmaps. These complementary data sources allow for more comprehensive extraction of both subject location and human body movement signatures. The raw data is then fed into a CNN classifier for accurate user identification, offering a more holistic and efficient solution for gait-based person identification.

III. Background: FMCW mmWave Radar Sensing

mmWave radar operates by transmitting electromagnetic waves with short wavelengths (1–10 mm). With its wide bandwidth of 4 GHz, it provides a high range resolution of approximately 4 cm, making it effective for differentiating between subtle human movements. FMCW is a widely used modulation technique for automotive mmWave radars [9]. The radar transmits linear "chirps" and receives reflections from objects in its surroundings. By processing the reflected signal, the radar can determine the range, velocity, and angle of the detected objects. The frequency of the chirps increases linearly over time. When a reflected chirp, delayed by a time interval τ, is received, it is mixed with the transmitted chirp to generate an Intermediate Frequency (IF) signal. This IF signal is used to calculate both the distance and velocity of the object.

A. Range Estimation

FMCW radars emit chirps with a transmission time of T_C. For an object located at a distance d, the transmitted chirp (TX chirp) and the reflected chirp (RX chirp) are separated by a time delay τ. The chirp's slope S is defined as $S = \frac{B}{T_C} = \frac{f_b}{\tau}$, where B is the chirp's bandwidth, and f_b is the beat frequency between the transmitted and received signals. The time delay τ is expressed as $\tau = \frac{2d}{c}$, where c is the speed of light. Substituting this into the relationship for f_b, the object's distance can be calculated as:

$$d = \frac{c}{2} \cdot \frac{T_C}{B} \cdot f_b. \tag{1}$$

To determine the beat frequency f_b, a Fast Fourier Transform (FFT) is applied to the IF signal. Peaks in the range FFT represent detected objects, and their corresponding distances are calculated using Equation 1.

B. Velocity Estimation

To compute the velocity of a moving object, the radar transmits N chirps, each spaced by the transmission time T_C. After performing the range FFT to identify the object's location, the motion of a moving object results in phase changes between successive chirps. The phase difference $\Delta\phi$ caused by an object moving at velocity v is given by $\Delta\phi = \frac{4\pi v T_C}{\lambda}$, where λ is the radar's wavelength. A second FFT, called the Doppler FFT, is applied to the phase changes across chirps, providing the object's velocity.

C. Range-Doppler Map

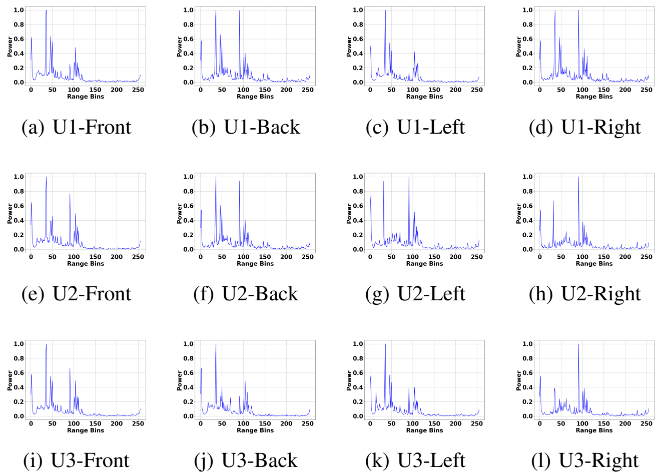
By combining the range information from the range FFT with velocity information from the Doppler FFT, a two-dimensional range-doppler map is created. Each element in the map represents the reflected signal's power at a specific range and velocity. This map captures both the spatial and motion characteristics of objects within the radar's field of view and forms the basis for gait analysis.

D. Gait Recognition with mmWave features

The range profile, derived from the range-FFT of the IF signal, represents the spatial distribution of reflected radar energy as a function of distance. This profile captures key aspects of gait, such as the spatial localization of motion and amplitude variations from different body parts. For instance, reflections from the torso, legs, and arms are recorded at varying distances, corresponding to their relative positions to the radar. The amplitude of these reflections varies with body shape, size, which are often unique to an individual. Over time, the temporal changes in the range profile reflect the periodic motion of the user's gait cycle, making it a critical feature for characterizing walking behavior.

The range-doppler map, on the other hand, combines spatial and velocity information together. The doppler dimension reveals unique movement patterns of the arms and legs during a gait cycle. Additionally, by associating specific doppler shifts with corresponding ranges, the range-doppler map provides a detailed segmentation of motion dynamics, distinguishing faster-moving legs from the relatively slower torso.

Thus both the range profile and range-doppler features enable robust human gait-based user identification. The range profile emphasizes spatial characteristics, while the range-doppler map integrates the velocity information, creating a comprehensive representation of gait. This synergy ensures distinctiveness in identifying individuals, robustness against variations in walking conditions, and consistency over time.

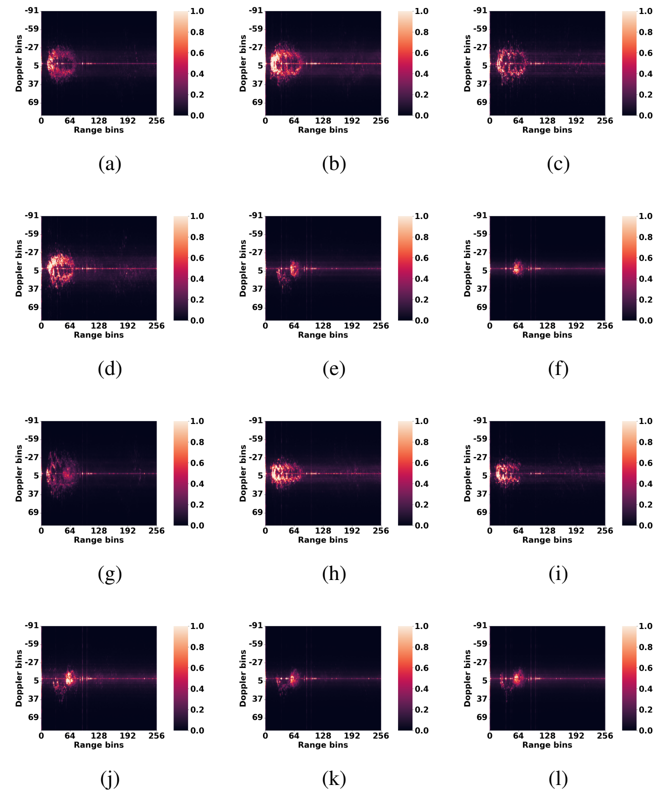


(a) U1-Front (b) U1-Back (c) U1-Left (d) U1-Right

(e) U2-Front (f) U2-Back (g) U2-Left (h) U2-Right

(i) U3-Front (j) U3-Back (k) U3-Left (l) U3-Right

Fig. 1: Patterns in range profile for front, back, left, right movements (from left to right) across 3 users (from top to bottom)



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

(j) (k) (l)

Fig. 2: Range-doppler Patterns for Front, Back, Left, Right Movement (from top to bottom) across three users (from left to right).

IV. Methodology

A. Data Collection

We create the gait dataset using an `IWR1843BOOST` [10] mmWave sensor with DCA1000EVM data capture board [11]. The sensor was positioned to capture full-body movement at a height of 2.5 feet and facing towards the subject who is performing the activity in an empty room. Simultaneously with mmWave data recording, we captured video footage to aid in labeling the radar data. A timestamp was recorded at the start of each session to synchronize mmWave data and video. As mmWave data lacks inherent labels, the video served as a reference for later annotation of the feet movements (like "left-leg-up", "right-leg-up", etc.). A `Python` script was used to overlay timestamps on the video footage, aiding in precise labeling. This script parsed video frames and added a timestamp to each frame. The output was a timestamped video file, enabling us to map gait cycle moments to specific mmWave data points.

TABLE I: Description of Features

Feature	Description
Datetime	Precise date and time of each moment within the gait cycle
Activity	Indicates which leg is raised (e.g., `l` for left, `r` for right)
User	The name or identifier of the person
Type	Describes movement type (e.g., front-back or left-right)
Direction	Specifies direction of movement of the person (e.g., `front` or `back`)

Using the timestamped video, we reviewed each recording to label distinct gait activities, creating a structured `CSV` file with the columns as shown in TABLE I:

To train the model on diverse gait patterns, data collection was repeated session wise for two movement types. **(1) Front-Back Movements:** User walked toward and away from the sensor, and **(2) Left-Right Movements:** User walked side-to-side relative to the sensor. Each session involved the same steps of video recording, mmWave data capture, timestamp synchronization, and labeling in the CSV file.

B. Data Preprocessing

The raw ADC data from the IWR1843BOOST sensor are first organized into a multi-dimensional array with shapes number of chirps (128), number of range bins (256), number of virtual antennas (3 TX & 4 RX). These data cubes represent the radar readings across different time intervals, capturing both the range and velocity of objects detected by the sensor. The data preprocessing pipeline extracts essential information from raw ADC data, converting it into a meaningful set of data that includes spatial and velocity information for detected human subjects. The key features extracted from the pipeline are as follows.

1) Range Information: The range informmation is an 1D Feature Vector of size 256, representing the aggregated range information across multiple channels and chirps. This feature captures the intensity of reflections at different range bins, providing insight into the distance and reflectivity of objects. Fig. 1 represents the range profile of all the users in the different directions of motion.

2) Range-doppler Map: This feature provides information on the distribution of the range and doppler (velocity) across different bins, showcasing how different distances (range bins) are associated with various velocities (doppler bins), which helps identify moving subjects, their range, and their relative velocity. Fig. 2 represents the range-doppler patterns of the different users in the different directions of motion.

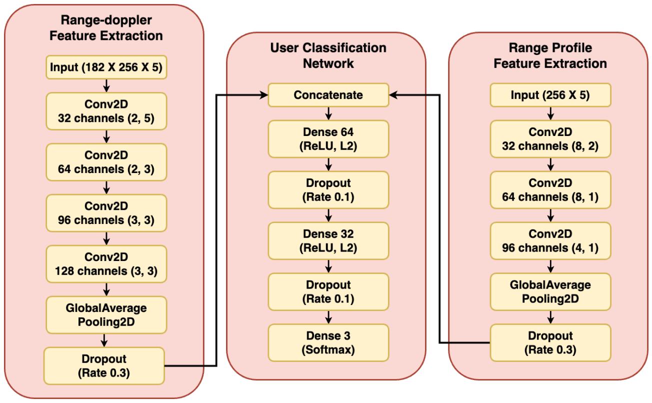


Fig. 3: Model Architecture

C. Synchronization with Annotated Data

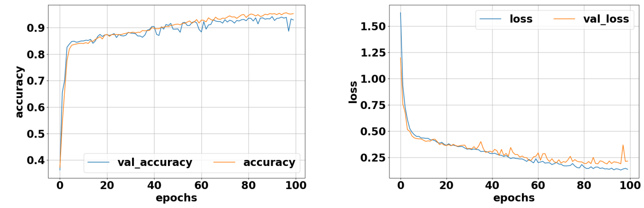
Finally the processed data was aligned with annotated timestamps in the CSV file. This synchronization annotates the mmWave data to it's corresponding user and the direction of gait performed at the time of recording the data.

D. Model Architecture

The model consists of two primary branches for feature extraction: 2D Convolutional Network (cnn2d) for 2D range-doppler heatmaps and 1D Convolutional Network (cnn1d) for 1D range profile features. The CNNs extract hierarchical spatial and sequential features from the sensor data. After feature extraction, the output from both CNN modules is passed to the user classifier network for final classification. The classifier consists of fully connected layers with ReLU activation and dropout to avoid overfitting. The final classification layer uses softmax activation to output the probability of the data belonging to one of the 3 possible subjects considered in this work. Dropout layers are included in the architecture to prevent overfitting and improve generalization. The model architecture is shown in Fig. 3.

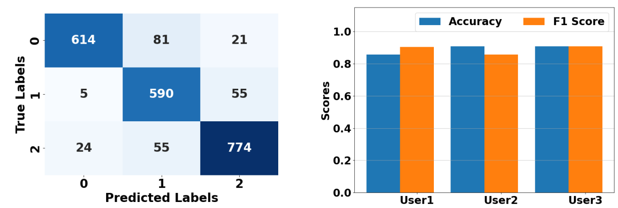
V. Evaluation

In this section we evaluate *milliGait* using the proposed 1D and 2D CNN-based model architecture, assessing its effectiveness in identifying different users based on gait patterns. In Fig. 4 we show the convergence curves for accuracy and loss during training. As shown in Fig. 4(a), we observe steady improvement in accuracy across epochs, with the model stabilizing near the final accuracy value as training progresses. Similarly, the loss convergence as shown in Fig. 4(b) illustrates that the model's loss declines smoothly, reflecting effective learning without overfitting. Fig. 5(a) reveals the model's classification performance on different users in terms of confusion matrix. The model achieves strong accuracy in user identification, showing minimal misclassification among users. However, we note occasional misclassification between specific users with similar gait patterns, as shown by the overlaps in the off-diagonal elements in the matrix. Fig. 5(b) provides the final overall accuracy and F1-score, with the model achieving high accuracy and F1 score for all the users



(a) (b)

Fig. 4: (a) Accuracy convergence, (b) Loss convergence



(a) (b)

Fig. 5: (a) Confusion matrix of user identification, (b) Overall Accuracy and F1-Score

during testing. The model achieves over 80% accuracy for all the users. These metrics confirm the robustness of our CNN-based approach to successfully identify users in a small scale.

VI. Conclusion and Future Works

In conclusion our proposed *milliGait* with combined distinct CNNs based model for processing radar data improved classification accuracy, achieving an accuracy and F1 score of over 80% on all users. Our evaluation also revealed that User 1 and User 2 had slightly lower accuracy than User 3, possibly due to User 1 and 2 having similar gait patterns, also evident from the confusion matrix. Finally we conclude our work with the following future directions.

1) Expanding the Dataset with Additional Users: Collecting data from a more diverse set of users would improve the model's generalizability and robustness in identifying unique gait signatures as real world applications would require the model to classify more number of users.

2) Enhanced Feature Extraction from ADC Data: Developing advanced feature extraction methods to capture additional aspects from ADC data, such as micro-movements or complex doppler signatures, would provide the model with richer information. Such features could yield more distinctive patterns and improve classification precision.

3) Automating Video Annotations: To reduce manual labor and improve efficiency, future work could involve implementing automated video annotation tools. Leveraging computer vision techniques to label frames automatically would streamline the preprocessing phase, allowing for quicker and more scalable data preparation.

4) Exploring Different Baselines: In future we will be evaluating our model with other baseline approaches like [2], [1] to understand it's effectiveness compared to other approaches.

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