Person Re-Identification Using WiFi Signals

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ABSTRACT

Person re-identification (Re-ID) has become increasingly important as it supports a wide range of security applications. In this work, we propose a WiFi-based person Re-ID system in 3D space, which leverages the advances of WiFi and deep learning to extract the static body shape and dynamic walking patterns to recognize people. In particular, we leverage multiple antennas on WiFi devices to capture signal reflections of the human body and produce a WiFi image of a person. We then leverage deep learning to extract both the static body shape and dynamic walking patterns for person Re-ID. Our evaluation results show that our system achieves an overall rank-1 accuracy of 87.1%.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**; • **Security and privacy → Security services**.

KEYWORDS

Person Re-Identification, WiFi Signals

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1 INTRODUCTION

Intelligent surveillance is gaining increasing attention due to the growing demand for public and private security. It has been deployed for a wide range of security applications such as facility security, perimeter monitoring, and abnormal behavior detection. Among these applications, person re-identification (Re-ID) is a fundamental one, which identifies individuals across time and locations. Traditional methods for person Re-ID mainly rely on computer vision approaches. However, camera-based systems have several limitations. For example, it cannot work in non-line-of-sight (NLoS) or poor lighting conditions. Moreover, it is sensitive to the variation in an individual's appearance due to changes in clothes.

In recent years, WiFi devices have become more and more ubiquitous in public and private places [2–6]. While nearly 1 billion surveillance cameras have been deployed worldwide in 2021, this number is about 22.2 billion for WiFi devices. The number of WiFi devices is thus an order of magnitude larger than that of the cameras. We ask the question of whether we can leverage the more pervasive WiFi signals to illuminate the human body and analyze the reflections for person Re-ID. Compared to camera-based systems, the WiFi-based approach can work in NLoS or poor lighting conditions as the WiFi signal can traverse occlusions and illuminate the human body in dark environments. Moreover, as the WiFi signal traverses clothes but is reflected off the human body, it is less affected by an individual's appearance.

In this work, we propose a WiFi-based approach for person Re-ID in 3D physical space. We leverage the advancement of WiFi technology and deep learning to help WiFi devices extract both the static body shape and dynamic walking patterns for person Re-ID. In particular, we leverage the multiple antennas on WiFi devices to estimate the WiFi signal reflections from the human body. Then, we can produce an image of the human body to illustrate the silhouette and the activity of a person in the 3D physical space. Once we have an image of the human body, we leverage deep learning to extract intrinsic features of a person including both the

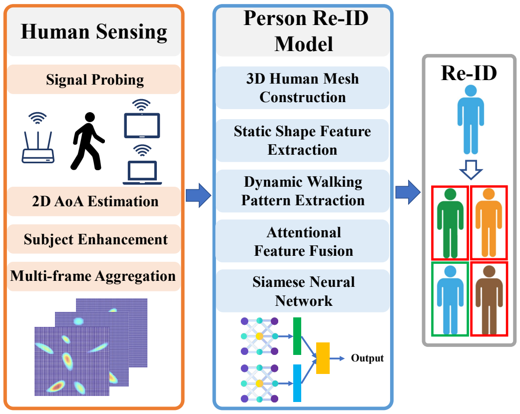


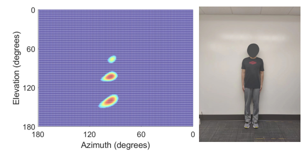
Figure 1: System overview.

static body shape and dynamic walking patterns for person Re-ID. These features are essentially the static and dynamic biometrics of the human, which are relatively stable over time, enabling a more robust person Re-ID system.

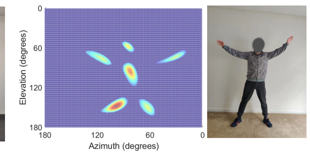
2 SYSTEM DESIGN

Human Sensing. The system overview is illustrated in Figure 1, the system takes as input channel state information (CSI) measurements at multiple antennas of the WiFi receivers when a person is walking around in the environment. The system can re-use existing WiFi devices and take advantage of CSI measurements from existing traffic, or if insufficient network traffic is available, the system might also generate periodic traffic for measurement purposes. The WiFi signals reflected from the human body (e.g., head, torso, arms, and legs) will travel through different paths and arrive at the receiver in various directions (i.e., azimuth and elevation angles). The CSI measurements of received signals then go through the two-dimensional angle of arrival estimation component to calculate the azimuth and elevation angles of the signal reflections using the MUSIC algorithm [2].

Next, our system performs subject enhancement to segment signal reflections of the human body from irrelevant reflections of the surrounding environments. It then performs multi-frame aggregation to capture the full picture of the human body. Figure 2 shows the captured full picture of the human body based on the two-dimensional angle of arrival of signal reflections for various people and activities. In particular, Figure 2(a) show the images of a person is stand and the WiFi image can show the body shape. Figure 2(b) show that another person is lifting arms and the corresponding signal reflection image can display the poses of that person. To summarize, the signal reflection image is capable of revealing information about both body shape and



(a) A person is standing.



(b) A person is lifting arms.

Figure 2: WiFi images for various people and activities.

pose, thus providing the foundation for WiFi-based person Re-ID.

Person Re-ID Model. Once we obtain a sequence of images of the human body while the user is walking around in the physical space, we can build a novel deep neural network to extract both static shape and dynamic walking patterns for person Re-ID. As shown in Figure 3, we first build the 3D human mesh including body shape and pose with SMPL model [7]. We extract static features from the body shape by using a graph convolution network (GCN)-based method, which considers the 3D mesh as a graph and produces a vector representing the person's static shape biometrics. The dynamic walking pattern features contain the gait pattern, arm and torso gestures, head and body movements. Thus, we compute the acceleration of each joint. Then, we make acceleration information flow between time steps by using GRUs and all time steps are combined using temporal pooling.

Next, these static shape and dynamic walking pattern features are fused using an attention-based mechanism with fusion weights. Lastly, the two-stream sub-networks for two sequences of images from two different people are constructed following the Siamese network architecture, in which the parameters of sub-networks are shared. Given a pair of time-series images from the same person, the Siamese architecture is trained to produce feature vectors that are close in feature space, while given a pair of time-series images from different persons, the network is trained to produce feature vectors that are separated. Given the fused feature vectors (F_i, F_j) for person i and person j, we utilize the Euclidean distance Hinge loss $L_{Siamese}(F_i, F_j)$ to train our model. We also calculate the identity loss $L_{ID}(F_i)$ and $L_{ID}(F_j)$ using the cross-entropy loss. The final loss function is written as $L_{ReID} = L_{Siamese} + L_{ID}(F_i) + L_{ID}(F_j)$.

3 PERFORMANCE EVALUATION

Experimental Setup. We conduct experiments using one WiFi transmitter and two receivers. Specifically, the WiFi transmitter is equipped with a linear antenna array of three antennas. Each receiver is equipped with a 5×5 L-shaped antenna array. Linux 802.11 CSI tools [1] are used to extract CSI measurements from 30 subcarriers. The packet rate is

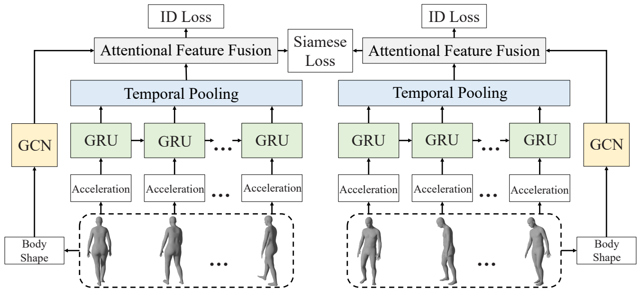


Figure 3: The person Re-ID model.

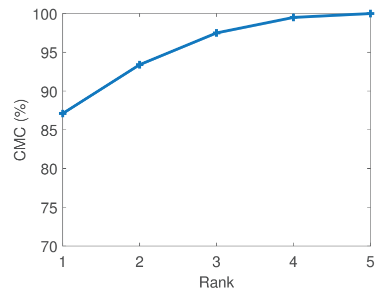


Figure 4: Overall system performance.

set at 1000 packets per second. We utilize a camera to record the ground truth. We evaluate our system in two different laboratories.

Dataset. In this work, 12 participants (8 males, 4 females) were recruited. We collected synchronized WiFi and vision data of random everyday activities of these participants over two months time period. Moreover, we ask these 12 participants to walk randomly in different environments over one month for person Re-ID. For calculating ranking accuracy, the whole dataset is randomly split into two non-overlapping parts: 50% of people for training and the remaining 50% of people for testing. The experiments are repeated 10 times with different training and test splits and the results are averaged to ensure stable results.

Evaluation Metrics. We leverage the ranking accuracy to evaluate our system. The system is given a WiFi sample of a test person and only one of the candidates can match the queried WiFi sample of the person. The top-k accuracy is defined as the percentage of cases where the correct test person is ranked among the top k positions of all the candidates in a test. We also show the performance with the average Cumulative Matching Characteristics (CMC) curves.

Overall Performance. We study the overall performance of our system. The person can appear in one environment and walk into another one or appear in the same environment at different times with different appearances. We note that our system is trained in only one environment and tested in another environment that has never been seen by the system. As shown in Figure 4, we can observe that our system has overall top-1, top-2, and top-3 accuracies of 87.1%, 93.4%, and 97.4%, respectively. This shows our system has high overall ranking accuracies. It is because our system focuses on the 3D body shape and walking style of a person, which remain unaffected even when the person wears different clothes. This also demonstrates that our system is capable of re-identifying a person even if the environment has never been seen before.

4 CONCLUSION

Person Re-ID in traditional optical camera-based systems is challenging due to changes in the appearance of people and occlusions. We propose a WiFi-based person Re-ID system, which is very promising to mitigate these challenges and augment traditional camera-based systems. Specifically, we exploit multiple antennas on WiFi devices to extract WiFi signal reflections from the human body in the physical environment. Our system extracts intrinsic features of the body shape and dynamic walking patterns from humans for person Re-ID. Experiment results demonstrate that our system is effective in identifying a number of people.

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