LoRa-based Privacy-Aware and Contactless Surveillance in Next-generation Smart Homes

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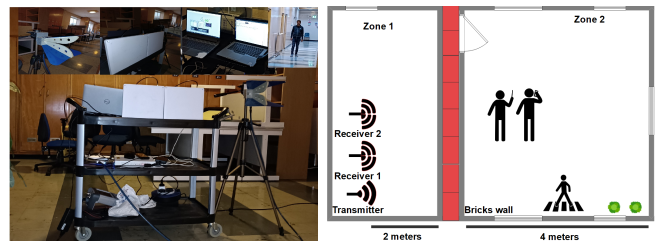
Abstract—**There are many security and surveillance applications in which camera-based or invasive human activity recognition is not permissible due to privacy, insecurity, and discomfort issues. Moreover, vision-based surveillance systems have a few key technical challenges that limit their practicality such as bad illumination, obstacles, and occlusion. In such cases, we require a more reliable system which can work in challenging situations such as in darkness, long-range, through walls or obstacles, a rainy and smoky environment where vision-based systems do not deliver good results. Only high-energy and long-range wireless sensors which can identify targets through obstacles, walls, worst climate or surrounding conditions can serve the purpose. In this paper, we propose to use the LoRa transceiver to identify different persons from their walking patterns through bricks and a concrete wall where people other than the target person are moving freely. Moreover, we employed three different deep-learning models to evaluate the efficacy of the proposed system. Our highly accurate 99% results encourage the use of contactless LoRa sensors in many privacy-critical applications such as healthcare, security, and surveillance, where short-range and low-energy signals have limited utilisation.**

I. Introduction

Different from traditional sensor-based sensing, contactless sensing does not require any sensors but relies on the signal itself for detection. The sensor-free and contact-free nature make contactless sensing appealing in many real-life applications including security and survival in life-saving operations, intrusion detection, indoor and outdoor human activity recognition and vitals monitoring. Diverse contactless sensors such as WiFi [1], long range radio (LoRa) [2], RFID [3], radars [4], ultrasonic and visible light had been deployed for sensing purpose.

The underlying principle of contactless sensing is that wireless signals get reflected from the target and the reflection signals vary with target movements [5]. By carefully analysing the movement-induced signal variations, rich contextual information regarding the target's movements can be obtained. As compared to other contactless sensing technologies such as WiFi, RFID, FMCW radars, and ultrasounds, which have a few meters sensing range, LoRa has a relatively very high range and high energy signal which can easily pass through obstacles and brick walls. This makes it highly suitable for applications where low range, low energy, and high power consumption signals do not work.

In this paper, we present a LoRa signal by using a pair of universal software radio peripherals (USRP), one as a transmitter having one antenna and another as a receiver have two antennas to detect people from their walking patterns through a thick brick wall. Human activity include strolling outside the room wall and the resulting information is person detection from their walking patterns. Below sections include experimental setup, data collection, pre-processing of the complex I/Q signal data and walking patterns results for the strolling activities of six different people.



(a) Hardware and Software Setup (b) Experimental Setup

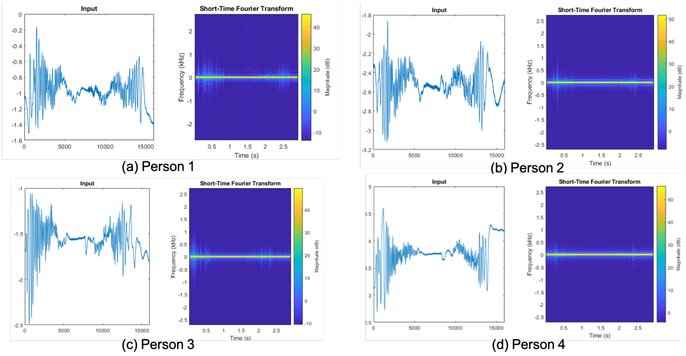
Fig. 1: Illustration of hardware and software setup (Fig. 1(a)) and experimental setup (Fig. 1(b)) used for data collection.

II. Methodology

A. Experimental Setup and Data Collection

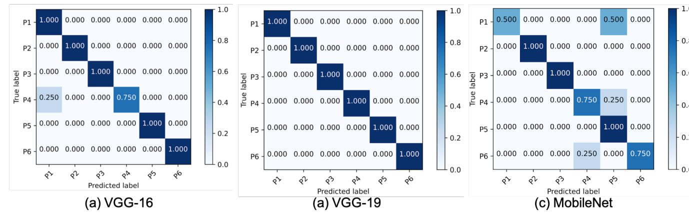
Our data collection setup includes two 310 USRPs, where one is used as a transmitter and another as a receiver. Transmitter has one Aaronia Ag vertical polarized antenna and the receiver has two Slimline A5010 circular polarized antennas with 8.5 dB gain as shown in Figure 1(a). LoRa signal is generated on the transmitter end through USRP simulated using LabVIEW and USRP on receiving end is operated using two receivers' physical layer setup. The transceiver as a module for GNU Radio 3.10 has been used for software defined radio (SDR) implementation of the LoRa transceiver. This module operates correctly even at exceptionally low signal to noise ratio (SNR), which is available as an open source in [6].

All the apparatus USRPs, antennas, laptops and power wires are setup on a wheeled moveable trolly near the outer wall of the room at a two-meter distance away from the separation wall, while activities have performed inside the room away from the separation wall all over in the four meters long and six-meter-wide area floor. Rom has a door near the one end of the separation wall in between the transceiver and the activities performed area.



(a) Person 1 (b) Person 2 (c) Person 3 (d) Person 4

Fig. 2: Depiction of data variations in the received LoRa signals reflected from individuals' walking patterns in time and frequency domains.



(a) VGG-16 (a) VGG-19 (c) MobileNet

Fig. 3: Classification performance of three different models in recognising six different persons using proposed LoRa-based contactless sensing.

Data collection setup has been established in a room available in Communication, sensing and imaging (CSI) lab at the James Watt School of Engineering in the University of Glasgow, United Kingdom. Setup is divided into two zones; zone one is outside the room where USRPs, antennas, laptops, and other apparatus are placed, and zone two is inside the room where activities have been performed for data collection, where zone one and zone two are separated by a twelve-inch thick double brick wall. Area details inside and outside the room and activity details are illustrated in Figure 1(b). The activities include persons strolling other side of the brick wall and resultant information includes the person identification from their walking patterns. Total six people; four males and two females aged in-between 22-30 years old took part in the data collection activities.

B. Data Pre-Processing and Machine Learning

The transceiver consists of one separate USRP and antenna to generate LoRa signal as a transmitter and another separate USRP and two antennas as a receiver. Baseband signal is I/Q complex data which provides amplitude and phase information (having same magnitude but different phases) on both individual antennas on the receiver end. Walking information comes from the phase difference of receiving antennas. To get phase differences, as a first step we need conjugated multiplication of two received LoRa signals, and separate the phase and magnitude the second step is to further downsample the data to apply a threshold filter to get precise phase information and the third step is resampling the conjugated LoRa signal. Finally, we compute spectrograms of the preprocessed signals for the training of three different deep learning (DL) architectures. These images were cropped to eliminate colour bars and titles prior to using them for model training and testing. All images have the same dimensions of $224 \times 224 \times 3$.

III. Results and Discussions

We demonstrate the data variations that are reflected by the individuals' walking movements that were used to identify persons in Figure 2. The figures suggest that the collected data contains distinct characteristics in terms of measuring LoRa signal that makes it suitable for training DL models to identify persons in a privacy-aware fashion. Specifically, we have trained and tested three widely used DL models namely VGG16, VGG19, and MobileNet. These models were trained and tested using 80% and 20% of the collected data for training and testing, respectively. Furthermore, to ensure efficient training, we employed $4\times$ data augmentation to increase the size of the training set. The experimental results in terms of confusion matrix are summarized in Figure 3. We can see that the VGG19 outperformed VGG16 and MobileNet, while effectively recognising each individual. Moreover, the figure reveals that the performance of the MobileNet is the worst, which can be due to the fact that the architecture of the MobileNet is much smaller than the other two models.

IV. Conclusions

In this paper, we propose to use the LoRa transceiver to identify individuals from their walking patterns. Highly accurate 99% results advocate long-range, low power, low SNR and high energy LoRa capability to be used as a reliable system in many contactless sensing applications in next-generation smart houses, hospitals and public places. In our future work, we plan to optimize our proposed framework and to incorporate more critical activities.

Acknowledgments

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