Deep Learning-Based Human Activity Recognition via Power Lines

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***Abstract*—This paper presents a novel method for recognizing human activities using ubiquitous power lines. With the assistance of a Universal Software Radio Peripheral (USRP), high-frequency electromagnetic signals are injected into power lines. These signals are then radiated from and received by a power line while individuals move nearby. Doppler spectrograms of the received signals are processed and used for activity recognition. A DenseNet-201 network is trained to classify the types of human activity using the Doppler spectrograms, achieving accurate predictions of activities such as walking, running, and jumping.**

I. Introduction

Over the past two decades, radio frequency sensing systems have gained significant attention as effective and reliable solutions [1]-[5]. In addition, a novel idea of leveraging ubiquitous and cheap power lines for human sensing offers a promising alternative. This concept is based on the fact that power lines without shielding can radiate electromagnetic fields into the surrounding environment. As individuals perform activities around the power line, the radiated energy can reflect and couple into the power line. By measuring the differences in transmitted and received signals, human activities can be inferred.

The power lines have been widely used for human localization. [6] proposes a system that achieves sub-room level precision, where a room is typically segmented into five regions. It uses a fingerprinting technique based on the amplitude of tones generated by two modules placed at opposite ends of the home. The density of electrical wiring at various locations within the home creates a time-independent spatial variation in signal propagation. [7] introduces a wideband approach to power line positioning, injecting up to 44 different frequencies into the power line. This method improves overall positioning accuracy, offers significantly enhanced temporal stability, and has the added benefit of functioning in commercial indoor spaces. Additionally, [8] proposes a device-free indoor localization system by measuring the electromagnetic coupling between a human body and existing power lines. The occupant's location could be inferred by measuring the received signal change. However, these studies primarily rely on fingerprinting techniques, are largely influenced by the surrounding environment, and are not used to recognize human activity.

In this paper, a novel technique to recognize human activities leveraging power lines is proposed. In the proposed technique, Doppler spectrogram is utilized to analyze the changes in the coupled signal received by the power line, enabling a sense of human movement. By collecting Doppler spectrograms for different activities and executing a classification network based on deep learning, human activities are recognized.

II. Methodology

The basic framework is illustrated in Figure 1. Data is initially collected from the power line using a USRP to transmit and receive signals. The received data is then processed through Doppler analysis. Finally, deep learning is employed to perform activity recognition.

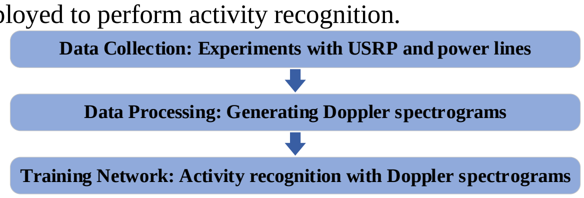

Figure 1 Basic scheme for human activity recognition via power line.

The experimental setup is presented in Figure 2. The transceiver unit comprises a host computer for control and display, a peripheral component interconnect express (PCIe) card, and a USRP. In the transmission process, the USRP upconverts the signal to the designated carrier frequency, amplifies it to 20 dBm, and transmits it to the transmitting power line via the coupler, which is designed to decrease the insertion loss. For reception, the USRP also receives the signal from the power line via the designed coupler. Subsequently, it downconverts the received signal to a specified low frequency and transfers it to the host computer through the PCIe connection. In this study, a carrier frequency of 1.7 GHz is selected. To mitigate errors and noise caused by single-channel simultaneous transmission and reception with the USRP, two separate channels and two standard H05VV-F power lines are employed for transmission and reception. Each power line is 30 meters long and positioned 1 meter above the ground. By moving around the power line, the resulting signal variations are observed and analyzed.

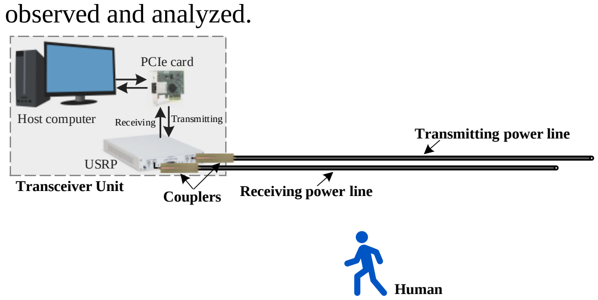

Figure 2 Experimental setup for human activity recognition based on USRP and power lines.

The received signals are recorded for ten seconds and processed using Doppler analysis to generate a Doppler spectrogram. Once sufficient Doppler spectrograms are collected for various human activities, the DenseNet-201 model is utilized to train a classification network for activity recognition.

III. Results and Discussion

In this study, three activities, walking, running, and jumping, are analyzed for recognition using the experimental setup. After processing the signals received from the USRP, the characteristic Doppler spectrograms corresponding to these activities are presented in Figure 3.

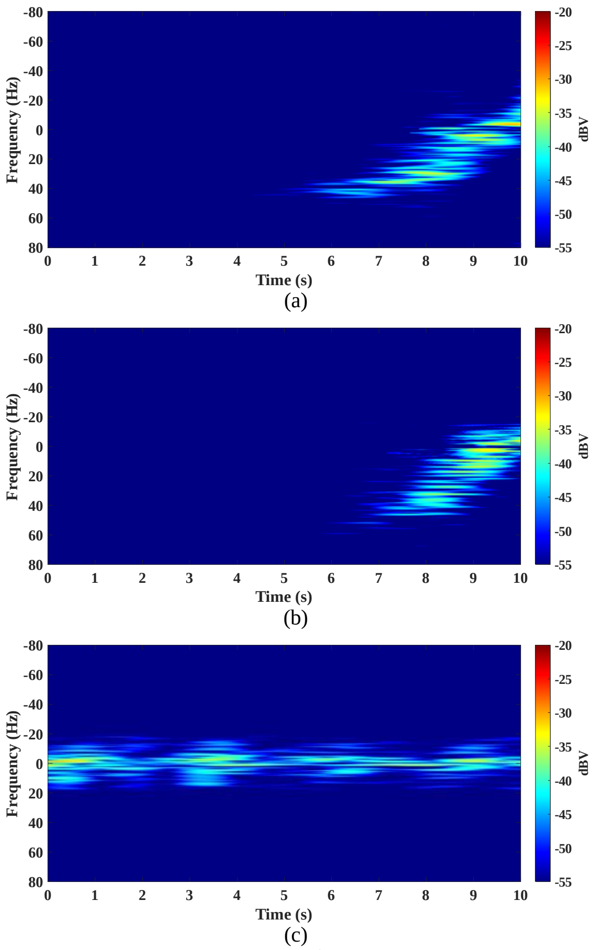

Figure 3 Typical Doppler spectrograms for (a) walking, (b) running, and (c) jumping, obtained by processing the data collected by a power line.

A total of 50 data samples are collected for each activity, with 35 samples used for training the network and 15 for validation. DenseNet-201 is chosen for activity recognition due to its efficient feature reuse and enhanced gradient flow. The network parameters are optimized using stochastic gradient descent with momentum. The final confusion matrix showing the accuracy of the trained network is presented in Figure 4. The results indicate that the activities of walking, running, and jumping are accurately predicted. These differences in Doppler spectrograms arise from variations in velocity and direction relative to the power line. Walking is characterized by a relatively low velocity, resulting in a lower Doppler frequency range and a longer duration. Running, on the other hand, involves a higher velocity, leading to a higher Doppler frequency range and a shorter duration. Jumping exhibits periodic variations, with the lowest Doppler frequency range, as its motion is primarily perpendicular to the direction of the power line.

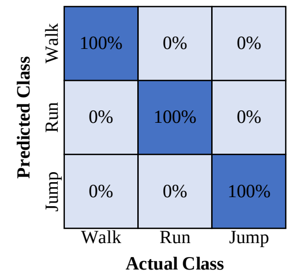

Figure 4 The confusion matrix of training DenseNet-201 for human activity recognition

IV. Conclusion

This study proposes a power line sensing approach that combines Doppler analysis and deep learning for human activity recognition. Data is collected using a USRP and power lines while individuals move near the line, followed by Doppler analysis for signal processing. By training Doppler spectrograms of various activities with the DenseNet-201 model, activities such as walking, running, and jumping are accurately recognized.

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