In-Home Activity Monitoring Using Radars

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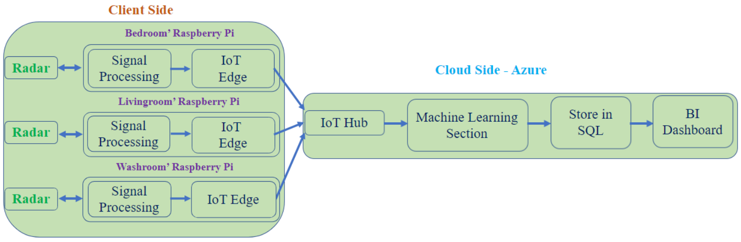

Fig. 1: Diagram of the proposed system. Three standalone sensors are installed at the subject's living environment collecting stream data and sending it to the cloud.

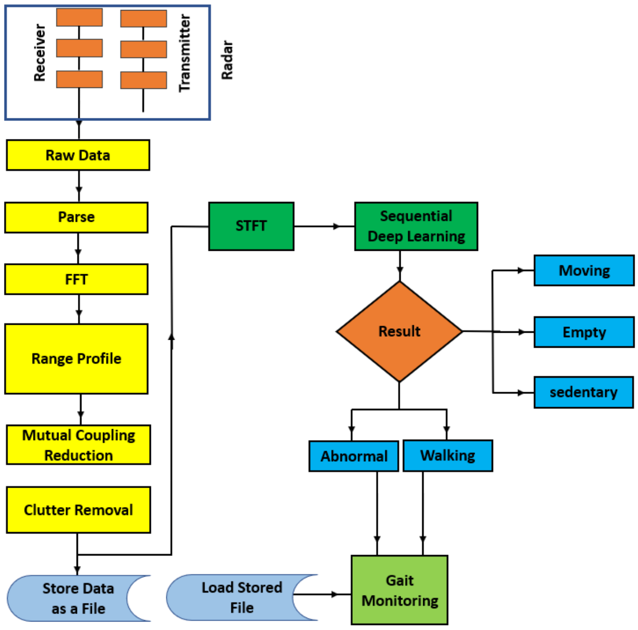

Fig. 2: Proposed System Flowchart. Firstly, features for the sequential deep learning will be provided and delivered to GRU. If walking cycles are identified, a gait extraction algorithm will be applied.

Abstract

We propose novel non-contact real-time cloud-based in-home activity recognition and gait monitoring systems. We present standalone IoT-based mm-wave radar systems coupled with deep learning algorithms as the basis of an autonomous in-home free-living physical activity recognition and gait monitoring system. Using the mm-wave radar system, human spectrograms (time-varying micro-Doppler patterns) are used to train deep Gated Recurrent Network (GRU) to identify physical activities performed by a subject in his/her living environment. An overall model accuracy of 93% was achieved to classify in-home physical activities.

1 Introduction

Radar sensors have been widely used in human gait assessment and activity recognition [1–5]. However, the use of radar has been less explored in real-life applications [5], such as in-home activity recognition and gait monitoring. The primary purpose of this research is to perform in-home free-living daily activity recognition and gait periods detection using radar technologies to have a record of subject's activity level and gait patterns during daily life activities. We perform gait and activity recognition studies in a familiar and commonly used environment, such as one's home. Moreover, unlike the work reported in [6] that used a complex radar system including four AWR1243 chips to create 192 channels to provide human point cloud information for 2D-DCNN, we used only one AWR1443Boost radar sensor. Note that for a real-time everyday application, we need a fast and simple algorithm, whereas an expensive high-resolution radar and complex signal processing are required to prepare point cloud information, as shown in [6]. Moreover, to make the system affordable, it is preferred to have fewer and inexpensive radar sensors. In this paper, we show that, without the need for an expensive high-resolution radar leading to complicated and computational-costly algorithms for detection, clustering and associations to extract point cloud information (x-y-z) [6], Joint Time-Frequency (JTF) representation of a human body obtained from a low-cost radar is reliable, rich and enough feature to be delivered to a sequential deep learning algorithm to be trained and so to predict in-home activities. In addition to the simplicity, compared to the point cloud information of the subject, another advantage of JTF patterns is that only one single transmitter and a receiver can provide spectrograms leading to a less expensive system.

2 System Design

The diagram of our proposed system is presented in Fig. 1, where the main components of the system include Client Side and Cloud. To provide a detailed representation of the subject's daily activity, we focus our attention on the living room as this is the main area of the house where the subjects spend time and perform most of their activities, followed by the bedroom (to record the sleeping time and duration) and the washroom (to record washroom frequency, enter, exit, and duration). Therefore, to enable tracking a subject in the three main living areas, we installed a standalone system (a radar integrated with a single board) at the subject's bedroom, living room and washroom. Each system is used to send the radar configuration commands to run the radar, to store received raw signals, to preprocess the raw data, and then to transfer it to the cloud.

3 PROPOSED ALGORITHM

The block diagram of our proposed algorithm flowchart is illustrated in Fig. 2. As shown, the proposed algorithm consists of two separate processes: walking periods identification/activity recognition and gait extraction. In this paper, we cover the method of in-home walking period identification and activity recognition. Our system uses JTF patterns of activities to recognize in-home human activities, as well as to identify walking intervals. We demonstrate that GRU can extract temporal characteristics of the radar data and thus achieves sufficient recognition accuracy with relatively low complexity without the need for the subject's point cloud information [7].

3.1 Results

For scenarios of free-living in-home activities, the system achieves 93% accuracy. As shown in Fig. 3, the network can easily identify an empty room and sedentary behavior. Moreover, only a few samples were incorrectly identified as walking cycles. This is one of the strengths of the proposed network as the primary purpose is to accurately identify walking cycles and extract gait parameters which are health indicator.

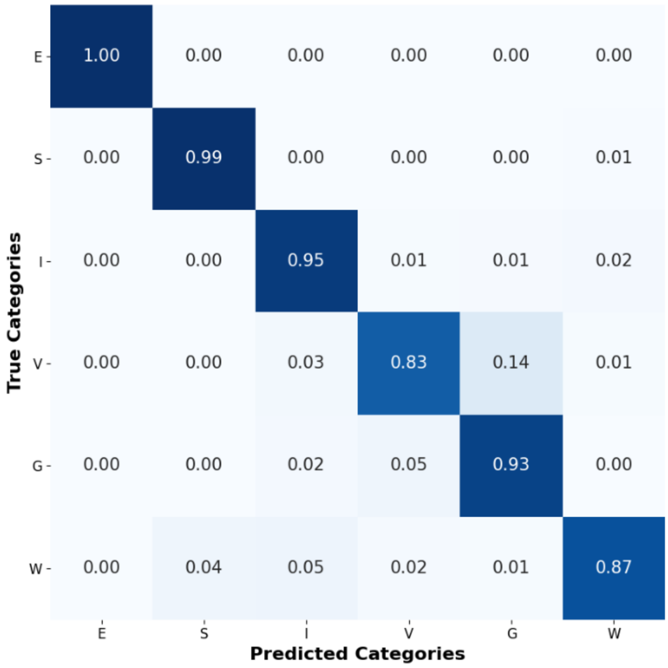

Fig. 3: Confusion matrix yielded by the GRU method applied to test datasets collected at the small apartment . Note that “E”, “S”, “I”, “V”, “G” and “W” stand for Empty, Sedentary, In-place movement, Vacuuming, Walking and Washing, respectively.

4 Conclusion

In this paper, we proposed an IoT-based, in-home gait monitoring and activity recognition system. We used mm-Wave FMCW radar sensors coupled with sequential deep learning to generate stream data of human free-living in-home activities. By leveraging the wealth of continuous data, the proposed system can identify the type of activity a person is performing. This system is poised to be a significant achievement in the development of autonomous continuous human monitoring systems as it not only identifies walking cycles and recognizes the type of activity but also has the potential to report the activity level of the subject such as sedentary vs. active, in addition to the washroom frequency and sleep time.

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