RFiDARFusion: Enhancing Contactless Activity Monitoring with Radar and RFID Fusion

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***Abstract*—Indoor human activity recognition (HAR) faces challenges due to the limitations of single-sensor systems in terms of privacy and cost. Our contactless *RFiDARFusion* system aims to reduce healthcare costs by swiftly identifying unforeseen activities through artificial intelligence and wireless communication. The system accurately discerns complex human activities by employing the LSTM-VAE fusion algorithm for multi-sensor data extraction, proving effective in long-range and non-line-of-sight environments. Two data fusion algorithms were studied across five distinct activities, significantly improving HAR accuracy by a minimum of 4.5% and 6.5% under data and feature-level fusion, respectively. The resulting *RFiDARFusion* system is contactless, precise, and robust, promising to enhance the quality of life for elderly patients in assisted living.**

I. Introduction

Indoor human activity recognition (HAR) is essential for improving living standards and safety, especially for the elderly. The need for accurate, cost-effective, and non-intrusive monitoring has led to the adoption of contactless radio frequency (RF) sensing technologies, including RFID and radar. These technologies are increasingly relevant in healthcare applications, such as elderly monitoring and smart living environments [1]. Contactless methods employing Wi-Fi, radar, and RFID offer comfort and reliability, which is particularly important in elderly care [2]. Despite their advantages, RFID systems are limited by line-of-sight (LOS) requirements, while ultra-wideband (UWB) radar systems face challenges with range accuracy and indoor performance. UWB radar, however, offers high-resolution information through high-frequency pulse signals, addressing some of these issues [3]. Integrating cost-effective radar with COTS RFID readers, combined with battery-less UHF RFID tags, presents a promising solution for accurate and privacy-aware indoor HAR.

Single-modality deep learning (DL) solutions in HAR are often limited by low accuracy in recognizing similar activities and susceptibility to interference. To address this, we present *RFiDARFusion*, a fusion system that combines RFID and radar data using LSTM with variational autoencoder (VAE) units. This system is adept at understanding complex activities, demonstrating its potential as a long-term HAR solution for home environments.

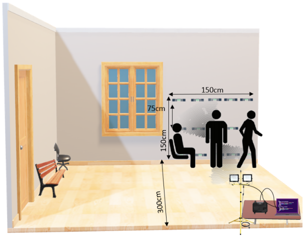
II. Related Work

Contactless multi-modal fusion in activity detection offers significant advantages over traditional RFID or radar systems, providing real-time adaptability to dynamic conditions. Fusion techniques in Wi-Fi CSI, radar, and RFID have been shown to increase HAR precision by using diverse sensing modalities [4]. In this realm, predominant approaches include data and score fusion, which combine decisions through methods such as weighted averaging or learning models, and feature fusion, integrating discriminative features for enhanced accuracy [5]. While recent advancements in smart sensing, exemplified by systems like *RF-Focus* [6] and *TagVision* [7], use RFID and computer vision for object recognition, they diverge from the specific focus on HAR. Notably, there is a gap in systems that integrate RFID with radar for contactless HAR without compromising privacy.

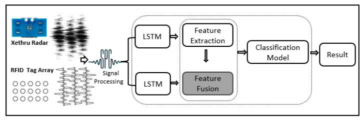
The *RFiDARFusion* system is designed to identify activities such as sitting, standing, leaning, and walking in a designated area, showcasing its applicability in healthcare patient monitoring. To address the shortcomings of both RFID and radar sensors, complemented by DL models like LSTM, RNN, and CNN, the system achieves complex HAR. This paper is unique in its approach, utilizing RFID and radar sensor data, including amplitude and RSSI, through data and feature fusion for human monitoring. This method represents a departure from traditional image-based time complexity approaches, like spectrogram analysis, highlighting its potential for accurate indoor activity classification in healthcare applications.

III. Methodology

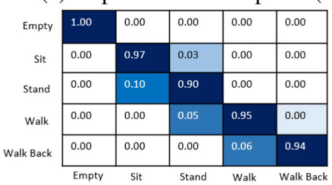
RFiDARFusion introduces a novel multi-modal system for HAR, addressing limitations in RFID and radar-based systems, particularly in long-range and LOS environments. The system combines an RFID reader, RFID tags, and a UWB Xethru radar connected to a laptop. The system captures time-series data during various activities, including *tag ID, RSSI, timestamps, and raw IQ data*, stored in CSV and .dat formats. This setup enables *RFiDARFusion* to detect contactless interactions and activities through data and feature-level fusion, enhancing HAR accuracy. The fusion LSTM-VAE model, along with data classification, is employed for precise activity recognition.



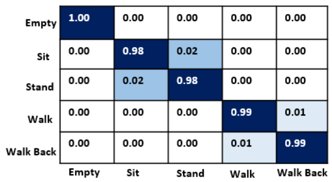
(a) Experimental Setup



(b) Data flow of feature-level fusion



(c) Data-level



(d) Feature-level

Figure 1: Normalized confusion matrix of LSTM after data level and feature level fusion.

Visual representations of the system, including the fusion process and confusion matrices, are detailed in Fig. 1.

A. Experimental Setup

The experiments were conducted in a $5 \times 5m^2$ room at the University of Glasgow using a *RFiDAR-Wall* structure ($1.5 \times 1.5m^2$) with five columns, each containing three RFID tags. The setup includes a *RFiDAR-Wall*, an Impinj $R700$ series reader, an Impinj Times-7 $A5010$ antenna, UHF RFID tags, and a Novelda Xethru $X4M03$ UWB radar. The RFID system, operating between $865-868$ MHz with a transmission power 32.5 dBm, captured data from activities performed close to the *RFiDAR-Wall*. The circularly polarized antenna, positioned at various distances, collected activity data, which was then processed on a robust Dell PC equipped with an Intel Core i7-10850H CPU and 16 GB of RAM.

B. Data Preprocessing and System Calibration

Preprocessing of raw RSSI and IQ data involves cleaning, formatting, and transforming using mathematical and signal processing techniques, including various filters. For radar data, initially, in a $2D$ format $(301, 91)$, where 301 and 91 denote data points and range bins. the mean across range bins for each sample (3 seconds) is calculated, resulting in a single value per sample reshaped (301, 1). Transposing gives a final shape of $(1, 301)$ for streamlined representation with 50 frames per second (FPS), generating 50 rows for each radar range-time frame. Background subtraction is used to remove clutter and DC noise, while RFID data is normalized into a $1D$ format. Minimum and maximum values, along with scale, are determined for both radar and RFID datasets, and normalization procedures are applied for standardization. Finally, the system calibration addresses challenges due to inconsistencies in data collection samples across sensors, such as continuous-wave radar at 50 FPS and RFID at 12 Sample per/sec. Consequently, downsampling the radar data is necessary to align its timestamp with the RFID data collection frequency.

Table I: Sensor Model Performance Before and After Fusion

Sensors	Input Data	Model	Accuracy (%)
Radar	Amplitude	CNN	82%
		LSTM	**91%**
		RNN	86%
RFID	RSSI	CNN	76%
		LSTM	**92%**
		RNN	88%
Data Level	Amplitude + RSSI	CNN	87%
		LSTM	96%
		RNN	82%
Feature Level	Statistical Features	CNN	81%
		LSTM	**98%**
		RNN	93%

IV. Results and Discussions

The efficacy of the *RFiDARFusion* system is illustrated in Table. I. Utilizing the LSTM-VAE model, the system achieved a remarkable accuracy of 98%, surpassing the CNN and RNN models, which recorded average accuracies of 81% and 93%, respectively. These models reliably detected five distinct activities within a 2-meter distance. This enhanced performance is largely due to the effective utilization of RSSI and amplitude measurements, which are significantly influenced by the proximity of the subject to the transmitter.

V. Conclusions

The *RFiDARFusion* system effectively combines RFID and radar with advanced deep learning fusion models to accurately recognize indoor human activities. Its high accuracy shows great potential for improving monitoring in assisted living environments.

ACKNOWLEDGEMENT

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