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Review Paper on Radio Sensors

Mr. Jayanth Kumar A Rathod[1], Poorvika B M[2], Prajwal Gowda MM[3], Prasad R[4], Rahul R Poojary[5]
Assistant Professor, Department of Information Science and Engineering[1]
Students, Department of Information Science and Engineering[2,3,4,5]
Alva's Institute of Engineering and Technology, Mijar, Mangalore, Karnataka, India

Abstract: *The creation and widespread use of human-centric applications, such as health monitoring, assisted living, etc., are made possible by recognizing human actions in daily life. To recognize user behaviors at an aggregator, traditional activity recognition approaches frequently are used on physical sensors (camera, accelerometer, gyroscope, etc.) that continuously collect sensor data. Although standard activity identification techniques have been shown to be useful in earlier research, they are not without privacy, energy, and implementation cost issues. Recent years have seen the development of a brand-new activity recognition method that makes use of wireless radio's body attenuation and/or channel fading. Compared to conventional activity recognition techniques, radio-based techniques make use of wireless transceivers as infrastructure and take use of radio communication features to achieve high Accurate recognition, lower energy costs, and protection of user privacy. ZigBee radio-based activity recognition, Wi-Fi radio-based activity recognition, RFID radio-based activity recognition, and other radio-based activity recognition are the four categories into which radio-based approaches are divided in this work. Each category's body of work is introduced and thoroughly reviewed. Then, we contrast a few example techniques to demonstrate their benefits and drawbacks. Finally, we highlight some potential future avenues for this new study field.*

Keywords: Radio, Sensors

I. INTRODUCTION

Based on a preset activity model, activity recognition seeks to accurately identify human daily activities. It is a Widely employed in several human-centric applications, including health and fitness monitoring, assisted living, context-enabled gaming and entertainment, social network Physical sensors (camera, accelerometer, gyroscope, etc.) are frequently used in environments, attached to objects, or worn by people to continuously collect sensor readings to recognize human behaviors. Then, at an aggregator for upper layer applications, the activity kinds are detected based on predefined pattern recognition models.

In this paper, these sensor-based techniques are referred to as classic activity recognition techniques. They fall into three categories: camera sensor-based methods, which use cameras to record video sequences and identify activities using computer vision algorithms. wearable motion sensor-based methods, which use on-body motion sensors (accelerometer, gyroscope, etc. to sense the movements of body parts, such as. The footage may vary depending on the type of camera raking, and sport tracking, ubiquitous computing is a popular area for research.

Physical sensors (camera, accelerometer, gyroscope, etc.) are used to identify human activities. are frequently used in environments to continuously collect sensor readings by being worn or attached to objects. The activity types for upper layer applications are then identified at an aggregator using predefined pattern recognition models.

In this paper, we refer to these sensor-based methods as traditional activity recognition methods. They fall roughly into the following three categories: 1) techniques based on wearable motion sensors , which make use of on-body motion sensors like accelerometers, gyroscopes, and so forth to detect body parts' movements, such as camera sensor-based methods , which make use of the camera to record the video sequence and use computer vision algorithms to identify the activities. The video may be RGB video (for example, depth video (for example, or RGB-D video (for example methods based on environmental variables that make use of physical sensors (such as pressure, proximity, RFID, and so on) to deduce human activities from the condition of discarded items or changes in environmental variables, such as Traditional methods for recognizing activities perform well and are well-liked; however, they necessitate specific sensing modules and raise a number of concerns regarding privacy, energy consumption, and deployment costs.

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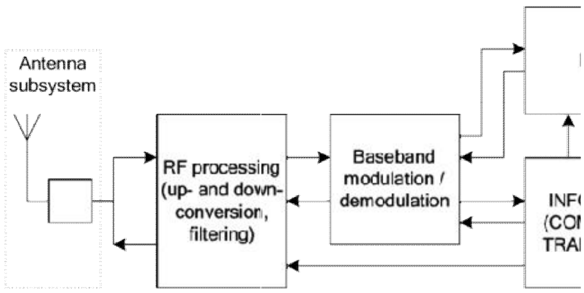
A novel radio-based method for activity recognition has emerged in recent years. Radio-based activity recognition uses body attenuation and/or the characteristics of channel fading to distinguish human activities or gestures because the presence and movement of a human body in a radio field can reduce the radio strength and alter communication patterns (channel fading, for example) between the transmitter and receiver. Radio-based activity recognition techniques, in contrast to conventional methods, only make use of the characteristics of wireless communication. As a result, no physical sensor module is required. As a result, there is less of a need to deploy the device, less energy is needed for sensing and data transmission, and users' privacy is protected.

Wireless radios such as ZigBee, Wi-Fi, RFID, and so on are used in radio-based activity recognition techniques. We roughly divide the radio-based methods into four categories due to the possibility that distinct radio data will have distinct characters and processing steps: Other types of radio-based activity recognition include ZigBee, Wi-Fi, RFID, and other types of radio-based activity recognition. In the introduction and review of this paper, we first discuss some related work in each category. The benefits and drawbacks of a few representative approaches are then contrasted. Finally, we talk about some possible directions for this new research topic's future research.

1.1 Activity Recognition based on ZigBee Radio

ZigBee is a wireless mesh network standard that uses little power and is cheap [43]. In wireless sensor networks, such as body sensor networks [44–48], it is frequently utilized. Qi and others 40] propose Radio Sense, a ZigBee-based activity sensing prototype system. Fig. Radio Sense's sensor deployment and system architecture are depicted in Figures 1 and 2. There are three main components in Radio Sense: 1) Two distinct on-body sensor nodes at the user's ankle and wrist. They transmit radio signals. 2) A sensor node in the middle of the user's body. It serves as the radio receiver and serves as the body sensor network's base station. 3) A laptop consolidates data. Each arrival message's time and Received Signal Strength Indicator (RSSI) value are recorded at the aggregator. Radio Sense deduces 18 statistical features (max, min, max min, mean, var, median, mean crossing rate, values of the RSSI histogram with 10 bins, and interquartile range) from RSSI values for each sensor node based on the observation that distinct human activities cause distinct wireless communication patterns between the sensor nodes and the base station. The best features are then chosen using the sequential forward strategy feature selection algorithm. The support vector machine (SVM)-based classification model is trained for online testing based on the selected features. Fig. The runtime accuracy of classifying seven activities for three. subjects. Subjects 1, 2, and 3 have total accuracies of 86.3 percent, 92.5 percent, and 84.2 percent, respectively. This indicates that the accuracy of Radio Sense is comparable to that of conventional methods for recognizing activities.



In the body sensor network, Radio Sense makes use of body attenuation and path loss of wireless radio. For frequencies between 2 and 6 GHz, "the energy from transmitted waves does not penetrate the human body," according to some researchers. Path losses are not related to direct Line-of-Sight (LOS) paths through the body but rather to paths along the body because the energy diffuses around it. Akure and others provide a theoretical analysis of the body sensor network's radio-based activity sensing. The path loss of the channel that runs along the human body is modeled using the following equation.

P 14% 3:2 10 log10 d 9:3 1 With the same sensor deployment shown in Fig. First, the shortest body distances between the transmitters and receivers are measured for eight people as they perform six different activities, as shown in Tab. 1. The statistical features for training and testing of the classification model are then extracted using the calculated path loss values. The results of the experiments show that the above path loss model works well for the human body.

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1.2 Activity Recognition based on a Wi-Fi Radio

Wi-Fi radio-based activity recognition, in contrast to ZigBee radio-based activity recognition, can utilize an office building's or shopping mall's existing Wi-Fi infrastructure. Sigg and others propose a passive activity recognition system that does not require a device and makes use of a mobile phone as a Wi-Fi receiver to measure RSSI values. To identify the situations, actions, and gestures of the subject, it extracts straightforward time domain features. also introduces similar work. Wang and others make use of Wi-Fi links between Wi-Fi devices (such as desktop computers, thermostats, refrigerators, smart TVs, laptops, and so on). and without the use of a device, collect fine-grained channel state information (CSI) to identify location-oriented home activities. RSSI measurement is a packet-level estimator that gives a single amplitude for the signal power across a packet. In contrast, CSI is the frequency domain channel response at the receiver.

It "contains separate measurements of amplitude and phase for each orthogonal frequency division multiplexing (OFDM) subcarrier." Wang and others take CSI signal measurements as location-activity profiles and collect subcarrier measurements of daily home activities at specific locations. The proposed method can uniquely identify both in-place activities (cooking, eating, dishwashing, brushing teeth, taking a bath, watching TV, etc.) by comparing online measurements with profiles. and home-based walking movements.

Pu et al. [58] show a signal acknowledgment framework named Wise through recognizing the diminutive Doppler shifts and multi-path mutilations of Wi-Fi signals starting from human movement. To distinguish the exceptionally little Doppler shifts (a few Hertz) of hand signals, the creators propose to transform the gotten Wi-Fi flag into narrowband beat by "repeating an OFDM image and performing a huge Fast Fourier Change (FFT) operation [58]". At that point, the Wise receiver can track the narrowband beat to capture the Doppler shifts. Other than that, Wise takes advantage of MIMO capability to isolate the remote reflections from multiple people through considering the reflections from each human as signals from a remote transmitter. Exploratory results demonstrate that Wiegerts the normal location and classification precision of 94% over nine whole-body gestures (thrust, evade, strike, drag, drag, kick, circle, punch and bowling). Chen et al. [59] utilize portable phones to get Wi-Fi signals and section fragment nonstop Wi-Fi follow into stationary segments and moving sections based on RSSI variance detection. All the stationary fragments are clustered to extricate frequent going to areas in one's day by day living. Other than, Wang et al. [60] utilize Wi-Fi radio to track human lines in a coffee shop and an air terminal. With extricated one of a kind Wi-Fi signal design, the time periods of holding up, benefit and leaving can be recognized

II. RFID RADIO-BASED ACTION RECOGNITION

Allseed has a specially designed receiver that uses an envelope detector to extract amplitude information, as shown in Fig. 6. Through eliminating power-intensive analog components such as oscillators by using passive and low power analog components (diodes, resistors, and capacitors), "Allseed consumes three to four orders of magnitude lower power than state-of-the-art systems and can enable always-on gesture recognition for smartphones and tablets [42]". With the collected amplitude information, the structure of magnitude changes and the timing information are combined to classify different gestures. The authors develop RFID-based and TV-based prototypes to evaluate Allesee's identification performances on eight gestures (flick, push, pull, double flick, punch, lever, zoom in, and zoom out). The results show an average accuracy of 97% and 94.4% on RFID- and TV-based prototypes, respectively. At the same time, Allseed obtains some good characteristics, such as low false positive rate (0.083 events per hour over a 24-h period), small response time (80 as) and low power cost (5.85 µW). In addition, the hardware prototype is integrated with an off-the-shelf Nexus phone to reclothe above gestures in through-the-pocket scenarios and 92.5% accuracy is achieved.

Wang et al. [61] present a virtual touch screen system, RF-I Draw, which utilizes multi-resolution positioning technique to trace the trajectory shape of RFID tag on user's finger and enables the user to input characters or words in air. Existing RF-based positioning systems often leverage the beam steering capability of antenna array to detect the source location. To achieve high accuracy, many antennae are required. Therefore, there is a tradeoff between resolution and unambiguity. We can see from Figure 7 that, "as the separation of the antenna pair (marked in red) increases, the number of beams increases accordingly, causing ambiguity in localizing the source (marked in blue). On the other hand, each beam gets narrower, leading to a higher resolution [61]". To remove ambiguity while maintaining high resolution,

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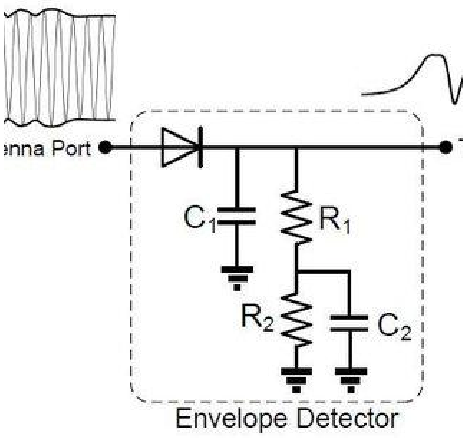
RF-I Draw combines a few antenna pairs with different separations. The pairs with smaller separation have wider beams and act as filters to eliminate the ambiguity; the pairs with larger separation have narrower beams and hence define the resolution. Fig. 8 shows the result when combining two resolutions in Fig. 7(a) and (c).



To evaluate Frida's performance, a handwriting recognition Android app is used to recognize RF-I Draw's reconstructed trajectories for letters and words. The results show that the accuracies on character recognition experiment and word recognition experiment are 97.5% and 92%, respectively. Liu et al. [62] deploy an array of active RFID tags on ground. When a subject moves through the tag covered area, the signal fluctuation of the tags is collected and analyzed to infer the subject's activities

2.1 Other Radio-based Activity Recognition

Except ZigBee, Wi-Fi and RFID radio, there are some other radios that can also be used for activity recognition, such as FM radio, microwave, etc. Shi et al. [63] propose an FM broadcast signals-based localization and activity recognition method. The authors observe that the FM signal strength is correlated with receiver’s positions. Besides, the signals show different fluctuation patterns for different activities. Accordingly, simple amplitude-based features are extracted, and classification model is trained to recognize lying, standing and walking of one subject in two locations. Experimental results show an overall accuracy of more than 70% for Naive Bayes, k-Nearest Neighbors and Decision Tree classifiers

Scholz et al. [64,65] place two USRP software defined radio (SDR) devices with 900 MHz transceiver to both sides of a door to detect the door state, talking on mobile phone and walking activity. Sigg et al. [66] deploy several USRP SDR devices on the ground in indoor environments to distinguish five activities (walking, crawling, standing, lying and empty) conducted simultaneously by two subjects. Sekine et al. [67] utilize Doppler Effect of 24.1 GHz microwave for activity monitoring. One hundred and one features in time domain, frequency domain and time-and frequency domain are extracted to recognize eight daily human activities. Adib et al. [68] present a wireless breath monitoring system, Vital-Radio, which detects the reflections of low-power wireless signal off the human body and identifies the minute chest motion due to the inhale and exhale process (as shown in Fig. 9).

2.2 Comparison of Radio-Based activity Recognition Methods

Each method introduced above does have its advantages and disadvantages, and only suits specific application scenarios. We select some representative methods from four categories and give a qualitative comparison, based on technical metrics such as coverage, activity type, accuracy, existing infrastructure usage, system deployment cost, nobody device, etc. Coverage indicates the scope of valid recognition area. Activity types include body motion, home activity, gesture, etc. Accuracy shows the experimental recognition performance reported in the paper, which is roughly divided into three grades: high (Z80%), middle (o80% and Z60%), and low (o60%). Existing infrastructure usage means whether the recognition system can (partially) utilize existing infrastructure in our daily living such as FM broadcast station, Wi-Fi access point (AP), smart TV, desktops, etc. System deployment cost indicates the labor cost of recognition system construction. On-body device means whether the user needs to wear on-body device or not. The comparison results are shown in Tab.2, which contains 10 activity recognition methods.

III. FUTURE RESEARCH DIRECTION

Free infrastructure-based recognition methods: As we introduced above, different radio stations can be used for activity recognition. However, in a specific application environment, there are some existing radios that can be used for free, such as Wi-Fi radio in an office room. Taking full advantage of free infrastructure will eliminate the burden of specific device deployment, decrease system cost, and increase user acceptance. Besides, free infrastructure-based recognition methods are easier to be widely spread. Apart from Wi-Fi, there are some other free radios that have not been explored yet. For example, the Bluetooth radio in wearable device network.

Multi-radio combination-based acknowledgment strategies: Sometimes, an application requires tall acknowledgment Recognition acknowledgment precision, which is out of reach for single radio-based acknowledgment. At that point, one possible way is to combine two or more sorts of radios and implement acknowledgment errands at the same time and cooperatively. As distinctive radios have diverse transmission characters, their combination will certainly progress the recognition execution. Be that as it may, how to characterize the most excellent radio combination and how to combine numerous radios are still under investigation and require encourage investigation.

Combining radio detecting with customary sensors: Another way to move forward acknowledgment exactness is to combine radio detecting with customary sensors, especially in body sensor organize based action recognition. Because conventional acknowledgment strategies require collect physical sensor information and send it to an aggregator or base station utilizing remote communication, the conventional sensor information and the radio highlights are accessible at the same time. Combining radio detecting with conventional sensors can upgrade the execution and steadiness of recognition framework particularly when the remote data transmission isn't satisfactorily steady. But, on the other hand, the combination brings additional computation cost. Therefore, a methodology is vital to adjust the gain and taken a toll and help choose when to combine these two information sources. In expansion, the combination algorithm ought to adjust to diverse application requirements to minimize framework fetched.

Context-aware acknowledgment procedure: As movement recognition calculation may be utilized completely different scenarios, the application layer settings (exactness requirements, difference in human subjects, etc.) and the lower layer settings (control cleared out, gadget accessibility, network condition, etc.) may be diverse or alter dynamically. Fixed acknowledgment technique may not get the maximum system execution. Hence, context-aware recognition technique is necessary. For illustration, with the consideration of distinction in human subjects, a self adaptive procedure may be outlined to advance fixed recognition demonstrate to individual acknowledgment show. The context-aware recognition procedure would take one or more settings into thought, concurring to the application prerequisites. Ordinarily, the more contexts a procedure incorporates, the more complex it'll be.

Parameter optimization: As appeared in [40], a recognition algorithm may contain a few parameters, such as transmission control level, bundle sending rate and smoothing window measure. Each parameter may have a big impact on the ultimate acknowledgment that comes about. The situation becomes more regrettable when the parameters are related to each other. It is exceptionally difficult to optimize all the parameters through manual adjustment. Therefore, one research question to reply is: how to optimize all algorithm parameters at the same time and consequently? To deal with this issue, a few existing theories may be helpful, such as control hypothesis within the field of mechanization.

Hypothesis premise for radio-based action acknowledgment: Almost all previously mentioned related works illustrate the effectiveness of radio detecting through genuine Real Genuine world experiments. There may be a few inclinations as the dataset is constrained and often collected beneath control. Up till presently, there's no theory premise for radio-based movement acknowledgment, which can numerically show and analyze the relationship between human exercises and comparing radio transmission highlights or framework parameters. Information theoretic examination may pick up crucial bits of knowledge to guide the ideal plan of radio-based acknowledgment framework.

Protection issue: Compared with conventional recognition methods, radio-based approaches have no physical sensing components and are more appropriate for privacy protection. Be that as it may, private data may moreover be dogged out from remote radio highlights. How to keep user’s security amid acknowledgment is another important research point.

IV. CONCLUSION

This paper gives a brief audit on radio-based activity recognition, a modern inquire about theme within the field of ubiquitous computing. Distinctive with conventional movement recognition methods that depend on particularly physical sensors, radio-based acknowledgment strategies take advantage of body attenuation and/or channel blurring of remote radios. This paper introduces and compares a few existing works in ZigBee, Wi-Fi, RFID and other radio-based action acknowledgment. In addition, a few headings for future inquiries are provided and talked about it.

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