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Review

A review and categorization of techniques on device-free human activity recognition

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ABSTRACT

Human activity recognition has gained importance in recent years due to its applications in various fields such as health, security and surveillance, entertainment, and intelligent environments. A significant amount of work has been done on human activity recognition and researchers have leveraged different approaches, such as wearable, object-tagged, and device-free, to recognize human activities. In this article, we present a comprehensive survey of the work conducted over the 10-year period of 2010–2019 in various areas of human activity recognition with main focus on device-free solutions. The device-free approach is becoming very popular due to the fact that the subject is not required to carry anything. Instead, the environment is tagged with devices to capture the required information. We propose a new taxonomy for categorizing the research work conducted in the field of activity recognition and divide the existing literature into three sub-areas: *action-based*, *motion-based*, and *interaction-based*. We further divide these areas into ten different sub-topics and present the latest research works in these sub-topics. Unlike previous surveys which focus only on one type of activities, to the best of our knowledge, we cover all the sub-areas in activity recognition and provide a comparison of the latest research work in these sub-areas. Specifically, we discuss the key attributes and design approaches for the work presented. Then we provide extensive analysis based on 10 important metrics, to present a comprehensive overview of the state-of-the-art techniques and trends in different sub-areas of device-free human activity recognition. In the end, we discuss open research issues and propose future research directions in the field of human activity recognition.

1. Introduction

Human activity recognition (HAR) has been a very active research topic in the past two decades for its applications in various fields such as health, remote monitoring, gaming, security and surveillance, and human-computer interaction. Activity recognition can be defined as the ability to recognize/detect current activity on the basis of information received from different sensors (Yang et al., 2011). These sensors can be cameras, wearable sensors, or sensors attached to objects of the daily use or deployed in the environment.

With the advancements in technology and the reduction in device costs, the logging of daily activities has become very popular and practical. People are logging their daily life activities, such as cooking, eating, sleeping, or watching TV. To capture these activities, different approaches have been used. These approaches can be broadly classified into vision-based and sensor-based (Chen et al., 2012). One of the pioneer approaches in this area are vision-based approaches, in which a camera is used to capture the information about the activities of human. By applying computer vision techniques on this captured data, activities can be recognized. Although computer vision-based techniques are easy to use and can provide good results, there are many issues related to this approach. For example, it violates the privacy of human being. Another issue with this approach is light dependency. Traditional cameras fail to work if there is no proper light (e.g., at night time). Therefore, vision-based techniques are not included in our survey. Due to low cost and innovations in sensor technology, most of the research in the field of HAR has shifted towards sensor-based approaches (Chen et al., 2012). In the sensor-based approaches, sensors are used to capture the behavior of humans while they perform daily life activities. Sensor-based solutions can further be divided into three major categories on the basis of sensor's deployment, which are: i) wearable, ii) object-tagged (device-bound), and iii) dense sensing (environment

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tagged/device-free) (Wang and Zhou, 2015). In the wearable approach, users have to carry the sensors as they perform any activity. A significant amount of work has been done on activity recognition using wearable sensors. Due to the increased popularity of wearable sensors, a new technology called Body Sensor Network (BSN) has emerged which comprises of various wearable sensors capturing different physiological signals on human body. These BSNs collect the data from wearable sensor and process it to extract useful information. BSNs have application in various fields of activity recognition such as health-care, elderly care, fitness, and sports activities monitoring (Gravina et al., 2017; Fortino et al., 2015). A major problem with this kind of approach, however, is that wearing a tag is not often feasible. For example, the elderly may forget to wear the tags or maybe, they resist to wear the tags at all. For solutions which use object-tagged approaches, sensors are attached to objects of daily use. Based on a user's interaction with these objects, activities are recognized. This is a device-bound approach, i.e., users are required to use specific objects (tagged-objects) only. Like wearable approach, this approach may also not be feasible all the time because it bounds the users to use tagged-objects.

Over the past few years, researchers are focusing on device-free (dense sensing) approaches in which users are not required to carry any tag or device (Chen et al., 2012). The idea is to deploy sensors in the environment (the facility in which the activity is being performed) and when a person performs any activity, the data will be captured through those sensors, which can then be used for activity recognition. The device-free approach is more practical because it does not require the user to carry any device while performing an activity. But there are some challenges in this approach as well such as interference from the environment. The data captured by the sensors can be disturbed from the surroundings which can cause noise in the data.

In this survey, we provide an overview of the research works conducted over the 10-year period of 2010–2019 in the field of human activity recognition with a focus on device-free approaches, especially the ones based on Radio Frequency Identification (RFID) technology (Sheng et al., 2008). We have explored the major databases such as IEEE Xplore, ACM Digital Library, Springer, and Science Direct. We have searched for works related to human activity recognition using the search term such as activity recognition, gesture recognition, posture recognition, behaviour recognition, motion detection, and ambient assisted living. We have focused on the articles published during the last decade (2010–2019) and selected around 50 papers for our detailed review. We divide the existing literature in activity recognition into three main categories, which are: i) action-based, ii) motion-based, and iii) interaction-based activities. These categories are further divided into 10 sub-areas. The research works for the action-based activities are divided into gesture recognition, posture recognition, fall detection, activities of daily living, behavior recognition, and ambient assisted living. Motion-based activities are divided into tracking, motion detection, and people counting. Research works for the interaction-based activities are grouped in a single category which is human-object interaction. We present the latest research in all these sub-areas of human activity recognition. We discuss and analyze the latest work in these areas to offer the reader a comprehensive overview of the current research trends in the field of device-free human activity recognition.

The rest of the paper is organized as follows. Section 2 presents some related work and Section 3 provides technical details on the different technologies used in the area of HAR. Section 4 provides different categories of HAR and details of the work conducted in each category. Section 5 provides future challenges and open research issues in HAR. Section 6 discusses the issues faced while reviewing the literature and finally Section 7 concludes this work.

2. Related work

There are many surveys that summarize the research work in the area of activity recognition. These surveys focus on different approaches used for activity recognition and can be broadly classified into three main categories which are given as follows.

2.1. Surveys on radio frequency-based techniques

Surveys in this category focus on radio frequency (RF) based approaches for human activity recognition. Scholz et al. (2011) presented a survey of the research work in the field of device-free radio-based activity recognition. This survey categorizes the existing work in device-free radio-based localization (DFL) and device-free radio-based activity recognition (DFAR). For DFL, the authors provide a description of different topics such as accurate presence detection, spatial coverage, adaptive machine learning, radio tomographic, and statistical modeling. For DFAR, the literature is sub-divided as adaptive threshold-based DFAR, machine learning-based DFAR, and statistical modeling-based DFAR. Amendola et al. (2014) presented a survey summarizing the use of RFID technology for the Internet of Things (IoT) based health-related applications. This work describes the various uses of RFID tags such as environmental passive sensors which include volatile compound sensors and temperature sensors and body-centric tags which include wearable tags and implantable tags. This work also provides some applications of RFID technology in human behavior analysis such as tracking, gesture recognition, and remote monitoring. This work discusses the possible use of RFID technology in various applications but does not provide any details about the work done in those application areas. Wang and Zhou (2015) summarized research work in the field of radio-based activity recognition. This survey categorizes the existing work in four major categories: i) ZigBee radio-based, ii) Wi-Fi-based, iii) RFID-based, and iv) other radio-based (e.g., FM radio, microwave). The authors present a comparison of all these techniques using metrics like coverage, accuracy, activity types, and deployment costs. Ma et al. (2016) provided a short survey of the research in activity recognition using WiFi-based approach. The paper gives a brief overview of the key technologies in WiFi related work from the literature, to formulate a framework for activity recognition system, based on WiFi. The major steps for this framework are base signal selection, pre-processing, feature extraction, and classification techniques. This survey categorizes the literature in activity recognition into two major groups: coarse-grained activities and fine-grained activities. The survey presented by Cianca et al. (2017) outlines the work conducted in the field of HAR using RF signals. The authors classify HAR into sub-categories such as presence detection, fall detection, activity detection, gesture and posture recognition, people counting, personal characteristic identification, breathe and vital sign detection, and human-object interactions. This work is mainly focused on device-free passive sensing approaches and divides these approaches on the bases of signal characteristics (bandwidth, carrier frequency, and transmission mode), type of measurement on the received signal (directly generated CSI or raw data from SDR platform), and type of signal descriptor used.

2.2. Surveys on sensor-based techniques

This section presents the surveys that focus on sensor-based approaches for activity recognition. These sensors can be used as wearable or attached to objects of the daily use. Chen et al. (2012) presented a detailed survey of the sensor-based work in human activity recognition. This survey classifies the existing research efforts in two main categories: i) vision-based vs sensor-based, and ii) data-driven based vs knowledge-driven based. In the first categorization, the survey focuses on sensor-based approaches. Different techniques are discussed which use wearable sensors (e.g., accelerometer, GPS, and biosensors) and dense sensing. In the second way of classification, authors categorize the literature into data-driven vs knowledge-driven approaches. For data-driven approaches, the authors discuss techniques using generative modeling and discriminative modeling. For knowledge-driven approaches, techniques are further divided into logic-based, ontologybased, and mining based approaches. Another survey by Wang et al. (2017b) highlighted the different deep learning approaches for HAR, using sensors. This work classifies the literature on the basis of sensor modality, deep model, and application area. On the basis of modality, the literature is divided into four aspects: body-worn sensors, object sensors, ambient sensors, and hybrid sensors. On the basis of the deep model, the related work is categorized as discriminative deep architecture, generative deep architecture, and hybrid deep architecture. With respect to the application area, the related work is classified as activities of daily living, sleep, sports, and health.

Lara and Labrador (2013) outlined the work conducted in activity recognition using wearable sensors. This survey presents a detailed discussion of different design issues in HAR system, such as selecting sensors and attributes, data collection and protocol, recognition performance, processing methods, and energy consumption. This survey categorizes the existing work into supervised online, supervised off-line, and semi-supervised off-line systems. Cornacchia et al. (2017) presented a detailed survey and divides the existing research work in two major categories: global body motion activity, which involves the movement/displacement of the whole body (e.g., walking, climbing, and running) and local interaction activity, which involves the movement of extremities (e.g., use of objects). This paper also provides a classification based on the type of sensor used and the placement of the sensor on the human body such as waist mounted and chest mounted. Techniques using various sensors like gyroscope, accelerometer, magnetometer, wearable cameras, and hybrid sensors (combination of multiple sensors) have been discussed by the authors.

Cheok et al. (2019), presented a detailed survey for gesture recognition focusing on sensor-based and vision-based approaches. The paper categorizes the literature based on different stages of HAR such as data acquisition, pre-processing, segmentation, feature selection, and classification and provides the comparison of different techniques in the literature.

Some surveys also focus on mobile phone-based solution for HAR because many techniques use a mobile phone (built-in sensors) for activity recognition. One such survey is presented by Shoaib et al. (2015) which outlines the research work using mobile phones.

2.3. Surveys on vision-based techniques

This section presents the surveys which focus on vision-based solutions for activity recognition. Vrigkas et al. (2015) presented a survey of existing research work which uses vision-based approach for activity recognition and classified the literature in two main categories: unimodal and multi-modal approaches. The unimodal methods use data from a single modality and are further classified as stochastic, rule-based, space-time based, and shape-based methods. The multi-modal approaches use data from different sources and are further divided into behavioral, effective, and social-networking methods. Herath et al. (2017) provided a detailed overview of the major research undertaken in the field of action recognition, using vision-based approaches. This survey categorizes the overall work into two major categories: solutions based on representation and solutions based on deep neural network. The representation-based solutions are further classified into Holistic and local presentations and aggregation methods. Solutions based on the deep neural network are sub-classified as multiple stream networks, temporal coherency networks, generative models, and spatiotemporal networks.

2.4. Summary

The surveys discussed above are summarized in Table 1. Most of these surveys highlight the work conducted in human activity recognition but the focus is mainly on a single approach. Some focus on sensor-based approach while others focus on vision-based approach. Also, these surveys do not provide details about the weaknesses and strengths of different approaches for activity recognition.

Recently, with the new developments in RFID technology, many solutions have been proposed for activity recognition using device-free RFID technology. Previous surveys missed the details about these solutions. To the best of our knowledge, there is no previous survey which provides a comprehensive and detailed analysis of RFID-based device-free approaches for activity recognition. Our goal is not only to provide an overview of the latest research conducted in HAR with main focus on device-free approaches, especially RFID, but also to compare different techniques and understand the advantages and disadvantages of each technique.

3. Technical background

Human activity recognition is a composite process and can be divided into four major phases (Chen et al., 2012). These phases are: i) selection and deployment of sensors ii) collection of data from sensors, iii) pre-processing and feature selection from the data, and iv) use of machine learning algorithm to infer or recognize activities. Over the past decade, considerable research has been done in HAR using sensor-based approach. Some of the most common sensors which are used for activity recognition are: accelerometer, motion sensors, biosensors, gyroscope, pressure sensor, proximity sensor, etc. Some of the sensors are radio frequency (RF) based such as Wi-Fi, Radio, Radar, and RFID. These sensors can be used in various ways. They can be attached to different objects or can be used as wearable or be deployed in the environment. Nowadays, various types of cheap and portable sensors are available which have the ability to sense and communicate the information using wireless networks. In this section, we provide the details about some of the technologies which are being used for HAR. We also provide some details about publicly available data sets for human activity recognition.

3.1. Surveillance cameras

The most basic and traditional way of activity recognition is to install surveillance cameras in the facility and monitor the activities of humans. Monitoring can be done through human (a person watching the videos and images coming from the cameras) or through an automatic process. Different computer vision techniques have been developed which can process and analyze the data (videos and images) from the camera and can automatically recognize activities.

3.2. Depth cameras

One of the issues with traditional cameras is dependency on light i.e., they cannot work in darkness. The development of depth cameras such as Kinect solved this issue because it can work in total darkness. Different data streams can be obtained from Kinect such as RGB, depth, and audio (Maret et al., 2018). It can capture the information about human body and can construct a 3D virtual skeleton. Using this information, activities can be recognized because different movements of the body (skeleton) are related to different activities. Apart from complex computation, cost of depth cameras is high, which is a disadvantage of this approach.

3.3. Sensors

In the twenty-first century, significant research has been done in the field of sensors and numerous kinds of sensors have been produced. These sensors are very useful and have the ability to sense the environment and communicate the information wirelessly. Some of the sensors which are widely used in the research for activity recognition are given in Table 2.

Table 1
Summary of the previous surveys.

Categories	Paper	Main Focus	Future Research Directions	Comparisons of Different Techniques
RF-Based	Scholz et al. (2011)	Applicability of radio sensors in activity recognition	Yes	No
	Amendola et al. (2014)	Applications of RFID technology in various fields	Yes	No
	Wang and Zhou (2015)	Use of radio signals for activity recognition	Yes	Yes
	Ma et al. (2016)	Wi-Fi based techniques	No	No
	Cianca et al. (2017)	FM radio and Wi-Fi based methods	No	No
Sensor-Based	Chen et al. (2012)	Data-centric activity recognition techniques.	Yes	Yes
	Wang et al. (2017b)	Deep models for sensor based approaches	Yes	Yes
	Lara and Labrador (2013)	Wearable sensors based approaches	Yes	Yes
	Shoaib et al. (2015)	Mobile Phones based techniques	Yes	Yes
	Cornacchia et al. (2017)	Wearable sensor based techniques	No	Yes
	Cheok et al. (2019)	Sensor and vision-based techniques for gesture recognition	Yes	Yes
Vision-Based	Vrigkas et al. (2015)	Vision based approaches	Yes	Yes
	Herath et al. (2017)	Vision based solutions	Yes	Yes

Table 2
Sensors used for activity recognition.

Sensor	Description
Accelerometer	An accelerometer is an electromechanical device used for measuring the acceleration. It can sense acceleration in multiple directions. To do that, the accelerometer is designed with multi-axis (i.e., x, y, and z) sensors. A multi-axis accelerometer can measure acceleration in x, y, and z-direction at the same time. The accelerometer is widely used in solutions for gesture recognition, posture recognition, fall detection, tracking, ambient assisted-living, activities of daily living, etc.
Magnetometer	A magnetometer is used to measure the magnetic field and sometimes the direction of the magnetic field. This sensor is used in various fields of activity recognition (e.g., gesture recognition) because of its ability to detect changes in the magnetic field caused by human activity.
Motion Sensor	Motion sensors are used to detect the motion or presence of a subject in a particular area. Motion sensors are widely used in the field of human activity recognition especially in motion detection, tracking, and people counting.
Proximity Sensor	It is an electronic sensor which can detect the presence of nearby objects without making any physical contact. Proximity sensors are widely used in gesture recognition techniques.

3.4. Radio frequency (RF) based technologies

Recently, various RF-based technologies are finding its use in the area of human activity recognition due to its contact-less nature. RF signals are very sensitive to changes in the environment and can capture changes caused by human motion or activity. Human bodies absorb, reflect and scatter the RF signals, causing variations in the signal which can be interpreted for human activity recognition. Some of the most commonly used RF technologies are WiFi, Radar, and RFID. The following sections provide the details about these technologies and Table 3 summarizes the pros and cons of these technologies.

3.4.1. WiFi

In the last decade, there is a paradigm shift in human activity recognition research from device-bound approaches to device-free approaches. Researchers have explored the properties of wireless networks, such as Channel State Information (CSI) and started to use it for activity recognition (Ma et al., 2016; Yan et al., 2019; Ding and Wang, 2019). The disturbances caused by the presence or movement of the humans can be captured by the CSI of wireless signal which can be used to recognize different activities. Many solutions have been proposed for localization, tracking, fall detection, etc., using WiFi. A major advantage of WiFi is that it is unobtrusive and users are not required to carry any device.

3.4.2. Radar

Radar is also becoming popular in the research community for activity recognition. Like other RF-based technology, radar is ubiquitous and can be used to recognize human activities in a contact-less manner. The basic working principal of a radar is signal reflection. It transmits a radio signal which is reflected by the object in the path. Radar receives the reflected signal and creates an image of the object using the differences between the transmitted and the reflected signal. Numerous solutions have been proposed for HAR using radar (Avrahami et al., 2018; Markopoulos et al., 2019; Li et al., 2019).

3.4.3. RFID

Radio Frequency Identification technology has seen a boom in the last decade. Originally developed for military purposes to differentiate

Table 3
RF-based technologies.

Technology	Datatype	Advantages	Disadvantages
Wi-Fi	CSI	Cost-effective, pervasive	Environmental interference, cannot provide fine-grained recognition
RFID	RSSI, Phase, Doppler Velocity, Read Rate	Passive, cost-effective, pervasive	Environmental interference
Radar	Doppler Effect	Pervasive	Environmental interference, cannot provide fine-grained recognition

between friendly and hostile aircrafts (Landt, 2005), this technology has seen momentous advancement in recent years (Wu et al., 2011). It is widely used in tracking and supply chain management. Initially, the range of RFID technology was very small (few centimeters) which is now increased up to a great extent (7 m for passive tags and 100 m for active tags) (Ko, 2017). The RFID technology has two main parts; reader and tags.

- Reader is a device which is used to collect information from tags. The reader has an antenna which emits radio waves. These radio waves are received and modulated by RFID tags with their information such as ID. The reader can capture these backscattered signals through an antenna, which has the information of tags.
- Tags are the small electronic chips which can be easily attached to any objects. These tags have a chip and an antenna. The antenna receives the signal transferred by the reader through the antenna. The chip modulates the received signal (to induce changes) which is then sent back to the reader by the tag's antenna.

Types of RFID. Based on the powering option, RFID tags can be classified into the following three different categories.

Passive Tags. Passive tags do not have their own battery source but instead they use the energy received from the reader (through antenna) and convert it to electrical energy for operating its circuit (chip). Due to the lack of battery requirement, these tags have a very long operational life. The detection range of these passive tags is very limited (few meters). These chips are cheap as compared to the other types and are mainly used in large quantities for tracking in supply chain management.

Active Tags. These tags have their own battery source which can energies the chip. Due to its own battery source attached, the size is large and the price is high for active tags as compared to the passive tags. The detection range of these tags is high (up to 500 m). Active tags are usually used for tracing different objects of interests over long distances.

Semi-passive Tags. This type of tags lies in-between active and passive category. These tags use their own power source to operate the electronic circuitry but harvest the energy from the signal received from the reader to sent out the modulated signal back.

The RFID technology has been adopted in various fields. Due to the low cost and the unobtrusive nature, the passive RFID is now widely used in human activity recognition research. Researchers are using RFID technology for posture recognition, gesture recognition, tracking, localization, behavior recognition, etc.

3.5. Data sets for device-free human activity recognition

Nowadays, there are open data sets in various research areas which are available for public use. These data sets can be used as benchmark to evaluate the performance of any proposed technique. There are several public data sets available for human activity recognition. Wang et al. (2019) have provided the details about 19 publicly available data sets for HAR in their survey paper. Murad and Pyun (2017) have also provided the details about some publicly available data sets in their paper. Most of these data sets comprise of data collected through different sensors (e.g., accelerometer, gyroscope, inertial sensor) wore by the participants or embedded in the objects of use. These data sets contain data collected for different categories of HAR such as gestures, postures, daily activities, ambient assistance, and kitchen activities. Unfortunately, there are not much data sets available for HAR using RF based approaches such as RFID, Wi-Fi, or radar. A possible reason could be the complexity involved in the collection of data through these approaches. Collecting data using wearable devices is easy as the users can wear them while doing their normal activities and can go anywhere with those devices. In the case of RF-based approaches, the user needs to be in a specific environment where the RF devices are installed. This restricts the users from doing many other activities because these RF devices cannot be installed everywhere due to processing complexity and interference from the environment. Table 4 provides some details about the publicly available RF-based data set for device-free HAR that we found in the literature.

4. Device-free human activity recognition categories

Activity recognition aims to identify or detect physical activities of a single person or a group of persons. These physical activities can be of different types. Some of these activities can be performed by a single person which involves the movement of the whole body such as walking, running and sitting. Some of these activities can be complex like jumping and dancing. Some activities involve a specific body part such as making gestures with the hand. Certain activities can be performed by interacting with objects, for example, preparing a meal in the kitchen. Detecting the presence or motion of a human in a certain environment also comes under the activity recognition (e.g., intrusion detection). Tracking the movement or trajectory of a human in a specific area can also be considered as activity recognition. Significant research has been conducted under the umbrella of human activity recognition. A schematic classification of different categories of human activity recognition is given in Fig. 1. In this paper, we will follow the taxonomy given in Fig. 1 and will provide an overview of the research work done in these areas with a focus on device-free techniques, especially RFID technology.

4.1. Comparison metrics

Prior to the discussion of different categories of device-free HAR techniques, we provide the comparison metrics in this section and these metrics will be used in Section 4.2, Section 4.3 and Section 4.4 for the comparison of different approaches. Following are the metrics that we have used for comparing various solutions presented in this survey.

- **Approach (M1)**: Various approaches have been used by researchers for HAR. These approaches can be device-free, wearable or hybrid. Hybrid approaches combine both wearable and object-tagged approaches. We have listed the approach used by solutions presented. *D* represents device-free approach, *W* represents wearable approach, whereas *H* represents the hybrid approach.
- **Technology (M2)**: Literature shows that different solutions have used different technologies. Some of the prominent technologies used in the area of HAR are RFID, Kinect, Infra-Red, Radar, Sensor Fusion, Wi-Fi, Hybrid (fusion of multiple technologies), etc. We have listed the technology used by different solutions.
- **Information Type (M3)**: Different techniques use different information as input for performing the required task. Solutions using the same approach and technology can use different information as input. We have provided the type of information used by different techniques as input for their processing.
- **Machine Learning Algorithm Used (M4)**: Machine learning is an essential part of human activity recognition. Different types of machine learning algorithms have been used in HAR. Some of the most famous algorithms are Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Random Forest (RF), Hidden Markov Model (HMM), Naive Bayes (NB), Decision Tree (DT), etc. We have given the machine learning tool used by the techniques presented.
- **Supervised/Unsupervised (M5)**: Machine learning algorithms can be supervised or unsupervised. Both are different approaches. Supervised techniques need training data while unsupervised techniques do not need any training data. We have provided this information for the presented papers. *Y* represents supervised whereas *N* represents unsupervised.
- **Application (M6)**: Human activity recognition is a very vast field. Different techniques focus on different applications. Some provide

Table 4
Publicly available data sets for device-free HAR.

Data set	Sensor type	#Sensors	Deployment	Type	#Subjects	#Activity	Sample size
Opportunity data set (Roggen et al., 2010)	A,S,R,M,G	72	W,O,E	ADL	12	5	701366
The TUM kitchen data set (Tenorth et al., 2009)	C,Rf,R,A,G,M	16	W,O,E	Kitchen	25	5	NA
Wiar data set (Guo et al., 2019)	Wi-Fi	2	E	Postures	10	16	4800
Ambient Kitchen (Pham and Olivier, 2009)	A,Rf,C,P	NA	O,E	Kitchen	20	11	NA

A = accelerometer, S = switch, R = reed switch, M = magnetometer, G = gyroscope, C = camera, Rf = RFID tag, M = microphone, P = pressure sensor, W = wearable, O = object-tagged, E = environment (dense sensing).

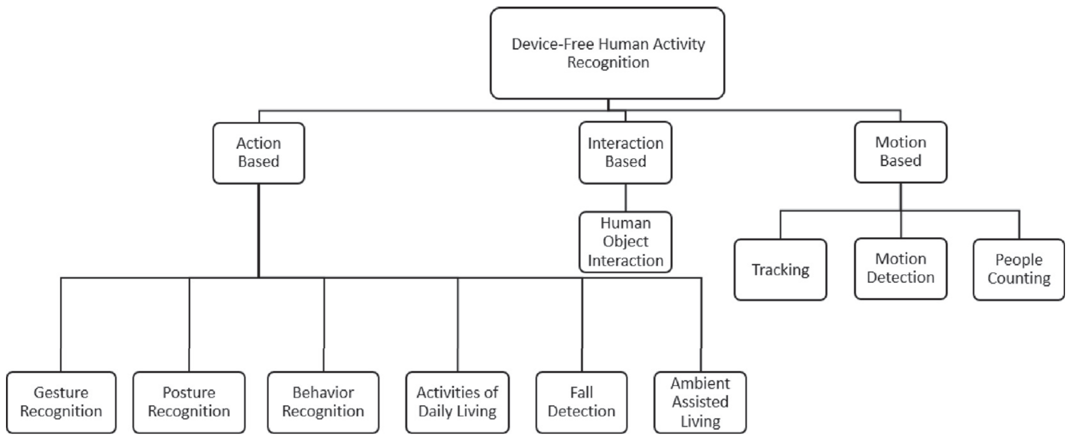

Fig. 1. Overview of human activity recognition which can be divided into three main categories and then into 10 sub-categories.

the solution for gesture recognition while others provide solution for tracking. We have provided the applications areas for the presented papers.

- **Cost (M7)** Cost is a key factor for any technique. If the accuracy of a solution is good but cost is too high, then it's of no practical use. We have provided information about the cost of the techniques discussed. The cost is divided into two categories: expensive (if device per person is used) and cheap (if single device is used for all participants).
- **Accuracy (M8)** A very important factor for the evaluation of a solution is its accuracy. We have provided information about the accuracy of the given techniques. We have categorized the accuracy in three categories; High (>90%), Medium (>80% & < 90%) and Low (<70%)
- **Latency (M9)** Latency is a critical factor, especially for real time applications. If a solution is accurate but takes long time to provide the results, it is not practical. We have provided the latency information about the presented solutions.
- **Real-time (M10)** Last but not least is whether a solution is real-time or not. This is important for human activity recognition because getting the results in real time is a compulsion in many situations. For example, in the case of gesture recognition, it is required to get the results in real time. We have included this factor in our comparison table. *Y* means the solution is real time whereas *N* means the solution is not real time.

4.2. Action-based activities

Action-based activities are those activities which involve some action of the human body. This action can involve either the whole body or a specific portion of a body. In this section, we provide an overview of the different solutions proposed for the recognition of action-based human activities.

4.2.1. Gesture recognition

Gesture recognition is one of the most important sub-topics in action recognition. In recent years, it has gained much attention for its role in human-machine interaction. Gesture recognition is also used in sign language recognition which is very important for special people. Recently, significant mount of work has been done in this field.

Table 5 provides the approach, technology, advantages, and disadvantages of the different techniques discussed in this section and some applications of gesture recognition. Some of these solutions are vision-based and use cameras to capture videos or images for gesture recognition (Daniels et al., ; Garg et al., 2009; Yao and Fu, 2014; Ohn-Bar and Trivedi, 2014; Ali et al., 2015; Sreekanth and Narayanan, 2017; Itkarkar et al., 2017; Singha et al., 2018; Cheok et al., 2019). But this approach has privacy issues, complex processing, and very high deployment cost. Some solutions use wearable devices for gesture recognition. These devices range from simple sensors to specially designed gloves and bracelets (Wang et al., 2014; Siddiqui and Chan, 2017; Liu et al., 2017a; Xie et al., 2018). Some techniques use objects tagged with sensors and users make gestures with these sensor-tagged objects, which can be recognized (Asadzadeh et al., 2012; Bouchard et al., 2014; Shangguan et al., 2017; Jayatilaka and Ranasinghe, 2017; Chen et al., 2017). One group of solutions use RF-based approaches such as Wi-Fi (Ma et al., 2019; Ahmed et al., 2020), Radar (Hazra and Santra, 2019), and RFID for gesture recognition which are device-free. The focus of this section is device-free RFID-based solutions for gesture recognition.

Ye et al. (2014) proposed a device-free solution called Link State Indicator (LSI), for gesture recognition, using passive RFID tag arrays. It uses the number of counts (tag being read successfully), to represent the state of an unobstructed link. LSI is the ratio of the tag's count read successfully to a reference count in a unit time. The reference count is obtained when there is no obstruction. For each gesture, this work calculates gesture matrix which represents the state for all the tags as fully obstructed, partially obstructed or not obstructed at all. Finally, Fisher's linear discriminant method is used for gesture recognition. This

Table 5
Summary of the works presented for gesture recognition.

Approach	Technology	Advantages	Disadvantages	Applications
Vision-Based	Surveillance camera	High accuracy	High cost, complex computation, privacy issue	Gaming, mart screen interaction, Sign language interpretation, Remote monitoring
Depth Sensor	Kinect	High accuracy	High cost, privacy issue	
Wearable Sensors	Gloves, Bracelet, Smart Watch	Low cost	Constraint to wear the device	
Object-Tagged	Accerelometer, Ultrosonic Sensor, Microphone	Low cost	Device-bound	
RFID	Passive RFID tags arrays	Low cost, passive	Environmental interference	
Radio Frequency	Radar, Wi-Fi	Low cost	Environmental interference	

technique is off-line and cannot provide real-time recognition. The gestures identified are very different from each other and the performance is poor for closely related gestures. Also, the number of experiments performed is not enough. There is no discussion about the issue of variability i.e. if the same gesture is performed by different persons or the same person performs the same gesture in different styles.

Smart surface (Parada et al., 2016) is a technique which combines RFID technology with machine learning for recognizing gestures. This technique uses passive RFID tags and antennas attached to a surface. The basic idea of this work is that the Received Signal Strength Indicator (RSSI) values from RFID tags are disturbed when a gesture is performed in front of the tags. These disturbances can be classified by the K-means algorithm into different clusters with each cluster representing a specific gesture performed. This work provides an initiative for making smart surfaces using passive RFID tags but it can identify very basic gestures only, which are some movements made in pre-defined directions. Every tag is required to have its own antenna (e.g., 10 tags will need 10 antennas). Also, this work lacks the details about the use of the system such as how far should be the user from the tags, while performing gestures.

Ding et al. (2017) proposed a device-free technique for gesture (hand motion and handwriting) recognition using passive RFID tags. This technique uses COTS RFID tags attached to a plate in a grid form. The system is based on the idea that when a motion (hand gesture) occurs in front of an RFID tag, significant changes can be seen in the RSSI and phase values received by the reader. Using these changes in RSSI and phase values combined with tag IDs, different hand gestures can be identified. The system works well when the gestures are performed at relatively slow speed but performance degrades when gestures are performed with high speed. Another limitation of this technique is the distance from the surface (plate with tags). User needs to be very close ($\leq$5 cm) to the plate while making any gestures otherwise, performance degrades.

GRfid (Zou et al., 2017) is a device-free approach for gesture recognition. It is capable of detecting a total of six hand gestures. The system uses the RFID signal phase changes for recognizing different hand gestures. Data collected from passive RFID tags is passed through several processing blocks namely, pre-processing, gesture detection, gesture profiling training, and gesture recognition. GRfid uses Dynamic Time Warping (DTW) as a metric for comparison and proposes an adaptive weighting algorithm for gesture matching. The proposed system achieved good results in different experiments but the gestures tested and recognized are very basic in nature. There is no discussion about the latency of the system which is a very important aspect for the gesture recognition system.

Yu et al. (2019), proposed a device-free technique using the time series data from passive RFID tags to recognize different gestures in real-time. The paper proposes a technique called EUIGR which is inspired by deep learning and can recognize real-time on-going gestures using the RSSI and Phase values of passive RFID tags.The proposed techniques combines Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) and uses adversarial learning to reduce the impact of environmental factors. The authors have implemented the system using COTS available RFID and preformed extensive experiments to evaluate the performance of the proposed techniques.

4.2.2. *Posture recognition*

Humans do many activities in their daily lives. These activities can be simple postures such as standing, sitting, lying or walking or may be complex such as running, doing exercise, and cooking. Many of these simple activities (postures) are of interest to recognize because of applications in various fields. Table 6 provides the approach, technology, advantages and disadvantages of the different techniques discussed in this section and some applications of posture recognition.

One group of solutions use wearable sensors i.e., sensors are attached to human body or clothes while performing activities (Wickramasinghe and Ranasinghe, 2015; Ronao and Cho, 2016; Castro et al., 2017; Ignatov, 2018; Benaissa et al., 2017; Xiao et al., 2018). Wickramasinghe and Ranasinghe (2015) presented a technique using wearable sensor for ambulatory monitoring to recognize activities such as transfer out of chair, bed or walking. This method requires the user to wear a computational Radio Frequency Identification (CRFID) sensor. Some solutions use inertial sensors embedded in the smartphone i.e., users need to carry their smartphone while performing any activity. A smartphone based technique is presented in (Torres-Huitzil and Alvarez-Landero, 2015) which uses accelerometer sensor embedded in the smartphones. This technique is fully implemented in the android smartphone and allows for different orientation and placement of the smartphone on human body. Ronao and Cho (2016) proposed a deep neural network based solution using embedded sensors in the smartphone (accelerometer and gyroscope). A similar approach is also proposed by Gani et al. (2019) for HAR which uses the accelerometer embedded in smartphone and is based on chaos theory and dynamical systems. Many other solutions have been presented for posture recognition using different wearable sensors (Castro et al., 2017; Ignatov, 2018; Benaissa et al., 2017; Xiao et al., 2018). A major problem with wearable sensors is that it is not always feasible to carry these devices, while performing an activity.

A more realistic approach is the device-free approach in which the users are not required to carry any device. RF-Care (Yao et al., 2015) proposed a device-free solution for posture recognition based on RFID technology. The passive RFID tag arrays are placed in the environment to capture the activity information. When a posture is performed in front of these tag arrays, the disturbance causes variation in the RSSI values. RF-Care uses these changes for posture recognition. This work also studies the issue of tags placement in an indoor environment and provides an optimal setting for the tag array's deployment to achieve the best results with minimum computation cost. RF-Care uses SVM for recognition of steady postures and for posture transition detection, Hidden Markav Model (HMM) is used. RF-Care provides a very simple and easy to implement solution but it has a latency of around 3.5 s which may be too long for some applications such as interactive environments. The accuracy for posture transition detection is low. The proposed solu-

Table 6
Summary of the works presented for posture recognition.

Approach	Technology	Advantages	Disadvantages	Applications
Vision-Based	Camera	High accuracy	High cost, complex computation, privacy issue	Smart homes, Smart offices, Hospitals, Care centers
Wearable Devices	Smartphone, accelerometer, gyroscope	Low cost	Constraint to carry the device	
Device-Free	RFID	Low cost, COTS available, passive	Environmental interference	
	Radar	Low cost	Customized hardware required	
	Wi-Fi	Low cost, COTS available	Environmental interference	

tion needs to be evaluated to check the affect of interference from the environment such as obstacle lying in the area or the presence of other people.

Yao et al. (2018) presented a device-free RFID-based technique for activity recognition. This work combines machine learning with RFID technology and proposes a dictionary-based approach which can learn the dictionaries for different activities in an unsupervised manner. The system uses RFID tags deployed in arrays for capturing activity information. Raw data from the tags is passed through a segmentation process in which the continuous sequence is divided into individual segments. Each segment represents a specific activity. The paper uses a sliding window segmentation algorithm which is based on slope variation. Seven features are selected by using a ranking method based on canonical correlation analysis. For activity recognition, this technique uses a sparse dictionary-based approach, in which a single dictionary is learned for each activity. A limitation of this work is the latency i.e., it takes around 4.5 s for recognition of an activity which may be too slow for some applications.

Li et al. (2018) presented a device-free technique called R&P, which uses passive RFID technology for human activity recognition. R&P extracts phase and RSSI values from the RFID tags deployed in the environment and uses these values for activity recognition. Unlike some other RFID-based techniques, this work combines both RSSI and phase values for recognition. For de-noising of RSSI and phase values, D-Gaussian algorithm (Zhong et al., 2013) and stein unbiased risk estimate based method (Candes et al., 2013) are used, respectively. R&P uses the DTW algorithm for feature matching and proposes a modified version of DTW called T-DTW, which can reduce the matching time by 60%. The proposed system is evaluated in real-world scenarios and showed good results but the tested activities are very different from each other and the system needs to be evaluated for activities which are very similar to each other such as standing & walking or sitting & lying.

An RF-radar based approach was presented by Avrahami et al. (2018) for recognizing human activities in a checkout counter of a convenience store and a typical office desk. The proposed technique uses Walabot Pro sensor which is an RF-radar with 18 antennas and is capable of constructing a 3D image from the reflected radio waves. This sensor is deployed under the work surface and when the subject performs pre-defined activities, data is captured in the form of RF samples. For comparison purpose, the proposed system also uses a wearable IMU sensor (Microsoft Band 2) and data is captured from the IMU sensor during the experiments. Different techniques such as SVM, Random Forest, and Naive Base, are used for classification of performed activities. Experiments in both scenarios (checkout counter and office desk) prove that RF-radar can perform better than IMU and by combining both approaches, accuracy can further be improved.

Recently, Liu et al. (2019), presented a solution called TagSheet for sleep posture recognition using passive RFID tags embedded in the sleeping mat. TagSheet uses passive RFID tags attached to the sleeping mat in form of matrix and uses the reflection from these tags to identify different sleeping postures. The system does not require any personalized training and can be used for any person without any prior training. TagSheet uses image processing techniques to differentiate between different postures. In addition to recognize six different sleeping postures, the proposed system is also capable of estimating the respiratory rate of the sleeping person. The authors implement TagSheet using COTS available RFID tags and evaluate the performance of the TagSheet in real-world environment.

4.2.3. *Behavior recognition*

Behavior recognition is an important sub-area of human activity recognition. The basic idea is to infer/recognize the behavior of a person from the data captured through different sensors. Behavior recognition is very useful in various scenarios such as smart environments (elderly care centers and smart homes) (Chua et al.,) and shopping centers. In elderly care centers, patients can be monitored remotely which can reduce the cost significantly because human resources are very expensive. Any abnormality in the behavior of elder people can be detected and the concerned people can be informed of the situation. In shopping centers, behavior identification of the customers can help owners to improve their business. Customer's shopping information such as interests, preferences, and brands, can be very useful to further improve the shopping experience for the customers.

Recently, considerable work has been done to identify the behavior of customers. Some applications of behavior recognition along with the approach, technology, advantages, and disadvantages of various techniques presented in this section are given in Table 7. One study proposes a technique based on the surveillance system for the analysis of shopping behavior (Popa et al., 2010). The given system uses multiple cameras to track the movements of customers. One other technique used a Kinect sensor for the behavior recognition of customers (Popa et al., 2011). Besides problems such as computation complexity and cost, privacy is a major issue with vision-based approaches. Zeng et al. (2015) proposed a Wi-Fi-based technique using CSI to recognize the behavior of customers while they shop. The given system is capable of detecting coarse-grained activities only, such as standing, walking and walking fast. The reason is, CSI cannot provide enough information to recognize fine-grained activities e.g., the customer is just looking at a specific item, the customer is looking in detail and is interested or customer is putting the item in cart.

Many solutions also use passive RFID technology for recognition of shopping behavior. Han et al. (2016a) proposed a behavior identification system called Customer Behavior Identification (CBID). The given system can analyze the wireless signals collected from RFID tags attached to different items in the shopping center. CBID is capable of detecting popular item (item picked by most customers), an explicit correlation between items (rivalry or complementary), and implicit correlation between items (items picked or purchased at the same time). CBID uses phase changes and Doppler frequency shift, which occur as a result of the movement of the items. CBID achieves good results in all realistic scenarios but the proposed system needs to be evaluated for metallic products to check the effect of interference with the signal.

Zhou et al. (2017) tried to solve the problem of customer shopping behavior mining by using COTS passive RFID tags. Passive RFID tags are attached to different items of the store. When the users interact with these items, significant changes occur in the phase readings of

Table 7
Summary of the works presented for behaviour recognition.

Technologies	Examples	Advantages	Disadvantages	Applications
Vision-Based	Surveillance camera	High accuracy	High cost, complex computation, privacy issue	Shopping centers, Theme parks, Care centers, Security & surveillance
Depth Sensor	Kinect	High accuracy	High cost, privacy issue	
Device-Free	Wi-Fi	Low cost, COTS available	Environmental interference	
	RFID	Low cost, COTS available, Passive	Environmental interference	

these tags. The proposed system exploits these changes for mining the customer's behavior. The basic idea is when a user is just passing by a rack (browsing), the phase values will be disturbed slightly and when an item is picked by a user (showing interest), the phase readings will change significantly. When multiple items are tried together, these can be detected by finding the correlation between the tags. Performance of the given system degrades in a crowded store, where a large number of customers are shopping.

4.2.4. Fall detection

Fall means when the position of the human body suddenly changes from the normal state (e.g., standing, sitting or walking) to reclining, without any control (Noury et al., 2007). Falls can result in injuries both minor and major. In recent years, significant work has been done in the field of fall detection. Table 8 gives some applications of fall detection along with the approach, technology, advantages, and disadvantages of different solutions discussed for fall detection.

Some of these solutions are based on wearable sensors (Cheng, 2014; Tsinganos and Skodras, 2017; Jatesiktat and Ang, 2017; Gia et al., 2018; Putra et al., 2017; Rescio et al., 2018). A major disadvantage in these types of solutions is that carrying a device is not always feasible, especially for elderly people and patients. They may forget about the sensors or may be bothered by wearing a device all the times.

Some of the device-free approaches use Wi-Fi for fall detection (Zhang et al., 2015; Wang et al., 2017a). Wang et al. (2017d) proposed a solution for fall detection, based on a wireless network. The basic idea of this work is that human activities can affect wireless signals and CSI is a good indicator for detecting human activity (fall). A technique proposed by Minvielle et al. (2017) uses special sensors deployed in the floor for fall detection. Kianoush et al. (2017) presented a solution based on RF signal using radio devices to detect fall in industrial workplaces.

Some techniques use passive RFID technology for fall recognition. Wickramasinghe et al. (2017) used passive RFID tags deployed on the floor, for fall recognition. This technique uses tags fitted inside the carpet in a two-dimensional grid and hidden from the users. Unlike their previous work (Torres et al., 2015), this technique uses binary tag observation information i.e., presence or absence of a tag instead of RSSI which is vulnerable to environmental noise. Tag observation information is formulated as a binary image i.e., presence or absence of a tag when activity happens. This allows the technique to focus on a specific area as a possible location of fall instead of the whole floor because the tags in that area will be marked as unread or absent. When the data from all the tags are received, it is treated as binary image i.e., some tags will be blocked by the person present while the rest will be read by the reader. The area with the maximum connected region is (where the tags are blocked) selected heuristically as a possible fall region. Only this area is considered for further processing instead of the whole carpet area which significantly reduces the processing cost. Eight features are selected from tag observation information and four different classifiers have been used to classify the activity as fall or not. Although the given technique performs better as compared to the previous work of the authors, the proposed system needs to be evaluated for multiple subjects as well as subjects with bags or pets. Also, it is not clear from the paper that how will this technique differentiate between a fall or normal sitting or lying, covering exactly the same number of tags as in a fall.

Ruan et al. (2015) proposed a device-free solution called TagFall, using passive RFID tags which can sense normal activities as well as falls. This technique not only can detect a fall but can also provide information about the direction of the fall. TagFall uses the abrupt fluctuation/changes in RSSI caused by falling. TagFall uses Angle Based Outlier Detection method to mine the clustering patterns of RSSI created by normal human activities and detects an anomaly pattern caused by a fall. To detect fall direction, Dynamic Time Warping algorithm is used in which a fixed length data stream is taken and compared with the previously collected profiling data to find the falling direction. After pre-processing, RSSI values are classified into four categories: sitting, lying, standing, and walking. The angle variance of vector pairs formed by the same category is calculated and the upper and lower boundaries of variance are decided. Also, the segmented data streams for falls with different directions, are collected for use in DTW calculations. The basic working principle of this approach is that the angles between different vector pairs from the same activity will differ widely, thus having a high angle variance. Angles between vector pairs from different activity are much smaller. Using this phenomenon, TagFall is able to cluster normal activities and can detect an outlier i.e., fall. One of the limitations of this work is that it is designed only for a single resident. This technique is also labor intensive in terms of user profiling and data collection.

Recently, Banno and Shinomiya (2019), proposed an RFID-based system for detecting falls in the staircase. The proposed system deploys passive RFID tags along the staircase (wall and handrail) and uses the RSSI values from these tags to differentiate between three activities; neutral, walking and fall. The tags on the handrail sense the hands' pressure while the tags on the wall detects the lower body movement. The authors have conducted different experiments in real-world scenar-

Table 8
Summary of the works presented for fall detection.

Approach	Technology	Advantages	Disadvantages	Applications
Wearable Device	Accelerometer + RFID, smartphone, barometer, magnetometer	Low cost	Constraint to wear the device	Elder care centers, Hospitals, Industrial workplace
Device-Free	Wi-Fi	Low cost, COTS available	Environmental interference	
	Radio devices	Low cost	Customized hardware required	
	RFID	Low cost, COTS available, passive	Environmental interference	

Table 9
Summary of the works presented for activities of daily living.

Approach	Technology	Advantages	Disadvantages	Applications
Vision-Based	Camera	High accuracy	High cost, complex computation, privacy issue	Security & surveillance, Smart home, Care centers
Wearable Devices	Accelerometer, temprature sensor, altimeter, gyroscope	Low cost	Constraint to carry the device	
Hybrid	RFID + Wearable device	Low cost	Customized harware required, constraint to wear the device	
Device-Free	Motion sensor, proximity sensors, temprature sensor	Low cost, freedom for user	Environmental interference	
Object-Tagged	Accelerometer, RFID	Low cost	Device bound	

ios to evaluate the performance of the proposed system.

4.2.5. Activities of daily living

Recognition of Activities of Daily Living (ADL) is identifying the daily activities in an indoor environment such as a home. These activities include eating, cooking, sleeping, sitting, bathing, dressing, toileting, etc. Recognition of such activities is of great importance for its applications in various areas such as smart homes and care centers. A smart home can adapt itself accordingly if it knows the activity of the resident. Recognizing the daily activities of patients or elder people in a caring facility or old homes, can help caregivers to monitor their health and provide the required treatment. Many solutions have been proposed over the past decade to recognize human daily activities. Table 9 presents the applications of daily activity recognition and provide details such as approach, technology, pros and cons of different techniques presented in this section. Some of these techniques use surveillance cameras to capture image or video and then apply computer vision techniques to recognize the activities performed (Xu et al., 2013; Yan et al., 2015). As mentioned in earlier sections, vision-based techniques have better accuracy but there are many limitations of this approach.

Sensor-based techniques use different sensors such as accelerometers, motion sensors, pressure sensors, and RFID tags for recognition of the daily activities. Chernbumroong et al. (2013) proposed a technique based on wrist-worn sensors, for recognition of elder people's activities to support independent living. Three types of sensors are attached to wrist-worn watch of the users which are: accelerometer, temperature sensor, and altimeter. This technique considers both basic ADL (BADL) and instrumental ADL (IADL). BADL includes activities such as grooming, feeding, stairs, dressing, and mobility (walking) while IADL includes activities such as ironing, sweeping, washing dishes and leisure activities (e.g., watching TV). A similar technique was presented by Liu et al. (2017b) for recognition of housekeeping tasks, using accelerometer and gyroscope as wrist-worn sensors. Wang et al. (2017c) proposed a solution for activity recognition by combining both the RFID system and wearable sensors. They use the RF signals from passive RFID tags connected to the subject's dress. A small reader is also attached to the user's dress, which further extends the coverage area.

Some techniques use a hybrid approach by combining both wearable and object-tagged mechanisms. In these techniques, users need to wear a device and the objects of daily use are also tagged with different sensors such as accelerometer or RFID. Stikic et al. (2008) proposed a technique which uses an accelerometer as wrist-worn sensor and the objects of daily use are tagged with RFID tags. The authors evaluated their technique in three ways: using data only from the accelerometer, using the data only from RFID tags and using the data from both accelerometer and RFID tags. The results show that the hybrid approach (i.e., combining data from both accelerometer and RFID tags) achieves better results as compared to separate approaches. A similar approach was presented by Hein and Kirste (2009) in which the user has to wear a device consist of an accelerometer, gyroscope, magnetometer, and an RFID antenna. Different objects of daily use are also tagged with RFID tags. The authors evaluated the proposed system in two scenarios: breakfast (preparing and having breakfast, washing the dishes, etc.) and home care. Instead of wearing special devices, inertial sensors which are embedded in mobile phones can also be used for recognition of daily life activities (Pires et al., 2018).

Some techniques use dense sensing and deploy different sensors such as motion sensors, pressure sensor, temperature sensor, and proximity sensor, in the environment (Hoque and Stankovic, 2012; Moriya et al., 2017). When a user performs any activity in the vicinity of these sensors, relative information can be captured through these sensors which can be used for recognition of activities. Oguntala et al. (2019), proposed a technique called SmartWall which uses passive RFID tags attached to a wall. When users perform any activity in-front of this wall, the changes caused in the reflected signal capture the information about the performed activity. The machine learning algorithm used is based on multivariant Gaussian algorithm using maximum likelihood estimation to recognize the activities. The proposed system can recognize 10 daily activities and can detect falls as well.The authors have implemented a prototype of the proposed solution and have performed various experiment to evaluate the performance.

A widely used approach for recognizing ADL is to attach different sensors to the objects of daily use and use the interactions of the users with these objects to recognize the activity. Various sensors have been used for this purpose but RFID tags and accelerometer are among the most common ones (Alsinglawi et al., 2017). Buettner et al. (2009) proposed a technique using Wireless Identification and Sensing Platform (WISP) which combines passive RFID tag and accelerometer. Objects of the daily use in the kitchen such as cup, bowl, milk-pack, and kettle are tagged with these WISPs and a reader captures the interaction of the users with these objects. After collecting the sensor data, HMM is used as an inference engine to infer the activities from the collected data.

4.2.6. Ambient assisted living

The population is aging around the world because of the low birth rate and increasing life expectancy. According to the Australian Institute of Health and Welfare, 15% of the Australian population is 65 or over and this number will double by 2056 (Center for Disease Control and Prevention, 2018). With the aging population, comes the problem of medical cost and caring of elder people. Most of the elder people live alone in their own homes or in elder care facilities. They also need someone to look after them which causes further problems for the workforce. In recent years, considerable research has been done to provide solutions for such problems. Researchers have developed many different technologies to assist humans in their daily lives, under a new paradigm called ambient intelligence. These technologies are called Ambient Assisted Living (AAL) tools and are helping people with issues such as remote monitoring, medication management, medication reminder, exercise management, and independent living. Over the last decade, many solutions have been proposed under the umbrella of AAL to support independent living of the elder peo-

Table 10
Summary of the works presented for ambient assisting living.

Approach	Technology	Advantages	Disadvantages	Applications
Vision-Based	Camera	High accuracy	High cost, complex computation, privacy issue	Elder care center, Medication management, Exercise management
Wearable Devices	Inertial sensors, RFID, infrared sesnsor	Low cost	Constraint to carry the device	
Hybrid	RFID + RF beacons + other sensors	High accuracy	High cost, customized hardware required	

ple (Rashidi and Mihailidis, 2013; Queiros et al., 2017; Hussain et al., 2019; Aldeer et al., 2019). Table 10 gives some details (approach, technology, advantages, disadvantages) about different solutions discussed in this section along with some applications of ambient assisted living. Some of these solutions are vision-based and use surveillance camera to capture the information about the activities of the residents (Anitha and Priya, 2018). As discussed before, vision-based systems have many issues.

A number of other solutions have been proposed using different sensors. Zhu and Sheng (2011) proposed a multi-sensor technique for recognition of daily activities in robot-assisted living. Two inertial sensors are attached to the body of the user, one on the waist and other on the foot. The sensors are connected to a PDA which transfers the sensor data (angular velocity and the acceleration) to a desktop computer through Wi-Fi for processing. A set of neural networks classify the data into three categories: transitional, stationary, and cyclic. The output from the neural networks is fed into a fusion module which further categorizes them as zero displacement activity, transitional activity, and strong displacement activity. Zero displacement activities are further classified into sitting or standing while transitional activities are classified into standing-to-sitting or setting-to-standing by using a heuristic discrimination module. Strong displacement activities are further classified by applying the HMM algorithm.

Soliman and Alrashed (2018) presented an RFID-based system for monitoring the activities of Alzheimer's patients at home. The basic idea of this work is to track the movement of a user from one room to another and to report any abnormal situation (e.g., staying in the washroom for a longer time). The user has to wear a passive RFID tag around the ankle because the ankle is the relatively stable position in the body. To enhance the system efficiency, two pressure mate sensors are deployed on either side of the door to detect whether a user is coming inside or going outside. When a movement is detected by the sensors, the system triggers the reader to energize the tags and collects the data for detecting the location of the user. An issue with this solution is that wearing a device all the time is not a good choice, especially when it comes to the elder people.

Many solutions have been proposed using the dense sensing approach. Fouquet et al. (2009) proposed a technique for telemonitoring of the elder people using dense sensing. The main objective of this study is to detect the nycthemeral shift in the daily routines of the elder people which can help in early the detection of dementia-related diseases. Infrared sensors are deployed in different locations of a flat (test facility) to capture the information about the daily activities of the resident. A total of eight months of data is recorded. A random process technique called Polya's urns is used to analyze the recorded data. Parada et al. (2015) presented a method called Weighted Information Gain (wIG) to detect the user-object interaction for assisting independent living. They use RFID technology i.e., RFID tags are attached to the objects (e.g., books). For proper training of the proposed system, light dependent resistors are used to represent the presence or absence of an object (e.g., book in a shelf). The wIG classifier uses the Information Gain algorithm to classify the RFID events as static or interacted.

Although RFID technology provides a better solution for autonomous identification and tracking of the objects, the range of RFID is an issue. The detection range of passive RFID is relatively low (up to 7 m) (Ko, 2017). To tackle this issue, many researchers have tried to merge RFID technology with other technologies such as Wireless Sensor Network (WSN). One such system called CUIDATS is proposed by Adame et al. (2018), for monitoring in a smart healthcare facility. The proposed system can track patients and assets and can also monitor the vital signs (e.g., temperature, fall alert, pulse). CUIDATS is a hybrid solution in which RF beacons and RF readers are deployed in the environment while patients need to wear a wristband which consists of different sensors and RF transmitter. The assets are tagged with passive and active RFID tags. The RFID reader and RF beacon are integrated into a single compact device which can collect the data and transfer it to the WSN. CUIDATS uses weighted centroid algorithm for tracking the patients with wristband and accelerometer readings are used for fall detection.

Summary. A summary of the work presented for action based activities is given in Tables 11 and 12. As seen from the tables, most of the solutions use device-free approaches. Some of the solutions also use wearable approach. Substantial works have been done in the areas of gesture recognition, posture recognition, using RFID technology. Many of the solutions especially in the areas of AAL and ADL, are sensor-based and are using sensors like accelerometer, proximity sensor, and other sensors. The accelerometer is the most common sensor used in the field of human activity recognition.

Because of its device-free nature and easy deployment, RF technology is finding its usage in many fields. A significant amount of works using RF technology can be found in HAR. Many solutions have been presented using RF technology, especially Wi-Fi. Wi-Fi is used as a device-free approach for solutions in behavior recognition, fall detection, and people counting. Due to the fact that Wi-Fi is present almost everywhere nowadays, researchers are using this technology for many applications in various fields and it is providing good results.

One approach which is becoming very common nowadays is the fusion approach. Instead of using a single technology like accelerometer or RFID, researchers are now using the hybrid approach by combining multiple technologies. One example of such an approach is combining wearable accelerometer sensor with RFID tags attached to the objects of daily use. The hybrid approach has the advantages of both approaches.

Machine learning plays an important role in activity recognition. Information can be collected through various approaches and technologies but after that, it is the job of machine learning algorithm to infer/recognize the activity. Some of the most common machine learning algorithms which are used in human activity recognition are; SVM, KNN, Random Forest, Naive Bayes, and HMM. Feature selection is also an important part before applying a machine learning algorithm. A good set of features can yield better results.

4.3. Motion-based activities

These types of activities are related to the motion of humans. Activities are not only those which are related to performing any specific action but presence or absence, motion detection, etc., in an area under observation can also be an activity. Recognizing motion based activities is very useful, especially in surveillance and security. In this section, we provide an overview of the motion-based activities.

Table 11
Comparison of different approaches for recognizing action-based activities.

M1 = Approach, M2 = Technology, M3 = Information Type, M4 = ML Algorithm, M5 = Supervised/Unsupervised

Category	Paper	M1	M2	M3	M4	M5
Gesture Recognition	Ye et al. (2014)	D	RFID	Tag ID	Fisher's Linear Discriminant	Y
	Parada et al. (2016)	D	RFID	RSSI	K-Means Clustering	N
	Ding et al. (2017)	D	RFID	RSSI, Phase, Tag ID	–	N
	Zou et al. (2017)	D	RFID	Phase Values	N-DTW, Weighted Matching Algorithm	Y
	Yu et al. (2019)	D	RFID	RSSI, Phase	Deep Learning	N
Fall Detection	Chen et al. (2017)	D	RFID	RSSI	KNN	Y
	Wang et al. (2017d)	D	Wi-Fi	CSI	Random Forst	Y
	Minvielle et al. (2017)	D	Piezoelectric Polymer Sesnor	Electric Signal	Random Forest	Y
	Kianoush et al. (2017)	D	Radio Frequency	RSSI	HMM	Y
	Wickramasinghe et al. (2017)	D	RFID	Tag IDs	NSVM	Y
	Banno and Shinomiya (2019)	D	RFID	RSSI	Random Forest	Y
Posture Recognition	Yao et al. (2015)	D	RFID	RSSI	DPGMM based HMM	Y
	Yao et al. (2018)	D	RFID	RSSI	SVM	Y
	Li et al. (2015)	D	RFID	Phase, RSSI	–	Y
	Cianca et al. (2017)	D	Radar	RF Samples	SVM,NB, KNN, RF, Logistic Regression	Y
	Wickramasinghe and Ranasinghe (2015)	W	CRFID	RSSI	NB, CRF, RF, LSVM, NSVM	Y
	Liu et al. (2019)	D	RFID	RSSI, TagID	Otsu's method	N
Behaviour Recognition	Popa et al. (2011)	D	Kinect Sensor	Silhouettes	SVM, K-NN, LDC	Y
	Zeng et al. (2015)	D	Wi-Fi	CSI	D-Tree, Simple Logistic Regre	Y
	Han et al. (2016a)	D	RFID	Phase, Doppler's Effect	Iterative Clustering Algorithm With Cosine Similarity	N
	Zhou et al. (2017)	D	RFID	Phase Values	–	N
ADL	Stikic et al. (2008)	W	Hybrid(RFID + Accelerometer)	Accelerometer data, Tag ID	NB, HMM, Joint Boosting	Y
	Buettner et al. (2009)	D	Hybrid(RFID + Accelerometer)	Accelerometer data, Tag ID	HMM	Y
	Hein and Kirste (2009)	W	Hybrid(RFID + Inertial Sensor)	Data from IMU, Tag ID	HMM, Weka C4.5	Y
	Chernbumroong et al. (2013)	W	Hybrid(Accelerometer, Altimeter, Temp. Sensor)	Data from All Sensors	SVM	Y
	Liu et al. (2017b)	W	Accelerometer, Gyroscope	Sensor Readings	NB, D-Tree, KNN, SVM	Y
	Oguntala et al. (2019)	D	RFID	RSSI	Multi-variant Gaussian	Y
AAL	Fouquet et al. (2009)	D	Infrared Sensors	Sensor Readings	Polya's urn	Y
	Zhu and Sheng (2011)	W	Inertial Sesnors	Sensor Readings	Neural Network, HMM	Y
	Parada et al. (2015)	D	RFID	RSSI, Phase, Tag ID	Information Gain Algorithm	Y
	Soliman and Alrashed (2018)	W	RFID, Pressure Sensor	RSSI, Sensor Reading	–	–
	Adame et al. (2018)	H	RFID, WSN	Data from All Sensors	–	–

Symbols used: D = device-free, W = wearable, H = hybrid, Y = yes, N = no, – = Not Available.

4.3.1. Tracking

Tracking is one of the important sub-areas in HAR. In an outdoor environment, tracking can be easily done using Global Positioning System (GPS) but GPS is not applicable in indoor environments. Tracking has many uses in various applications such as augmented reality, room occupancy detection, and indoor navigation. Due to its increasing importance, significant work has been done in this area. Table 13 gives some applications and details such as approach, technology, pros and cons for the techniques presented in this section. Existing research work in this area can be divided into device-bound (Ligorio and Sabatini, 2015) and device-free approaches. One of the limitations of the device-bound approaches is that the subject is required to carry a device or tag. But carrying a device or tag is not possible in all the cases, for example, in cases of animal tracking or unknown subjects. Most of the recent works focus on device-free approaches where the users are free from carrying any devices (Shukri and Kamarudin, 2017). One such example is the use of Wi-Fi signals for tracking the motion of humans (Qian et al., 2017; Li et al., 2017).

Another approach for device-free tracking is to use passive RFID technology (Zhang et al., 2011; Liu et al., 2012; Ruan et al., 2014, 2016, 2018; Yang et al., 2015; Han et al., 2016b; Chang et al., 2017; Ji et al., 2015). But the main challenge in this approach is the interference from the environment, which affects the accuracy of the solution (Ruan et al., 2016).

TASA (Zhang et al., 2011) proposed a device-free RFID-based approach for location sensing and frequent route detection. This approach uses the RSSI values of the tags arranged in arrays and deployed in the locality to find the frequent trajectories. To improve the accuracy, active tags are used as referenced tags with known locations. This technique models the whole tag array in a coordinate system in which each tag represents a specific coordinate value with respect to the reference tag. The entire process is divided into two phases: location sensing and frequent route detection. In the first phase, RSSI values of only the affected tags are taken into account and are stored in a database after sorting chronologically. Outliers are removed using the idea that only those tags are considered as affected if their neighbor tags are also affected otherwise these will be outliers. For locating objects along the trajectory, TASA makes use of the active tags deployed in critical positions along with passive tags. At the end of the first phase, raw RSSI data has been converted to a set of different routes in chronological order. Phase two is the activity sensing in which frequent routes are detected by using a two-step approach; frequent route set discovery with minimum support and online detection of frequent routes. TASA uses modified versions of Apriori (Agrawal et al., 1993) and FPGrowth (Han et al.,) algorithm called as iApriori and iFPGrowth for detecting frequent trajectories. TASA is also capable of tracking multiple objects simultaneously with the help of active reference tags, however, the accuracy is low for multiple subjects. Also, active tags require battery maintenance which is not feasible in some

Table 12
Comparison of different approaches for recognizing action based activities. Cont.

M6 = Application, M7 = Cost, M8 = Accuracy, M9 = Latency, M10 = Real-Time

Category	Paper	M6	M7	M8	M9	M10
Gesture Recognition	Ye et al. (2014)	12 Gestures	Low	High	–	N
	Parada et al. (2016)	2 Gestures	Low	High	2.95 s	Y
	Ding et al. (2017)	7 Gestures	Low	High	0.1 s	Y
	Zou et al. (2017)	6 Gestures	Low	High	–	–
	Yu et al. (2019)	8 Traffic Gestures	Low	High	0.18 s	Y
Fall Detection	Chen et al. (2017)	Postures, Fall Detection Direction of Fall	Low	High	–	–
	Wang et al. (2017d)	Postures, Fall Detection	Medium	Medium	–	–
	Minvielle et al. (2017)	Fall Detection	Low	High	–	–
	Kianoush et al. (2017)	Localization and Fall Detection	Medium	High	–	Y
	Wickramasinghe et al. (2017)	Fall Detection	Low	High	1.5 s	Y
	Banno and Shinomiya (2019)	3 Activities	Low	High	–	N
Posture Recognition	Yao et al. (2015)	Postures, Posture Transition	Low	High	3.5 s	Y
	Yao et al. (2018)	Postures, Actions	Low	High	4.5 s	Y
	Li et al. (2015)	Postures, Gestures	Low	Medium	–	–
	Cianca et al. (2017)	Office Desk & Checkout Counter Activities	Medium	High	–	N
	Wickramasinghe and Ranasinghe (2015)	Bed-exit, Chair-exit, walking	Medium	High	–	Y
	Liu et al. (2019)	6 Sleeping Postures	Low	High	–	N
Behaviour Recognition	Popa et al. (2011)	6 Actions/Activities	High	Medium	–	Y
	Zeng et al. (2015)	3 Coarse-grained Activities	Medium	High	–	–
	Han et al. (2016a)	3 Types of Behaviour	Low	High	–	N
	Zhou et al. (2017)	3 Types of Behaviour	Low	High	–	N
ADL	Stikic et al. (2008)	10 Housekeeping Activities	Medium	Medium	–	–
	Buettner et al. (2009)	14 Daily Life Activities	Medium	High	–	–
	Hein and Kirste (2009)	19 Daily Life Activities	Medium	Medium	–	–
	Chernbumroong et al. (2013)	11 Daily Life Activities	Medium	High	–	–
	Liu et al. (2017b)	12 Daily Life Activities	Medium	High	–	N
	Oguntala et al. (2019)	11 Daily Life Activities	Low	High	–	N
AAL	Fouquet et al. (2009)	Monitoring Daily Activities	Low	Low	–	–
	Zhu and Sheng (2011)	5 Gestures, 4 Postures	Low	High	–	–
	Parada et al. (2015)	Interaction with Objects	Low	Medium	–	Y
	Soliman and Alrashed (2018)	Movement Tracking	Low	Medium	–	–
	Adame et al. (2018)	Tracking, Localization, Status Monitoring	High	Low	–	Y

Symbols used: D = device-free, W = wearable, H = hybrid, Y = yes, N = no, – = Not Available.

Table 13
Summary of the works presented for tracking.

Approach	Technology	Advantages	Disadvantages	Applications
Wearable Device	Accelerometer, gyroscope	Low cost	Constraint to wear the device	Supply chain management, Indoor navigation, Augmented reality
Device-Free	Wi-Fi	Low cost, COTS available	Environmental interference	
RFID (passive)	Low cost, COTS available, passive	Environmental interference		
RFID(passive + active)	Low cost, COTS available, high accuracy,	Active tags need battery		

situations. Placement of active tags is another issue.

Liu et al. (2012), presented a device-free, RFID-based, approach for mining frequent trajectories. Active RFID tags along with readers are deployed. When an object moves around in this area, the tags along the path of the movement will be disturbed and the RSSI information from these tags is used for detecting a trajectory. Before the data collections, two base values are calculated in the absence of any objects. These values are neutral values of a tag which is the expected signal strength and sensitivity of the tag. When the data is collected from the tags, neutral value and RF values are used to find the interfered tags. If a tag is interfered, the signal strength value is replaced by 1 and if the tag is not interfered, it is replaced by 0. In this way, the data is transformed into a binary form. After the pre-processing stage, the next phase is to mine frequent trajectories. This task is done in two steps: training and monitoring. In the training phase, data is collected from the tags for a certain period of time and this data is used to find frequent trajectories which are modeled as normal activities. In the monitoring phase, activity is detected and is compared with the frequent trajectories. The activity is considered normal or suspicious based on the comparison results. To tackle the different issues associated with RFID tags (misread, false read etc.), this work identifies the border between interfered and non-interfered tags for an activity. Instead of the exact location, the ranges are located where the object possibly exists. To solve the problem of hidden objects (one object behind the other), this work uses multiple readers because the hidden object will be detected by at least one of the readers. It also uses fault-tolerant mining e.g., the hidden object may show up in next time periods. Mining algorithm consists of two parts. In the first part, frequent positions of the object are identified. In the second part, frequent trajectory segments are calculated. Starting with the short segment, frequent segments are extended using a depth-first search. This technique uses active tags which require maintenance for battery replacement. Also, parameter tuning is required which is not an easy task.

TagTrack (Ruan et al., 2014) is another device-free technique which uses passive RFID tags for tracking. The basic idea of this work is that RSSI shows different patterns when a person is present or absent in a given RSS field. When a person moves through different regions in a given RSS field, the RSSI pattern changes accordingly. This work focuses on two main problems: localization of a stationary object and tracking of a moving object. Localization is considered as a classification problem and different classification techniques are applied to locate a stationary object. TagTrack proposes two techniques: GMM-based HMM and kNN-based HMM, to track the moving object by learning the underlying patterns in different locations. Experimental results show that the given system can perform better for localization but the performance for tracking a moving object is poor.

Tadar is a system proposed by Yang et al. (2015) which can track moving objects, even beyond the wall. Passive RFID tags are attached to the outer walls with a reader fixed in the line of sight. The idea behind Tadar is that tags receive the signals from the reader via two paths; directly from the reader and reader's signal reflected by another object and then received by the tag. Tadar exploits this reflected signal for tracking the object. HMM is used for object tracking. The proposed system has some problems such as direction dependency and vulnerability to reflective (metallic) objects. The detection range of the system is low (around 4 m) for a concrete wall but most of the buildings use concrete walls. Also, the given system can track only one moving object and is not applicable for multiple objects.

Han et al. (2016b) presented a device-free RFID-based technique called Twins, for tracking and motion detection. This technique uses a phenomenon called the critical state, which is caused by the interference of different passive tags. The working principle of Twin is based on the critical state caused by the coupling effect among passive RFID tags. When two passive tags (e.g., A and B) are placed together at a certain distance with the same antenna, one of the tags (B) become unreadable. It's because of the shadow effect from the other tag (A) and because of this effect, tag B's antenna will receive a very weak signal from the reader and therefore, will not respond to the reader. But if an object (human) pass close to the twins, some of the RF waves get reflected or refracted. Because of this disturbance, tag B receives enough energy to break the critical stage and becomes readable again. In this way, a moving object can be detected.

4.3.2. Motion detection

Motion detection is a process to detect the presence of any moving entity in an area of interest. Motion detection is of great importance due to its application in various areas such as surveillance and security, smart homes, and health monitoring. A smart home is smart because it can adjust its environment according to the user's activity. The first and most basic thing for that is to know about the presence or absence of a resident. In security and surveillance, intrusion detection is very important and one of the basic tasks, which is basically detecting the presence or motion of outsiders. Motion detection also plays a key role in the field of health and remote monitoring of patients especially elder people.

Different approaches have been used to provide solutions for motion detection. Details such as technology, approach, advantages, and disadvantages for solutions discussed in this section are given in Table 14 along with the applications of motion detection. Some of these solutions are vision-based and use surveillance cameras (Ansari et al., 2015). Some techniques use wearable sensors attached to the subject, for motion and presence detection. But this approach requires a sensor or device to be worn by a subject which is not possible in some cases, for example, intruders or animals.

One class of solutions adopt a device-free approach for motion detection using different sensors (Moghavvemi and Seng, 2004; Singh et al., 2016). Some solutions use Wi-Fi for motion detection (Xiao et al., 2012; Liu et al., 2015; Gu et al., 2017). Zhao et al. (2015) proposed a technique called EMoD which is not only capable of locating a moving object but can also provide information about the direction of movement. EMoD is a device-free technique and uses passive RFID tags. Passive RFID tags are deployed in pairs (twins) at different points in an area under observation. The working principle of EMoD is the same as in Twins (Han et al., 2016b) i.e., critical state of the tags.

A device-free technique based on passive RFID technology called RF-HMS was presented by Wang et al. (2017e). Like Tadar (Yang et al., 2015) this technique uses RFID tags for seeing through the wall. By deploying passive tags on the outer side of the wall, RF-HMS can detect the presence of a stationary human, moving human, and also the direction of movement. RF-HMS characterizes each tag's multi-path propagation by channel transfer function using phase and RSSI measurements. It eliminates the noise and reflection from static entities such as furniture and walls, by dividing channel transfer function learned beforehand for each tag, irrespective of the presence or absence of a human in the room. Passive RFID tags are grouped in the form of an array to improve the sensing performance. Reflections from the walls, indoor furniture and various parts of the human body are captured by the tag arrays and are combined by RF-HMS into a reinforced result. Then phase shifts can be extracted to detect the presence or absence of a human in the room. This solution can provide information about only two directions i.e., towards the tag or away from the tag and cannot detect motion in other directions such as left or right. Also, this technique requires calibration of threshold values which is always a challenging task. The proposed solution needs to be evaluated for concrete walls as most of the buildings have concrete walls.

4.3.3. People counting

People counting means counting or estimating the number of people in a specific area, which can be a closed environment or an open area (Cianca et al., 2017). People counting is of great importance in various people-centric IoT applications like smart homes, elder care centers, and traffic management. This process has many applications both in normal and critical situations (Cianca et al., 2017). Some examples of critical situations are crowd control in huge festivals, public gathering, religious festivals, music concerts, sports stadium, etc.

An example of non-critical situations in which people counting has many applications is, counting the number of people visiting a specific facility (e.g., museum, retail store, train station, shopping mall, restaurant, art galleries or a library). People counting can be of two types: crowd counting in an area and counting the number of people going in or out of a specific closed environment. Different solutions have been proposed to solve the problem of people counting. Table 15 gives some applications of people counting along with some details for different techniques presented for people counting. These can be categorized as image-based and non-image-based (Cheng and Chang, 2017). Image-based techniques use cameras to capture an image or video of the area under surveillance and then analyze the image or video to find the number of people present (Hou and Pang, 2011; Junior et al., 2010). Some techniques use depth cameras and infrared lasers instead of traditional cameras (Kuo et al., 2016; Wu et al., 2018).

Non-image-based techniques use binary sensors, mechanical barriers and wireless signals for people counting. Mechanical barrier-based techniques use a turnstile gate which allows only one person at a time to pass through the gate. This allows counting the number of people passing the gate. Binary sensor-based solutions use break-beam sensors such as infrared or laser beam, deployed on a one-way gate (Teixeira et al., 2010). When a person passes by the gate, it causes the beam to break allowing to count the number of people passing by the gate. A major problem with this type of solutions is that they require the subject to pass through a specific area (gate) which is not feasible in many situations such as crowd present in an exhibition.

Some solutions use wireless signals (such as Wi-Fi and RF), which is a more economical and practical approach. These solutions do not affect the privacy of people and can use existing infrastructure such as commodity Wi-Fi. Received signal strength of the wireless signal is an indicator of the signal when it propagates through a region. RSS is sensitive to the number of people present in a specific environment and can provide information for finding the number of people. Cheng and Chang (2017) proposed a device-free technique for counting the

Table 14
Summary of the works presented for motion detection.

Approach	Technology	Advantages	Disadvantages	Applications
Vision-Based	Camera	High accuracy	High cost, complex computation, privacy issue	Security & surveillance, Smart homes
Radio Frequency	Wi-Fi	Low cost, COTS available	Environmental interference	
RFID	Low cost, COTS available, passive	Environmental interference		

Table 15
Summary of the works presented for people counting.

Approach	Technology	Advantages	Disadvantages	Applications
Vision-Based	Camera	High accuracy	High cost, complex computation, privacy issue	Crowd management, Shopping malls, Public gatherings, Smart environments
Depth Sensor	Kinect, infrared laser	High accuracy	High cost, privacy issue	
Gate-Based	Turnstile gate	High accuracy	Require the user to pass through a specific area (gate)	
Laser beam	High accuracy	Require user to pass through a specific area (gate)		
Device-Free	Wi-Fi	Low cost, COTS available	Cannot work if number of people increase	
RFID	Low cost, COTS available, passive	Cannot work if number of people increase		

number of people in an indoor environment using Wi-Fi channel state information. They use a transmitter (Wi-Fi access point) and a receiver for collecting the RSS values of the signals. Deep Neural Network model is used in this technique which is trained offline on CSI data for the different number of people present in the room and then tested online. The proposed system is robust to location variability of the people inside a facility.

With the recent popularity of RFID technology and a decrease in the cost of RFID tags, this technology has found its place in various fields. One such example is using passive RFID technology for counting the number of people. R# (Ding et al., 2015) is a device-free technique, which uses passive RFID tags to estimate the number of people present in a facility. The basic idea of this work is that variance in the RSS values of backscattered RF signal change according to the number of people present in the environment. Passive RFID tags are deployed in the area under consideration and RSS is captured by a reader when the different number of people are present in the region. The proposed solution provides an easy and cost-effective technique for counting the number of people. A limitation of this work is that it cannot count more than ten people. Also, the performance is poor when people are walking at relatively high speed.

Summary. A summary of the work presented for motion-based activities is given in Tables 16 and 17. During the literature review, we found that RFID technology is leading the area of tracking and indoor localization. Most of the solutions presented for tracking and localization are using RFID tags deployed in the environment and a fixed reader with antenna is used to collect data from these tags. Most of these solutions are low cost and have high accuracy.

Besides RFID, many solutions for motion detection and people counting are also using sensor-based and RF-based approaches. Various sensors such as infrared and pressure sensors are used to detect the presence of people in a specific place. Radio Frequency technology is also used for research in motion detection and people counting. Use of Wi-Fi is one such example.

In our opinion, people counting is the sub-area of motion-based HAR in which the least amount of work is done. Tracking and localization are two such areas in which a significant amount of research has been done. One possible reason for less research work in people counting would be the availability of sophisticated sensors in the market. These sensor can detect motion and can estimate the count with minimum processing required.

4.4. Interaction-based activities

Some activities can also be performed by interacting with objects or using the objects. A human can interact with objects in different ways. Interacting with the objects in different ways results in different activities. Recognition of these activities is important in many applications (e.g., entertainment). In this section, we discuss some of the activities which are based on human object interaction.

4.4.1. Human object interaction

Human-computer interaction (HCI) is a flourishing area of research about the interaction between users and different machines. A considerable amount of work has been done in this field and completely new ways of interacting with machines have been proposed. Recently, different techniques have been proposed for interaction with machines which are based on the interaction with objects.

RFID technology is playing an important role in the field of HCI. Numerous solutions have been presented using RFID tags attached to objects for interacting with machines. RFID Shakable (Kriara et al., 2013) is a technique in which passive RFID tags are attached to different toys. The basic idea of this work is the pairing of two objects on the bases of their gestures. When two objects are tagged with RFID and they move in the vicinity of an RFID reader, information about their movement can be captured by the reader from those attached tags. After applying gesture recognition, similar objects can be identified for pairing.

Li et al. (2015) proposed a technique called IDSense for detecting human-object interactions. The basic idea of IDSense is that it uses the changes in the signal parameters from RFID tags such as RSSI, Phase and Read-Rate to detect human-object interaction. A single tag is attached to different objects and a reader antenna is used to investigate these tags when interacted by a human. Using SVM, IDSense can classify these interactions into different states such as touch, still, swipe, and motion. Authors have demonstrated the application of this technique in three case studies which are: interactive storytelling with toys, interaction detection of the daily object for activity inferencing, and product interaction tracking in a superstore. The proposed technique is simple to implement and can provide results in real time but there are some limitations. Due to a single tag per object, similar interactions cannot be recognized correctly such as translation and rotation. This can be overcome by using multiple tags per object. The performance is

Table 16
Comparison of different approaches for recognizing motion based activities.

M1 = Approach,M2 = Technology, M3 = Information Type, M4 = ML Algorithm, M5 = Supervised/Unsupervised

Category	Paper	M1	M2	M3	M4	M5
Tracking	Zhang et al. (2011)	D	RFID	RSSI	Apriori, FPGrowth	–
	Liu et al. (2012)	D	RFID	RSSI	–	Y
	Ruan et al. (2014)	D	RFID	RSSI	GMM based HMM, kNN based HMM	Y
	Yang et al. (2015)	D	RFID	RSSI, Phase	HMM	Y
	Han et al. (2016b)	D	RFID	RSSI	KNN	Y
Motion Detection	Liu et al. (2015)	D	RF	CSI	–	–
	Zhao et al. (2015)	D	RFID	Critical Power of Tags	–	Y
	Singh et al. (2016)	D	Sensor Fusion	Raw Signal from Sensors	Mean-shift Clustering	Y
	Gu et al. (2017)	D	RF	CSI	–	Y
	Wang et al. (2017e)	D	RFID	RSSI, Phase	–	-
People Counting	Ding et al. (2015)	D	RFID	RSSI	NB	Y
	Kuo et al. (2016)	D	Kinect Sensor	Depth Image	–	–
	Cheng and Chang (2017)	D	Wi-Fi	CSI	DNN	Y
	Wu et al. (2018)	D	Infra Red Laser	Video	–	–

Symbols used: D = device-free, W = wearable, H = hybrid, Y = yes, N = no, – = Not Available.

Table 17
Comparison of different approaches for recognizing motion based activities. Cont.

M6 = Application, M7 = Cost, M8 = Accuracy, M9 = Latency, M10 = Real Time

Category	Paper	M6	M7	M8	M9	M10
Tracking	Zhang et al. (2011)	Tracking	Medium	High	~20 s	Y
	Liu et al. (2012)	Tracking	Medium	High	–	Y
	Ruan et al. (2014)	Tracking	Low	High	–	Y
	Yang et al. (2015)	Tracking	Low	High	–	–
	Han et al. (2016b)	Tracking	Low	High	–	–
Motion Detection	Liu et al. (2015)	Setting, walking, Fall	High	High	–	–
	Zhao et al. (2015)	Motion Detection, Tracking	Low	High	–	Y
	Singh et al. (2016)	Human Presence Detection	Low	High	–	–
	Gu et al. (2017)	Motion Detection, Daily Activities (Posture Related)	High	High	4.42 s	–
	Wang et al. (2017e)	Detection of Stationary & Moving Person, Direction	Low	High	<1 s	Y
People Counting	Ding et al. (2015)	Counting People	Low	High	–	–
	Kuo et al. (2016)	Counting People	High	High	–	–
	Cheng and Chang (2017)	Counting People	Low	Medium	–	Y
	Wu et al. (2018)	Counting People, Tracking	High	High	–	Y

Symbols used: D = device-free, W = wearable, H = hybrid, Y = yes, N = no, – = Not Available.

also sensitive to the speed of the interaction i.e., too slow or too fast interactions may not be detected correctly.

Li et al. (2016) presented a technique called PaperID through which a simple paper can be converted into an interactive input device using passive RFID tags. Different gestures like touch, swipe, cover, wave, slide and free air motion can be identified using this technique. The dense placing of multiple tags (on paper in this case) can cause interference in their signals. To overcome this problem, this work proposes a concept of half antenna in which the antenna of the tag is monopole i.e., only half of the antenna is present. As a result, the tag cannot harvest energy from the reader and is not readable. But when the antenna is completed (e.g., by touching), the tag becomes readable. This work also proposes techniques for making custom tags using conductive ink. Using these techniques, custom tags can be created very cheaply and on the spot, according to the need.

A similar technique called Rio is presented by Pradhan et al. (2017) through which any surface can be converted into a touchpad by attaching passive RFID tags. The basic theme of this technique is based on the change in impedance in tag antenna which occurs as a result of touching RFID tag. This change in impedance causes a phase change in the backscattered signal. Using this change in phase and machine learning algorithm, different gestures can be identified e.g., touch and swipe. The solution can work for both COTS and specially designed tags. No modification is required in the hardware. The technique can work for both single and multiple tags.

Shangguan et al. (2017) presented the design and implementation of a technique called Pantomime which is capable of gesture recognition with only one antenna per location. This technique uses passive RFID tags attached to objects (two per object). When this object is moved in the air, the system is capable of recognizing the trajectory of the attached tag and thus the gesture made by the object can be recognized. By attaching two tags per object, the tag population becomes double causing a decrease in the reading rate of the tags. Also, a small gap between tags can cause the coupling effect which may lead to errors in phase values. Pantomime addresses these challenges by reading only the target tags (who's phase changes significantly) and not the remaining tags (who remains stationary) in the coverage area. The application of Pantomime is demonstrated by two case studies: handwriting tracking on whiteboard and superstore item querying. In the later case, a user picks any tagged-object at random and makes different pre-defined gestures with it, in front of a reader antenna. The system can recognize the gestures made with the object.

Summary. Tables 18 and 19 summarize the work presented for interaction-based activities. This area has gained much popularity in recent years because of its application in various fields such as gaming, entertainment, and human-computer interaction. Many different approaches have been used for human-object interactions. We have tried to focus on device-free approaches. However, there are many solutions which use wearable approach.

Table 18
Comparison of different approaches for recognizing interaction-based activities.

M1 = Approach,M2 = Technology, M3 = Information Type, M4 = ML Algorithm, M5 = Supervised/Unsupervised

Category	Paper	M1	M2	M3	M4	M5
Human-Object Interaction	Kriara et al. (2013)	O	RFID	Tag ID	Cross-correlation	–
	Li et al. (2015)	O	RFID	RSSI, Phase, Tag ID	SVM	Y
	Li et al. (2016)	O	RFID	RSSI, Phase, ReadRate	SVM	Y
	Pradhan et al. (2017)	O	RFID	Phase Values	–	Y
	Xu et al. (2013)	O	RFID	Phase Values	–	-

Symbols used: D = device-free, W = wearable, H = hybrid, O = object tagged, Y = yes, N = no, – = Not Available.

Table 19
Comparison of different approaches for recognizing interaction-based activities. Cont.

M6 = Application, M7 = Cost, M8 = Accuracy, M9 = Latency, M10 = RealTime

Category	Paper	M6	M7	M8	M9	M10
Human-Object Interaction	Kriara et al. (2013)	Pairng	Low	High	–	–
	Li et al. (2015)	4+ Types of Interactions	Low	High	1 s	Y
	Li et al. (2016)	5+ Types of Interactions	Low	High	0.5 s	Y
	Pradhan et al. (2017)	Touch, Track	Low	High	<1 s	Y
	Xu et al. (2013)	English Letters Recognition, 4 Gestures	Low	High	–	Y

Symbols used: D = device-free, W = wearable, H = hybrid, O = object tagged, Y = yes, N = no, – = Not Available.

Use of RFID is very common in recognition of interaction-based activities because of its passive nature. The passive RFID tag can be attached to any object and can provide information via wireless communication to the reader. Using RFID technology, many solutions have been presented for smart surface, touchpads and gesture recognition using object interaction. These solutions are low cost (because RFID technology is cheap) and provide high accuracy.

Previously, specially designed hardware surface using different capacitors were used as an input device or touchpads. But now, with the help of research in human object interaction area, any common surface (e.g., paper) can be converted into a touchpad or a smart surface. Research in human object interaction area is providing new and interesting ways for communicating with machines (instead of traditional methods such as keyboard and mouse). Now, interaction with machines is possible by performing certain gestures and interacting with objects in a certain manner.

5. Open issues and future research directions

Although significant research has been done in the field of human activity recognition, there are some open issues which still need to be addressed. In this section, we present some of the open issues in HAR.

5.1. Complex activities

Existing work can recognize basic and atomic activities which are performed by a single subject. Also, the model needs to be trained for similar activities in advance. But there are many complex activities which existing solutions cannot recognize. Following are some types of activities which offer further research opportunities for researchers.

Composite Activity. Most of the current solutions are focused on the recognition of simple activities performed by a single subject such as walking, running, eating, and sitting. But daily life is not only about these simple activities. There are many activities which are composite and consist of multiple simple activities. For example, doing exercise is a composite activity which consists of atomic activities such as sitting, standing, and running. Recognizing such a composite activity is very challenging as compared to the recognition of atomic activities. Blanke and Schiele (2010) has discussed this issue in detail and has provided a potential solution for recognition of composite activities.

Multiple Subjects. Almost all solutions presented till now are capable of recognizing the activities of a single subject. Whether it is tracking, gesture recognition, posture recognition, or other areas, existing work is focused on recognizing the activity of a single person at a time. But in the real world, there are many situations in which activities are performed by multiple subjects simultaneously (e.g., people in the kitchen or living room) or multiple people involved in a single activity (handshake, hugging, etc.). Some researchers tried to solve this problem of recognizing activities in a multi-subject environment. Wang et al. (2009) proposed a solution for recognizing multi-users activities in a smart home, using dense sensing approach. Another work presented by Singla et al. (2010), proposed HMM model for recognizing the activities of two residents. Augimeri et al. (2011) also presented a Signal Processing in Node Environment (SPINE) based middleware for collaborative body sensor networks which can enable wearable systems for HAR with multiple subjects in pervasive environments. But still, this problem is not solved completely and requires further research.

Concurrent Activities. Existing work is based on the assumption that a person will perform only one activity at a time. It can be true for ambulatory activities such as running and walking. But there are many situations in which users are performing concurrent activities i.e., multiple activities at the same time. For example, a person can be reading a newspaper while drinking coffee or having lunch while watching TV. Very little research has been done in this area and there is a potential for further work in this area. Further details about this challenge can be found in (Helaoui et al., 2011).

Variability. Present solutions for activity recognition face the issue of variability. Variability means that if the same activity is performed by a different person or the same activity is performed by the same person at a different pace. Many existing systems cannot deal with variability problem i.e., if the same activity is performed by a different person, the system's recognition accuracy is very low. Also, if the same person performs the same activity in a different style, the system's performance degrades. Modern systems should be robust and should deal with the issue of variability. It is still an open issue and needs further research.

5.2. Intelligent solutions

Current solutions follow a traditional approach in which a model is trained for some activities and it can then recognize only that type of activities. Also, current HAR solutions are capable of recognizing only the past activities. But in today's world, there is a need for smart solutions which can detect normal activities (for which the model is trained) as well as abnormal activities and are also capable of predicting the future activities. Following are the two areas which need further research for making HAR solutions intelligent.

Detecting Abnormal Activities. Existing solutions are focused on recognizing activities which are normal daily life activities such as sitting, standing, sleeping, walking, and eating. Recognition of these activities is important but that is not the whole purpose of activity recognition, especially for those applications which intend to identify abnormal activities. Detection of abnormal activities is of great importance in applications like security and healthcare. In security and surveillance, any abnormal activity is suspicious and should be reported immediately so that proper action can be taken. In healthcare, the detection of abnormal activity is very important for remote monitoring. If anything abnormal is detected, proper assistance should be provided. Recognition of abnormal activities is a challenging task due to many reasons. There is no single definition of abnormal activity and many interpretations are available to define abnormal activity. According to (Yin et al., 2008), abnormal activities occur rarely and are not expected in advance. Another hurdle in recognition of abnormal activities is the availability of data. For normal activities, a substantial amount of data is available to train the model but data for abnormal activity is very scared. Some solutions have been provided to recognize abnormal activities. Dhiman and Vishwakarma (2019) summarizes state-of-the-art techniques for recognizing abnormal human activities but still there is a need for further research in this area.

Predicting Next Activity. Almost all of the existing solutions can recognize the past activity i.e., when activity happens, the given system can recognize it. This means that current HAR system can recognize previous activities, which is helpful in many situations. But an interesting thing would be that if the HAR system can predict future activity i.e., what will happen next. This function is very important, especially in applications like fall detection/prevention. If a HAR system can tell the caregivers that a patient or an elder person is about to fall, fall can be prevented which is very helpful. A possible research direction would be to make the HAR system not only recognize the current and past activities but should also predict future activities.

5.3. Experimental setup

Significant research work has been conducted for HAR but still dealing with environmental interference is a big challenge. Also, the existing solutions are labor intensive and need extensive training before testing. Currently, there is no benchmark (in terms of data and experimental setup) for evaluating the performance of HAR techniques. These areas offer future research opportunities and are discussed in this section.

Requirement of Extensive Training. Almost all the solutions proposed, required training. Getting training data is not an easy job, especially in the case of elder people. Many of these solutions are heavily dependent on training and required to be trained again if the environment is changed. For example, if you need to implement it in a different room or home, you have to train it again. Also, the training time for some solutions is too long and need to be trained offline. A good solution for activity recognition should be independent of the environment i.e., once trained, it should work in any similar environment. This aspect of HAR system needs further research.

Environmental Interference. Although the research in human activity recognition using device-free approach has become very advanced in many ways, still, dealing with environmental interference is an issue. Most of the solutions proposed are vulnerable to environmental factors and their performance is affected by the outside world. The device-free approach is getting more attention because of its advantage as users are not required to carry any device with them but dealing with environmental interference is still an open issue and requires more research to minimize its influence.

Need for Standard Testing Setup. Solutions proposed for different sub-areas of activity recognition use different approaches. The experimental setup is different and the environment is different. Therefore, it is very difficult to compare these techniques for evaluation. There is no standard set up or benchmark (e.g., benchmark data sets in data mining) for evaluating the performance of a solution. There is a need for such a system, through which the performance of any new or existing solution can be evaluated.

5.4. Security of the system

In the surveyed techniques of the human activity recognition system, almost all the solutions have ignored the security aspect. The proposed solution are more focused on accuracy, cost, and scalability, while ignoring the aspect of security. Security is an important aspect of the human activity recognition system. Information about the activity of a person should be available to authorized people only. Discussion about accessibility, privacy, and security of the information about human activities is missing from the literature and this area needs to be investigated.

6. Discussion

In this article, we discussed and analyzed different aspects of human activity recognition. We presented a review of the overall work conducted in different areas of the activity recognition with main focus on device-free approaches. As obvious from section 4, different approaches have been used for recognizing the activities of human. We found that the comparison of these techniques is difficult due to the following reasons.

Main Focus. We found that comparing these techniques is difficult due to various reasons. As shown in Fig. 1, we have divided human activity recognition research into different sub-areas. All these sub-areas come under the umbrella of activity recognition. We have provided a literature review for all these sub-areas and have covered different techniques proposed in these sub-areas. The main focus of the work discussed varies, as some of them focus on one sub-area while others focus on another sub-area. Because of this, it is difficult to compare all these techniques. For example, comparing a technique for gesture recognition with a technique for ADL recognition is difficult. In gesture recognition, the processing time is very important and the solution needs to provide the results in real time while in the case of ADL, time is not a big issue instead importance is given to the accuracy of the results. However, we have tried to provide the readers, a comparison of these techniques on some common ground.

Approach. Different techniques use different hardware. For example, some techniques use wearable devices while others use device-free approach, some use sensors attached to the objects while others use Wi-Fi. Also, these solutions use different classification methods (machine learning tools). Comparing such solutions, which are based on completely different approaches is not an easy job. Every approach has its pros and cons but comparing these approaches with others, is challenging. We tried our best to provide a detailed comparison to the reader.

Experimental Setup. There is no universal setup for evaluating these techniques. Experimental setups used in different solutions are different from each other. For example, some solutions use wearable devices and perform experiments in a room while other approaches use tagged-objects and perform experiments in a kitchen. Comparing solutions with the different experimental setup is challenging because accuracy and other factors depend on the experimental environment.

Missing Details. A major issue that we faced in our literature review, is the missing details, as you can see from Tables 9 and 10 and 14–17. There are some papers which lack information about very important things. For example, most of the papers lack the discussion about time and space complexity of their techniques. There is no discussion about the latency of the proposed approach which is a very important factor in activity recognition. Some papers are missing the details about the classifier (machine learning algorithm) used in the approach. There are papers in which there is confusion about the working of the proposed technique such as, whether the proposed technique is real-time or not and off-line or online. Authors should try to provide detailed information about everything involved in their approach. They should include a discussion section to provide details such as latency, complexity, and limitation.

7. Conclusion

In this paper, we have presented a comprehensive overview of the research works in human activity recognition. Unlike other surveys which focus only on a single type of activity, we covered almost all the sub-fields of activity recognition. We divided the research in activity recognition into three main categories: action-based, motion-based and interaction-based. We further divided these into 10 different sub-categories and presented the latest literature for each category, over the last decade. The main focus of this survey is *device-free approaches* with a focus on RFID technology. We discussed the latest literature using device-free approaches for human activity recognition and provided a comprehensive comparison of the different techniques included in the literature review. We also discussed some important open research issues in activity recognition and hope to stimulate further research in this important research and development area.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Adame, T., Bel, A., Carreras, A., Meli-Segu, J., Oliver, M., Pous, R., 2018. Cuidats: an rfidwsn hybrid monitoring system for smart health care environments. Future Generat. Comput. Syst. 78, 602–615.

Agrawal, R., Imielinski, T., Swami, A., 1993. Mining association rules between sets of items in large databases. In: Acm Sigmod Record. ACM, pp. 207–216.

Ahmed, H.F.T., Ahmad, H., Aravind, C., 2020. Device free human gesture recognition using wi-fi csi: a survey. Eng. Appl. Artif. Intell. 87, 103281.

Aldeer, M., Alaziz, M., Ortiz, J., Howard, R.E., Martin, R.P., 2019. A sensing-based framework for medication compliance monitoring. In: Proceedings of the 1st ACM International Workshop on Device-free Human Sensing, pp. 52–56.

Ali, M.H., Kamaruzaman, F., Rahman, M.A., Shafie, A.A., 2015. Automated secure room system. In: 4th International Conference on Software Engineering and Computer Systems (ICSECS). IEEE, pp. 73–78.

Alsinglawi, B., Nguyen, Q.V., Gunawardana, U., Maeder, A., Simoff, S., 2017. Rfid systems in healthcare settings and activity of daily living in smart homes: a review. E-Health Telecommun. Syst. Netw. 6, 1.

Amendola, S., Lodato, R., Manzari, S., Occhiuzzi, C., Marrocco, G., 2014. Rfid technology for iot-based personal healthcare in smart spaces. IEEE Internet of Things J. 1, 144–152.

Anitha, G., Priya, S.B., 2018. Posture based health monitoring and unusual behavior recognition system for elderly using dynamic bayesian network. Cluster Comput. 18.

Ansari, A.N., Sedky, M., Sharma, N., Tyagi, A., 2015. An internet of things approach for motion detection using raspberry pi. In: International Conference on Intelligent Computing and Internet of Things. IEEE, pp. 131–134.

Asadzadeh, P., Kulik, L., Tanin, E., 2012. Gesture recognition using rfid technology. Personal Ubiquitous Comput. 16, 225–234.

Augimeri, A., Fortino, G., Galzarano, S., Gravina, R., 2011. Collaborative body sensor networks. In: 2011 IEEE International Conference on Systems, Man, and Cybernetics. IEEE, pp. 3427–3432.

Avrahami, D., Patel, M., Yamaura, Y., Kratz, S., 2018. Below the surface: unobtrusive activity recognition for work surfaces using rf-radar sensing. In: 23rd International Conference on Intelligent User Interfaces. ACM, pp. 439–451.

Banno, W., Shinomiya, N., 2019. Monitoring system for the elderly on staircase using passive rfid sensor tags. In: IEEE 8th Global Conference on Consumer Electronics (GCCE). IEEE, pp. 816–817.

Benaissa, B., Kppen, M., Yoshida, K., 2017. Activity and emotion recognition for elderly health monitoring. Int. J. Affect. Eng. IJAED1700020.

Blanke, U., Schiele, B., 2010. Remember and transfer what you have learned-recognizing composite activities based on activity spotting. In: International Symposium on Wearable Computers (ISWC). IEEE, pp. 1–8.

Bouchard, K., Bouzouane, A., Bouchard, B., 2014. Gesture recognition in smart home using passive rfid technology. In: 7th International Conference on Pervasive Technologies Related to Assistive Environments. ACM, p. 12.

Buettner, M., Prasad, R., Philipose, M., Wetherall, D., 2009. Recognizing daily activities with rfid-based sensors. In: 11th International Conference on Ubiquitous Computing. ACM, pp. 51–60.

Candes, E.J., Sing-Long, C.A., Trzasko, J.D., 2013. Unbiased risk estimates for singular value thresholding and spectral estimators. IEEE Trans. Signal Process. 61, 4643–4657.

Castro, D., Coral, W., Rodriguez, C., Cabra, J., Colorado, J., 2017. Wearable-based human activity recognition using and iot approach. J. Sens. Actuator Netw. 6, 28.

Center for Disease Control and Prevention, 2018. Web-based Injury Statistics Query and Reporting System. https://www.cdc.gov/homeandrecreationalsafety/falls/fallcost.html. Online. (Accessed 3 July 2018).

Chang, L., Chen, X., Wang, Y., Fang, D., Wang, J., Xing, T., Tang, Z., 2017. Fitloc: fine-grained and low-cost device-free localization for multiple targets over various areas. IEEE/ACM Trans. Netw. 25, 1994–2007.

Chen, L., Hoey, J., Nugent, C.D., Cook, D.J., Yu, Z., 2012. Sensor-based activity recognition. IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.) 42, 790–808.

Chen, L.H., Liu, K.C., Hsieh, C.Y., Chan, C.T., 2017. Drinking gesture spotting and identification using single wrist-worn inertial sensor. In: International Conference on Applied System Innovation (ICASI). IEEE, pp. 299–302.

Cheng, S.H., 2014. An intelligent fall detection system using triaxial accelerometer integrated by active rfid. In: International Conference on Machine Learning and Cybernetics (ICMLC). IEEE, pp. 517–522.

Cheng, Y.K., Chang, R.Y., 2017. Device-free indoor people counting using wi-fi channel state information for internet of things. In: IEEE Global Communications Conference (GLOBECOM). IEEE, pp. 1–6.

Cheok, M.J., Omar, Z., Jaward, M.H., 2019. A review of hand gesture and sign language recognition techniques. Int. J. Mach. Learn. Cybernet. 10, 131–153.

Chernbumroong, S., Cang, S., Atkins, A., Yu, H., 2013. Elderly activities recognition and classification for applications in assisted living. Expert Syst. Appl. 40, 1662–1674.

Chua, S.L., Marsland, S., Guesgen, H.W.,. Behaviour recognition from sensory streams in smart environments, in: Australasian Joint Conference on Artificial Intelligence, Springer. pp. 666675.

Cianca, E., De Sanctis, M., Di Domenico, S., 2017. Radios as sensors. IEEE Internet of Things J. 4, 363–373.

Cornacchia, M., Ozcan, K., Zheng, Y., Velipasalar, S., 2017. A survey on activity detection and classification using wearable sensors. IEEE Sensor. J. 17, 386–403.

Daniels, M., Muldawer, K., Schlessman, J., Ozer, B., Wolf, W.,. Real-time human motion detection with distributed smart cameras, in: First ACM/IEEE International Conference on Distributed Smart Cameras (ICDSC07)., IEEE. pp. 187194.

Dhiman, C., Vishwakarma, D.K., 2019. A review of state-of-the-art techniques for abnormal human activity recognition. Eng. Appl. Artif. Intell. 77, 21–45.

Ding, H., Han, J., Liu, A.X., Zhao, J., Yang, P., Xi, W., Jiang, Z., 2015. Human object estimation via backscattered radio frequency signal. In: IEEE Conference on Computer Communications (INFOCOM). IEEE, pp. 1652–1660.

Ding, H., Qian, C., Han, J., Wang, G., Xi, W., Zhao, K., Zhao, J., 2017. Rfipad: enabling cost-efficient and device-free in-air handwriting using passive tags. In: IEEE 37th International Conference on Distributed Computing Systems (ICDCS). IEEE, pp. 447–457.

Ding, J., Wang, Y., 2019. Wifi csi-based human activity recognition using deep recurrent neural network. IEEE Access 7, 174257–174269.

Fortino, G., Galzarano, S., Gravina, R., Li, W., 2015. A framework for collaborative computing and multi-sensor data fusion in body sensor networks. Inf. Fusion 22, 50–70.

Fouquet, Y., Franco, C., Vuillerme, N., Demongeot, J., 2009. Behavioral telemonitoring of the elderly at home. Int. J. Assist. Robot. Syst. 10, 35–49.

Gani, M.O., Fayezeen, T., Povinelli, R.J., Smith, R.O., Arif, M., Kattan, A.J., Ahamed, S.I., 2019. A light weight smartphone based human activity recognition system with high accuracy. J. Netw. Comput. Appl. 141, 59–72.

Garg, P., Aggarwal, N., Sofat, S., 2009. Vision based hand gesture recognition. World Acad. Sci. Eng. Technol. 49, 972–977.

Gia, T.N., Sarker, V.K., Tcarenko, I., Rahmani, A.M., Westerlund, T., Liljeberg, P., Tenhunen, H., 2018. Energy efficient wearable sensor node for iot-based fall detection systems. Microprocess. Microsyst. 56, 34–46.

Gravina, R., Alinia, P., Ghasemzadeh, H., Fortino, G., 2017. Multi-sensor fusion in body sensor networks: state-of-the-art and research challenges. Inf. Fusion 35, 68–80.

Gu, Y., Zhan, J., Ji, Y., Li, J., Ren, F., Gao, S., 2017. Mosense: an rf-based motion detection system via off-the-shelf wifi devices. IEEE Internet of Things J. 4, 2326–2341.
Guo, L., Wang, L., Lin, C., Liu, J., Lu, B., Fang, J., Liu, Z., Shan, Z., Yang, J., Guo, S., 2019. Wiar: a public dataset for wifi-based activity recognition. IEEE Access 7, 154935–154945.
Han, J., Ding, H., Qian, C., Xi, W., Wang, Z., Jiang, Z., Shangguan, L., Zhao, J., 2016a. Cbid: a customer behavior identification system using passive tags. IEEE/ACM Trans. Netw. 24, 2885–2898.
Han, J., Pei, J., Yin, Y.,. Mining frequent patterns without candidate generation, in: ACM Sigmod Record, ACM. pp. 112.
Han, J., Qian, C., Wang, X., Ma, D., Zhao, J., Xi, W., Jiang, Z., Wang, Z., 2016b. Twins: device-free object tracking using passive tags. IEEE/ACM Trans. Netw. 24, 1605–1617.
Hazra, S., Santra, A., 2019. Short-range radar-based gesture recognition system using 3d cnn with triplet loss. IEEE Access 7, 125623–125633.
Hein, A., Kirste, T., 2009. A hybrid approach for recognizing adls and care activities using inertial sensors and rfid. In: International Conference on Universal Access in Human-Computer Interaction. Springer, pp. 178–188.
Helaoui, R., Niepert, M., Stuckenschmidt, H., 2011. Recognizing interleaved and concurrent activities: a statistical-relational approach. In: IEEE International Conference on Pervasive Computing and Communications (PerCom). IEEE, pp. 1–9.
Herath, S., Harandi, M., Porikli, F., 2017. Going deeper into action recognition: a survey. Image Vis Comput. 60, 4–21.
Hoque, E., Stankovic, J., 2012. Aalo: activity recognition in smart homes using active learning in the presence of overlapped activities. In: 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth). IEEE, pp. 139–146.
Hou, Y.L., Pang, G.K., 2011. People counting and human detection in a challenging situation. IEEE Trans. Syst. Man Cybern. Syst. Hum. 41, 24–33.
Hussain, Z., Sagar, S., Zhang, W.E., Sheng, Q.Z., 2019. A cost-effective and non-invasive system for sleep and vital signs monitoring using passive rfid tags. In: Proceedings of the 16th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, pp. 153–161.
Ignatov, A., 2018. Real-time human activity recognition from accelerometer data using convolutional neural networks. Appl. Soft Comput. 62, 915–922.
Itkarkar, R.R., Nandi, A., Mane, B., 2017. Contour-Based Real-Time Hand Gesture Recognition for Indian Sign Language. Springer, pp. 683–691.
Jatesiktat, P., Ang, W.T., 2017. An elderly fall detection using a wrist-worn accelerometer and barometer. In: 39th Annual International Conference of Engineering in Medicine and Biology Society (EMBC). IEEE, pp. 125–130.
Jayatilaka, A., Ranasinghe, D.C., 2017. Real-time fluid intake gesture recognition based on batteryless uhf rfid technology. Pervasive Mob. Comput. 34, 146–156.
Ji, H., Xie, L., Wang, C., Yin, Y., Lu, S., 2015. Crowdsensing: a crowd-sourcing based indoor navigation using rfid-based delay tolerant network. J. Netw. Comput. Appl. 52, 79–89.
Junior, J.C.S.J., Musse, S.R., Jung, C.R., 2010. Crowd analysis using computer vision techniques. IEEE Signal Process. Mag. 27, 66–77.
Kianoush, S., Savazzi, S., Vicentini, F., Rampa, V., Giussani, M., 2017. Device-free rf human body fall detection and localization in industrial workplaces. IEEE Internet of Things J. 4, 351–362.
Ko, C.H., 2017. Accessibility of radio frequency identification technology in facilities maintenance. J. Eng. Proj. Prod. Manag. 7.
Kriara, L., Alsup, M., Corbellini, G., Trotter, M., Griffin, J.D., Mangold, S., 2013. Rfid shakables: pairing radio-frequency identification tags with the help of gesture recognition. In: 9th ACM Conference on Emerging Networking Experiments and Technologies. ACM, pp. 327–332.
Kuo, J.Y., Fan, G.D., Lai, T.Y., 2016. People counting base on head and shoulder information. In: IEEE International Conference on Knowledge Engineering and Applications (ICKEA). IEEE, pp. 52–55.
Landt, J., 2005. The history of rfid. IEEE Potent. 24, 8–11.
Lara, O.D., Labrador, M.A., 2013. A survey on human activity recognition using wearable sensors. IEEE Commun. Surv. Tutor. 15, 1192–1209.
Li, H., Brockmeyer, E., Carter, E.J., Fromm, J., Hudson, S.E., Patel, S.N., Sample, A., 2016. Paperid: a technique for drawing functional battery-free wireless interfaces on paper. In: Conference on Human Factors in Computing Systems (CHI), ACM, pp. 5885–5896.
Li, H., Ye, C., Sample, A.P., 2015. Idsense: a human object interaction detection system based on passive uhf rfid. In: 33rd Annual ACM Conference on Human Factors in Computing Systems. ACM, pp. 2555–2564.
Li, L., Bai, R., Xie, B., Peng, Y., Wang, A., Wang, W., Jiang, B., Liang, J., Chen, X., 2018. R&p: an low-cost device-free activity recognition for e-health. IEEE Access 6, 81–90.
Li, X., He, Y., Jing, X., 2019. A survey of deep learning-based human activity recognition in radar. Rem. Sens. 11, 1068.
Li, X., Zhang, D., Lv, Q., Xiong, J., Li, S., Zhang, Y., Mei, H., 2017. Indotrack: device-free indoor human tracking with commodity wi-fi. In: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 1, p. 72.
Ligorio, G., Sabatini, A.M., 2015. A novel kalman filter for human motion tracking with an inertial-based dynamic inclinometer. IEEE (Inst. Electr. Electron. Eng.) Trans. Biomed. Eng. 62, 2033–2043.
Liu, F.T., Wang, Y.T., Ma, H.P., 2017a. Gesture recognition with wearable 9-axis sensors. In: IEEE International Conference on Communications (ICC). IEEE, pp. 1–6.
Liu, G., Li, Y., Li, D., Ma, X., Li, F., 2015. Romd: robust device-free motion detection usin phy layer information. In: 12th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON). IEEE, pp. 154–156.
Liu, J., Chen, X., Chen, S., Liu, X., Wang, Y., Chen, L., 2019. Tagsheet: sleeping posture recognition with an unobtrusive passive tag matrix. In: IEEE International Conference on Computer Communications (INFOCOM). IEEE, pp. 874–882.
Liu, K.C., Yen, C.Y., Chang, L.H., Hsieh, C.Y., Chan, C.T., 2017b. Wearable sensor-based activity recognition for housekeeping task. In: IEEE 14th International Conference on Wearable and Implantable Body Sensor Networks (BSN). IEEE, pp. 67–70.
Liu, Y., Zhao, Y., Chen, L., Pei, J., Han, J., 2012. Mining frequent trajectory patterns for activity monitoring using radio frequency tag arrays. IEEE Trans. Parallel Distr. Syst. 23, 2138–2149.
Ma, J., Wang, H., Zhang, D., Wang, Y., Wang, Y., 2016. A survey on wi-fi based contactless activity recognition. In: Intl IEEE Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCom/IoP/SmartWorld). IEEE, pp. 1086–1091.
Ma, X., Zhao, Y., Zhang, L., Gao, Q., Pan, M., Wang, J., 2019. Practical device-free gesture recognition using wifi signals based on meta-learning. IEEE Trans. Indust. Inform..
Maret, Y., Oberson, D., Gavrilova, M., 2018. Real-time embedded system for gesture recognition. In: IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, pp. 30–34.
Markopoulos, P.P., Zlotnikov, S., Ahmad, F., 2019. Adaptive radar-based human activity recognition with l1-norm linear discriminant analysis. IEEE J. Electromagn. RF Microwav. Med. Biol. 3, 120–126.
Minvielle, L., Atiq, M., Serra, R., Mougeot, M., Vayatis, N., 2017. Fall detection using smart floor sensor and supervised learning. In: 39th Annual International Conference of Engineering in Medicine and Biology Society (EMBC). IEEE, pp. 3445–3448.
Moghavvemi, M., Seng, L.C., 2004. Pyroelectric infrared sensor for intruder detection. In: IEEE Region 10 Conference (TENCON). IEEE, pp. 656–659.
Moriya, K., Nakagawa, E., Fujimoto, M., Suwa, H., Arakawa, Y., Kimura, A., Miki, S., Yasumoto, K., 2017. Daily living activity recognition with echonet lite appliances and motion sensors. In: IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops). IEEE, pp. 437–442.
Murad, A., Pyun, J.Y., 2017. Deep recurrent neural networks for human activity recognition. Sensors 17, 2556.
Noury, N., Fleury, A., Rumeau, P., Bourke, A., Laighin, G., Rialle, V., Lundy, J., 2007. Fall detection-principles and methods. In: 29th Annual International Conference of Engineering in Medicine and Biology Society, (EMBS). IEEE, pp. 1663–1666.
Oguntala, G.A., Abd-Alhameed, R.A., Ali, N.T., Hu, Y.F., Noras, J.M., Eya, N.N., Elfergani, I., Rodriguez, J., 2019. Smartwall: novel rfid-enabled ambient human activity recognition using machine learning for unobtrusive health monitoring. IEEE Access 7, 68022–68033.
Ohn-Bar, E., Trivedi, M.M., 2014. Hand gesture recognition in real time for automotive interfaces: a multimodal vision-based approach and evaluations. IEEE Trans. Intell. Transport. Syst. 15, 2368–2377.
Parada, R., Melia-Segui, J., Morenza-Cinos, M., Carreras, A., Pous, R., 2015. Using rfid to detect interactions in ambient assisted living environments. IEEE Intell. Syst. 30, 16–22.
Parada, R., Nur, K., Melia-Segui, J., Pous, R., 2016. Smart surface: rfid-based gesture recognition using k-means algorithm. In: 12th International Conference on Intelligent Environments (IE). IEEE, pp. 111–118.
Pham, C., Olivier, P., 2009. Slice&dice: recognizing food preparation activities using embedded accelerometers. In: European Conference on Ambient Intelligence. Springer, pp. 34–43.
Pires, I.M.S., Garcia, N.M., Pombo, N., Flrez-Revuelta, F., Zdravevski, E., Spinsante, S., 2018. Machine Learning Algorithms for the Identification of Activities of Daily Living Using Mobile Devices: A Comprehensive Review.
Popa, M., Koc, A.K., Rothkrantz, L.J., Shan, C., Wiggers, P., 2011. Kinect sensing of shopping related actions. In: International Joint Conference on Ambient Intelligence. Springer, pp. 91–100.
Popa, M., Rothkrantz, L., Yang, Z., Wiggers, P., Braspenning, R., Shan, C., 2010. Analysis of shopping behavior based on surveillance system. In: IEEE International Conference on Systems Man and Cybernetics (SMC). IEEE, pp. 2512–2519.
Pradhan, S., Chai, E., Sundaresan, K., Qiu, L., Khojastepour, M.A., Rangarajan, S., 2017. Rio: a pervasive rfid-based touch gesture interface. In: 23rd Annual International Conference on Mobile Computing and Networking. ACM, pp. 261–274.
Putra, I., Brusey, J., Gaura, E., Vesilo, R., 2017. An event-triggered machine learning approach for accelerometer-based fall detection. Sensors 18, 20.
Qian, K., Wu, C., Yang, Z., Liu, Y., Jamieson, K., 2017. Widar: decimeter-level passive tracking via velocity monitoring with commodity wi-fi. In: 18th ACM International Symposium on Mobile Ad Hoc Networking and Computing. ACM, p. 6.
Queiros, A., Dias, A., Silva, A.G., Rocha, N.P., 2017. Ambient assisted living and health-related outcomes - a systematic literature review. In: Informatics, Multidisciplinary Digital Publishing Institute, p. 19.
Rashidi, P., Mihailidis, A., 2013. A survey on ambient-assisted living tools for older adults. IEEE J. Biomed. Health inform. 17, 579–590.
Rescio, G., Leone, A., Siciliano, P., 2018. Supervised machine learning scheme for electromyography-based pre-fall detection system. Expert Syst. Appl. 100, 95–105.
Roggen, D., Calatroni, A., Rossi, M., Holleczek, T., Frster, K., Trster, G., Lukowicz, P., Bannach, D., Pirkl, G., Ferscha, A., et al., 2010. Collecting complex activity datasets in highly rich networked sensor environments. In: 2010 Seventh International Conference on Networked Sensing Systems (INSS). IEEE, pp. 233–240.
Ronao, C.A., Cho, S.B., 2016. Human activity recognition with smartphone sensors using deep learning neural networks. Expert Syst. Appl. 59, 235–244.

Ruan, W., Sheng, Q.Z., Yao, L., Gu, T., Ruta, M., Shangguan, L., 2016. Device-free indoor localization and tracking through human-object interactions. In: IEEE 17th International Symposium on World of Wireless, Mobile and Multimedia Networks (WoWMoM). IEEE, pp. 1–9.
Ruan, W., Sheng, Q.Z., Yao, L., Li, X., Falkner, N.J., Yang, L., 2018. Device-free human localization and tracking with uhf passive rfid tags: a data-driven approach. J. Netw. Comput. Appl. 104, 78–96.
Ruan, W., Yao, L., Sheng, Q.Z., Falkner, N., Li, X., Gu, T., 2015. Tagfall: towards unobstructive fine-grained fall detection based on uhf passive rfid tags. In: 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MOBIQUITOUS). ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), pp. 140–149.
Ruan, W., Yao, L., Sheng, Q.Z., Falkner, N.J., Li, X., 2014. Tagtrack: device-free localization and tracking using passive rfid tags. In: 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), pp. 80–89.
Scholz, M., Sigg, S., Schmidtke, H.R., Beigl, M., 2011. Challenges for device-free radio-based activity recognition. In: Workshop on Context Systems, Design, Evaluation and Optimisation.
Shangguan, L., Zhou, Z., Jamieson, K., 2017. Enabling gesture-based interactions with objects. In: 15th Annual International Conference on Mobile Systems, Applications, and Services. ACM, pp. 239–251.
Sheng, Q.Z., Li, X., Zeadally, S., 2008. Enabling next-generation RFID applications: solutions and challenges. Computer 41, 21–28.
Shoaib, M., Bosch, S., Incel, O.D., Scholten, H., Havinga, P.J., 2015. A survey of online activity recognition using mobile phones. Sensors 15, 2059–2085.
Shukri, S., Kamarudin, L.M., 2017. Device free localization technology for human detection and counting with rf sensor networks: a review. J. Netw. Comput. Appl. 97, 157–174.
Siddiqui, N., Chan, R.H., 2017. A wearable hand gesture recognition device based on acoustic measurements at wrist. In: 39th Annual International Conference of Engineering in Medicine and Biology Society (EMBC). IEEE, pp. 4443–4446.
Singh, M., Baruah, R.D., Nair, S.B., 2016. A voting-based sensor fusion approach for human presence detection. In: International Conference on Intelligent Human Computer Interaction. Springer, pp. 195–206.
Singha, J., Roy, A., Laskar, R.H., 2018. Dynamic hand gesture recognition using vision-based approach for humancomputer interaction. Neural Comput. Appl. 29, 1129–1141.
Singla, G., Cook, D.J., Schmitter-Edgecombe, M., 2010. Recognizing independent and joint activities among multiple residents in smart environments. J. Ambi Intell. Human. Comput. 1, 57–63.
Soliman, M.A., Alrashed, M., 2018. An rfid based activity of daily living for elderly with alzheimer's. Internet of Things (IoT) Technol. HealthCare 54.
Sreekanth, N., Narayanan, N., 2017. Dynamic gesture recognition - a machine vision based approach. In: International Conference on Signal, Networks, Computing, and Systems. Springer, pp. 105–115.
Stikic, M., Huynh, T., Van Laerhoven, K., Schiele, B., 2008. Adl recognition based on the combination of rfid and accelerometer sensing. In: 2nd International Conference on Pervasive Computing Technologies for Healthcare, (PervasiveHealth). IEEE, pp. 258–263.
Teixeira, T., Dublon, G., Savvides, A., 2010. A survey of human-sensing: methods for detecting presence, count, location, track, and identity. ACM Comput. Surv. 5, 59–69.
Tenorth, M., Bandouch, J., Beetz, M., 2009. The tum kitchen data set of everyday manipulation activities for motion tracking and action recognition. In: 2009 IEEE 12th International Conference on Computer Vision Workshops, ICCV Workshops. IEEE, pp. 1089–1096.
Torres, R.L.S., Wickramasinghe, A., Pham, V.N., Ranasinghe, D.C., 2015. What if your floor could tell someone you fell? a device free fall detection method. In: Conference on Artificial Intelligence in Medicine in Europe. Springer, pp. 86–95.
Torres-Huitzil, C., Alvarez-Landero, A., 2015. Accelerometer-based human activity recognition in smartphones for healthcare services. In: Mobile Health. Springer, pp. 147–169.
Tsinganos, P., Skodras, A., 2017. A smartphone-based fall detection system for the elderly. In: 10th International Symposium on Image and Signal Processing and Analysis (ISPA). IEEE, pp. 53–58.
Vrigkas, M., Nikou, C., Kakadiaris, I.A., 2015. A review of human activity recognition methods. Front. Robot. AI 2, 28.
Wang, H., Zhang, D., Wang, Y., Ma, J., Wang, Y., Li, S., 2017a. Rt-fall: a real-time and contactless fall detection system with commodity wifi devices. IEEE Trans. Mobile Comput. 16, 511–526.
Wang, J., Chen, Y., Hao, S., Peng, X., Hu, L., 2017b. Deep Learning for Sensor-Based Activity Recognition: A Survey. arXiv preprint arXiv:1707.03502.
Wang, J., Chen, Y., Hao, S., Peng, X., Hu, L., 2019. Deep learning for sensor-based activity recognition: a survey. Pattern Recogn. Lett. 119, 3–11.
Wang, J., Vasisht, D., Katabi, D., 2014. Rf-idraw: virtual touch screen in the air using rf signals. In: ACM SIGCOMM Computer Communication Review. ACM, pp. 235–246.
Wang, L., Gu, T., Tao, X., Lu, J., 2009. Sensor-based human activity recognition in a multi-user scenario. In: European Conference on Ambient Intelligence. Springer, pp. 78–87.
Wang, L., Gu, T., Tao, X., Lu, J., 2017c. Toward a wearable rfid system for real-time activity recognition using radio patterns. IEEE Trans. Mobile Comput. 16, 228–242.
Wang, S., Zhou, G., 2015. A review on radio based activity recognition. Digit. Commun. Netw. 1, 20–29.
Wang, Y., Wu, K., Ni, L.M., 2017d. Wifall: device-free fall detection by wireless networks. IEEE Trans. Mobile Comput. 16, 581–594.
Wang, Z., Xiao, F., Ye, N., Wang, R., Yang, P., 2017e. A see-through-wall system for device-free human motion sensing based on battery-free rfid. ACM Trans. Embed. Comput. Syst. 17, 6.
Wickramasinghe, A., Ranasinghe, D.C., 2015. Ambulatory monitoring using passive computational rfid sensors. IEEE Sensor. J. 15, 5859–5869.
Wickramasinghe, A., Torres, R.L.S., Ranasinghe, D.C., 2017. Recognition of falls using dense sensing in an ambient assisted living environment. Pervasive Mob. Comput. 34, 14–24.
Wu, H., Gao, C., Cui, Y., Wang, R., 2018. Multipoint infrared laser-based detection and tracking for people counting. Neural Comput. Appl. 29, 1405–1416.
Wu, Y., Ranasinghe, D.C., Sheng, Q.Z., Zeadally, S., Yu, J., 2011. Rfid enabled traceability networks: a survey. Distributed Parallel Databases 29, 397–443.
Xiao, F., Miao, Q., Xie, X., Sun, L., Wang, R., 2018. Shmo: a seniors health monitoring system based on energy-free sensing. Comput. Network..
Xiao, J., Wu, K., Yi, Y., Wang, L., Ni, L.M., 2012. Fimd: fine-grained device-free motion detection. In: 18th International Conference on Parallel and Distributed Systems (ICPADS). IEEE, pp. 229–235.
Xie, L., Wang, C., Liu, A.X., Sun, J., Lu, S., 2018. Multi-touch in the air: concurrent micromovement recognition using rf signals. IEEE/ACM Trans. Netw. 26, 231–244.
Xu, X., Tang, J., Zhang, X., Liu, X., Zhang, H., Qiu, Y., 2013. Exploring techniques for vision based human activity recognition: methods, systems, and evaluation. Sensors 13, 1635–1650.
Yan, H., Zhang, Y., Wang, Y., Xu, K., 2019. Wiact: a passive wifi-based human activity recognition system. IEEE Sensor. J. 20, 296–305.
Yan, Y., Ricci, E., Liu, G., Sebe, N., 2015. Egocentric daily activity recognition via multitask clustering. IEEE Trans. Image Process. 24, 2984–2995.
Yang, J., Lee, J., Choi, J., 2011. Activity recognition based on rfid object usage for smart mobile devices. J. Comput. Sci. Technol. 26, 239–246.
Yang, L., Lin, Q., Li, X., Liu, T., Liu, Y., 2015. See through walls with cots rfid system!. In: 21st Annual International Conference on Mobile Computing and Networking. ACM, pp. 487–499.
Yao, L., Sheng, Q.Z., Li, X., Gu, T., Tan, M., Wang, X., Wang, S., Ruan, W., 2018. Compressive representation for device-free activity recognition with passive rfid signal strength. IEEE Trans. Mobile Comput. 17, 293–306.
Yao, L., Sheng, Q.Z., Ruan, W., Gu, T., Li, X., Falkner, N., Yang, Z., 2015. Rf-care: device-free posture recognition for elderly people using a passive rfid tag array. In: 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), pp. 120–129.
Yao, Y., Fu, Y., 2014. Contour model-based hand-gesture recognition using the kinect sensor. IEEE Trans. Circ. Syst. Video Technol. 24, 1935–1944.
Ye, S., Zeng, H., Fan, J., Wang, X., 2014. Lsi-rec: a link state indicator based gesture recognition scheme in a rfid system. In: 9th Conference on Industrial Electronics and Applications (ICIEA). IEEE, pp. 406–411.
Yin, J., Yang, Q., Pan, J.J., 2008. Sensor-based abnormal human-activity detection. IEEE Trans. Knowl. Data Eng. 20, 1082–1090.
Yu, Y., Wang, D., Zhao, R., Zhang, Q., 2019. Rfid based real-time recognition of ongoing gesture with adversarial learning. In: Proceedings of the 17th Conference on Embedded Networked Sensor Systems, pp. 298–310.
Zeng, Y., Pathak, P.H., Mohapatra, P., 2015. Analyzing shopper's behavior through wifi signals. In: 2nd Workshop on Workshop on Physical Analytics. ACM, pp. 13–18.
Zhang, D., Wang, H., Wang, Y., Ma, J., 2015. Anti-fall: A Non-intrusive and Real-Time Fall Detector Leveraging Csi from Commodity Wifi Devices. Springer International Publishing, pp. 181–193.
Zhang, D., Zhou, J., Guo, M., Cao, J., Li, T., 2011. Tasa: tag-free activity sensing using rfid tag arrays. IEEE Trans. Parallel Distr. Syst. 22, 558–570.
Zhao, K., Qian, C., Xi, W., Han, J., Liu, X., Jiang, Z., Zhao, J., 2015. Emod: efficient motion detection of device-free objects using passive rfid tags. In: 23rd International Conference on Network Protocols (ICNP). IEEE, pp. 291–301.
Zhong, L., Cho, S., Metaxas, D., Paris, S., Wang, J., 2013. Handling noise in single image deblurring using directional filters. In: Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, pp. 612–619.
Zhou, Z., Shangguan, L., Zheng, X., Yang, L., Liu, Y., 2017. Design and implementation of an rfid-based customer shopping behavior mining system. IEEE/ACM Trans. Netw. 25, 2405–2418.
Zhu, C., Sheng, W., 2011. Wearable sensor-based hand gesture and daily activity recognition for robot-assisted living. IEEE Trans. Syst. Man Cybern. Syst. Hum. 41, 569–573.
Zou, Y., Xiao, J., Han, J., Wu, K., Li, Y., Ni, L.M., 2017. Grfid: a device-free rfid-based gesture recognition system. IEEE Trans. Mobile Comput. 16, 381–393.

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