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A review on radio based activity recognition

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Abstract
Recognizing human activities in their daily living enables the development and widely usage of human-centric applications, such as health monitoring, assisted living, etc. Traditional activity recognition methods often rely on physical sensors (camera, accelerometer, gyroscope, etc.) to continuously collect sensor readings, and utilize pattern recognition algorithms to identify user's activities at an aggregator. Though traditional activity recognition methods have been demonstrated to be effective in previous work, they raise some concerns such as privacy, energy consumption and deployment cost. In recent years, a new activity recognition approach, which takes advantage of body attenuation and/or channel fading of wireless radio, has been proposed. Compared with traditional activity recognition methods, radio based methods utilize wireless transceivers in environments as infrastructure, exploit radio communication characters to achieve high recognition accuracy, reduce energy cost and preserve user's privacy. In this paper, we divide radio based methods into four categories: ZigBee radio based activity recognition, WiFi radio based activity recognition, RFID radio based activity recognition, and other radio based activity recognition. Some existing work in each category is introduced and reviewed in detail. Then, we compare some representative methods to show their advantages and disadvantages. At last, we point out some future research directions of this new research topic.

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1. Introduction

Activity recognition aims to accurately detect human's daily activities based on a predefined activity model [1]. It is a hot research topic in the field of ubiquitous computing and widely used in many human-centric applications, such as health and fitness monitoring [2-10], assisted living [11-17], context-enabled games and entertainment [18-20], social networking [21,22] and sport tracking [23-25].

To recognize human activities, physical sensors (camera, accelerometer, gyroscope, etc.) are often deployed in environments, attached on objects or worn on human bodies to continuously collect sensor readings. Then, based on predefined pattern recognition models, the activity types are identified at an aggregator for upper layer applications. These sensor based methods are called traditional activity recognition methods in this paper. They can be roughly divided into three categories: (1) wearable motion sensor based methods [26], which utilize on-body motion sensors (accelerometer, gyroscope, etc.) to sense the movements of body parts, such as [4,5,11,27-32]; (2) camera sensor based methods [33], which take advantage of camera to record the video sequence and recognize the activities using computer vision algorithms. According to the camera type, the video may be RGB video (e.g. [34,35]), depth video (e.g. [19,36]) or RGB-D video (e.g. [37,38]); (3) environmental variable based methods, which use physical sensors (pressure, proximity, RFID, etc.) to infer human activities from the status of used objects or change of environmental variables, such as [16,17,39]. Although traditional activity recognition methods obtain good performances and are widely accepted, they require specific sensing modules and raise some concerns such as privacy, energy consumption and deployment cost.

In recent years, a new radio based activity recognition approach has emerged. As the existence and movement of human body in a radio field may attenuate the radio strength and change the communication patterns (e.g. channel fading) between the transmitter and receiver, radio based activity recognition takes advantage of body attenuation and/or the characters of channel fading to discriminate human activities or gestures. Compared with traditional activity recognition methods, radio based activity recognition methods only exploit wireless communication features. Thus, no physical sensing module is needed. This accordingly relaxes the device deployment requirement, reduces the energy consumption for sensing and data transmission, and protects user's privacy.

For radio based activity recognition methods, the wireless radio types include ZigBee [40], WiFi [41], RFID [42], etc. As different radio data may have different characters and processing steps, we roughly divide the radio based methods into four categories: ZigBee radio based activity recognition, WiFi radio based activity recognition, RFID radio based activity recognition, and other radio based activity recognition. In this paper, we first introduce and review some related work in each category. Then, some representative methods are compared to show their advantages and disadvantages. At last, we discuss some future research directions of this new research topic.

The rest of this paper is organized as follows. ZigBee radio based activity recognition is reviewed in Section 2. Section 3 introduces WiFi radio based activity recognition. Section 4 describes RFID radio based activity recognition. Other radio based activity recognition is presented in Section 5. Section 6 shows the comparison of radio based activity recognition methods. Section 7 presents future research directions. Conclusion is drawn in Section 8.

2. ZigBee radio based activity recognition

ZigBee is a low-cost, low-power, wireless mesh network standard [43]. It is widely used in wireless sensor network, e.g. body sensor network [44-48]. Qi et al. [40] propose RadioSense, a prototype system of ZigBee radio based activity sensing. Fig. 1 and 2 show the sensor deployment and system architecture of RadioSense, respectively. RadioSense contains three main components: (1) two dedicated on-body sensor nodes placed at user's wrist and ankle. They work as radio transmitters. (2) A sensor node placed at the center of user's body. It is the base station of body sensor network and works as the radio receiver. (3) A laptop works as an aggregator. At the aggregator, the time and the Received Signal Strength Indicator (RSSI) value of each arrival message are recorded.

With the observation that different human activities result in different wireless communication patterns between the sensor nodes and the base station, RadioSense extracts packet delivery ratio (PDR) feature from message arrival patterns and 18 statistical features (the max, min, max-min, mean, var, median, mean crossing rate, values of the RSSI histogram with 10 bins, and interquartile range) from RSSI values for each sensor node. Then, the feature selection algorithm with sequential forward strategy [49] is used to select the best features. Based on the selected features, the support vector machine (SVM) based classification model is trained for online testing. Fig. 3 shows the runtime accuracy of classifying seven activities for three

Fig. 1 Sensor deployment of RadioSense [40].

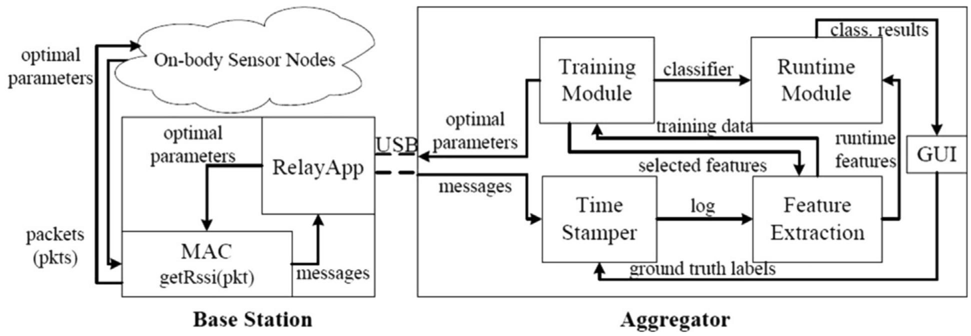

Fig. 2 System architecture of RadioSense [40].

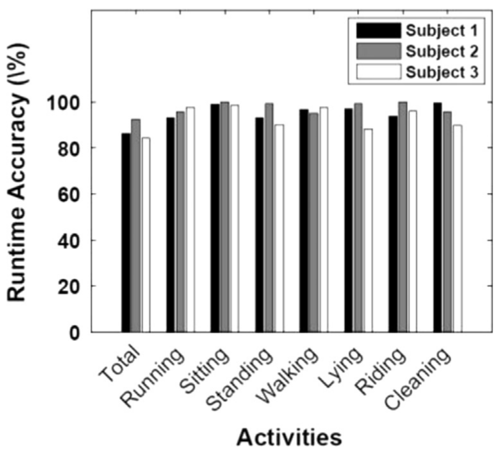

Fig. 3 The runtime accuracy of classifying seven activities for three subjects [40].

subjects. The total accuracies of subject 1, 2, and 3 are 86.3%, 92.5% and 84.2%, respectively. This indicates that RadioSense obtains comparable accuracy as traditional activity recognition methods.

RadioSense takes advantage of body attenuation and path loss of wireless radio in body sensor network. Some researchers [50] observe that “the energy from transmitted waves does not penetrate the human body for frequencies within the 2-6 GHz range. The energy rather diffracts around the body and thus path losses are not related to direct Line-of-Sight (LOS) paths through the body but rather paths along the body [51]”. Ekure et al. [51] present theoretical analysis of radio based activity sensing in body sensor network. The following equation in [52] is used to model the path loss for the channel along the human body.

$$P = 3.2 \times \left(10 \times \log_{10}(d)\right) - 9.3 \tag{1}$$

With similar sensor deployment in Fig. 1, the shortest distances around the body between the transmitters and the receiver are measured for 8 individuals while they perform 6 groups of activities, which are shown in Tab. 1. Then, based on the calculated path loss values, the statistical features are extracted for classification model training and testing. The experimental results demonstrate the effectiveness of above path loss model around the human body.

Efforts from Qi et al. [40] and Ekure et al. [51] are suitable for body sensor network that contains several on-body sensor nodes. Scholz et al. [53] deploy IEEE 802.15.4

Tab. 1 Activity group description. 4–7,10 are in group (i), 15,17–19,22,25,26 are in group (ii), 1–3,9,11,12,14 are in group (iii), 16,23,24 are in group (iv), 8,13 are in group (v), 20,21 are in group (vi). 1–14 are performed standing while 15–26 are performed sitting [51].

	Description		Description
1	Standing	14	Arms stretched forward
2	Walking1	15	Sitting
3	Walking2	16	Hands on knee
4	Arms folded	17	Arms folded under chest
5	Arms in pocket	18	legs crossed
6	Bicep curl1	19	Leg on table
7	Bicep curl2	20	Arms stretched on couch
8	Arms behind head	21	Hands behind head
9	Hands to face	22	Sleeping in chair
10	Praying hands	23	Hands on table
11	Leaning against wall	24	Sleeping on table
12	Quadriceps stretch	25	Leg stretch forward
13	Arms in the air	26	Legs tucked under seat

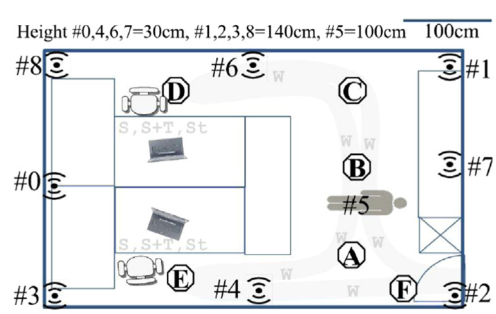

Fig. 4 Floor plan of the office room with deployed nodes [53].

wireless nodes in office room environment and recognize human activities through detecting the RSSI fluctuation in two different manners: (1) device-bound activity recognition, i.e. with one on-body wireless node; and (2) device-free activity recognition, i.e. without on-body node.

As shown in Fig. 4, eight fixed nodes are deployed in the room. One mobile node (5) is attached on the hip of the subject. The RSSI values for all links are recorded when the subject performs several activities, including walking (W), standing (St), sitting (S), sitting and typing (S+T), lie (L), lying and waving (L+Wa), and being outside the room (O). For device-bound activity recognition, features of all 8 links to the mobile node are extracted; for device-free activity recognition, features of all 28 links of the sensor network infrastructure are extracted. Ten-fold cross validation experiments are conducted, and the results show that device-bound and device-free activity recognitions obtain accuracies of 89.6% and 89.4%, respectively. Besides, the influences of network topology, subject and change of door state (open, closed, half open) are also investigated in this paper.

3. WiFi radio based activity recognition

Compared with ZigBee radio based activity recognition, WiFi radio based activity recognition can take advantage of existing WiFi infrastructure in an office building, shopping mall, etc. Sigg et al. [54] propose a device-free and passive activity recognition system that uses a mobile phone as WiFi receiver to measure RSSI values. It extracts simple time-domain features to recognize subject's situations, activities and gestures. Similar work is also introduced in [55]. Wang et al. [41] utilize WiFi links between WiFi devices (including WiFi access points, desktops, thermostats, refrigerators, smartTVs, laptops, etc.) and collect fine-grained channel state information (CSI) to identify location-oriented home activities, in a device-free manner. RSSI measurement is a packet-level estimator and represents the signal power over a packet as a single amplitude. Comparatively, CSI is the channel response at the receiver in frequency domain [56]. It "contains amplitude and phase measurements separately for each orthogonal frequency division multiplexing (OFDM) subcarrier [41]". Wang et al. [41] collect subcarrier measurements of daily home activities at specific locations and take the CSI signal measurements as location-activity profiles. Through comparing online measurements with the profiles, the proposed method can uniquely identify both in-place activities (cooking, eating, washing dishes, brushing teeth, taking a bath, watching TV, etc.) and walking movements at home.

Adib et al. [57] propose an interesting work that explores WiFi signals to detect and track moving objects behind the walls, identify their relative locations and even recognize some simple gestures, without wearing any on-body device. The authors utilize MIMO interference nulling to eliminate the reflections from static objects (e.g. the wall and static objects behind the wall). The channels from two transmit antennae to one receive antenna are measured first, then the signals at the receive antenna are nulled to exclude the reflections off static objects. To track the moving objects using only one antenna, the authors borrow a technique named inverse synthetic aperture radar (ISAR). Different from antenna array based tracking method that captures the target from spatially spaced antennae (as shown in Fig. 5(a)), ISAR takes one measurement at a time and uses consecutive measurements to emulate an inverse antenna array (as shown in Fig. 5(b)).

Pu et al. [58] present a gesture recognition system named WiSee through detecting the minute Doppler shifts and multi-path distortions of WiFi signals originating from human motion. To detect the very small Doppler shifts (a few Hertz) of hand gestures, the authors propose to transform the received WiFi signal into narrowband pulse by "repeating an OFDM symbol and performing a large Fast Fourier Transform (FFT) operation [58]". Then, the WiSee receiver can track the narrowband pulse to capture the Doppler shifts. Besides, WiSee takes advantage of MIMO capability to separate the wireless reflections from multiple people through considering the reflections from each human as signals from a wireless transmitter. Experimental results demonstrate that WiSee obtains the average detection and classification accuracy of 94% across nine whole-body gestures (push, dodge, strike, pull, drag, kick, circle, punch and bowling).

Chen et al. [59] use mobile phone to obtain WiFi signals and segment continuous WiFi trace into stationary segments and moving segments based on RSSI fluctuation detection. All the stationary segments are clustered to extract frequent visiting locations in one's daily living. Besides, Wang et al. [60] utilize WiFi radio to track human queues in a coffee shop and an airport. With extracted unique WiFi signal patterns, the time periods of waiting, service and leaving can be distinguished.

4. RFID radio based activity recognition

Kellogg et al. [42] propose a wireless signals (e.g. TV transmissions) based gesture recognition system named

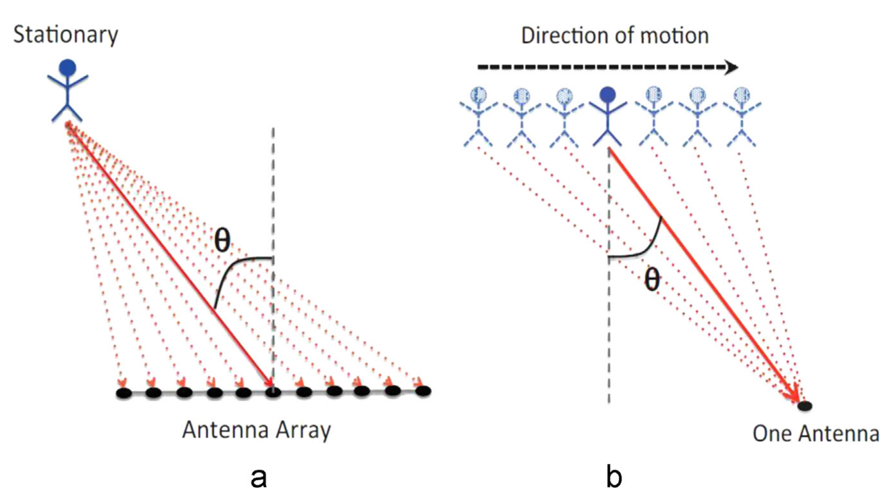

Fig. 5 Moving object tracking methods: (a) antenna array and (b) ISAR [57].

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

Wang et al. [61] present a virtual touch screen system, RF-IDraw, which utilizes multi-resolution positioning technique to trace the trajectory shape of RFID tag on user's finger and enables the user to input characters or words in air. Existing RF-based positioning systems often leverage the beam steering capability of antenna array to detect the source location. To achieve high accuracy, a large number of antennae are required. Therefore, there is a tradeoff between resolution and unambiguity. We can see from Figure 7 that, "as the separation of the antenna pair (marked in red) increases, the number of beams increases accordingly, causing ambiguity in localizing the source (marked in blue). On the other hand, each beam gets narrower, leading to a higher resolution [61]". In order to remove ambiguity while maintaining high resolution, RF-IDraw combines a few antenna pairs with different separations. The pairs with smaller separation have wider beams and act as filters to eliminate the ambiguity; the pairs with larger separation have narrower beams and hence define the resolution. Fig. 8 shows the result when combining two resolutions in Fig. 7(a) and (c). To evaluate RF-IDraw's performance, handwriting recognition Android app is used to recognize RF-IDraw's reconstructed trajectories for letters and words. The results show that the accuracies on character recognition experiment and word recognition experiment are 97.5% and 92%, respectively.

Liu et al. [62] deploy an array of active RFID tags on ground. When a subject moves through the tag covered area, the signal fluctuation of the tags is collected and analyzed to infer the subject's activities.

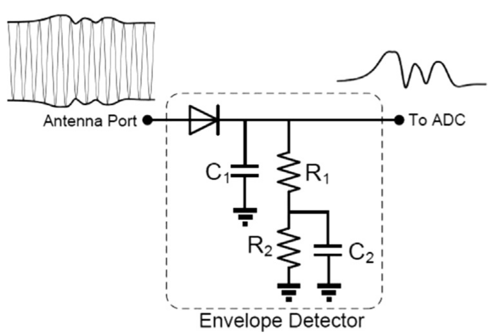

Fig. 6 AllSee's receiver circuit [42].

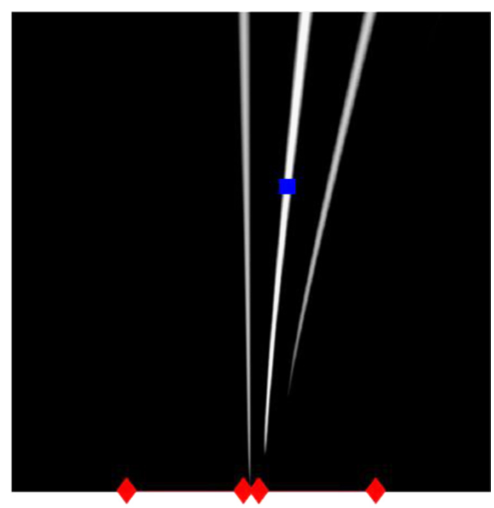

Fig. 8 Multi-resolution positioning [61].

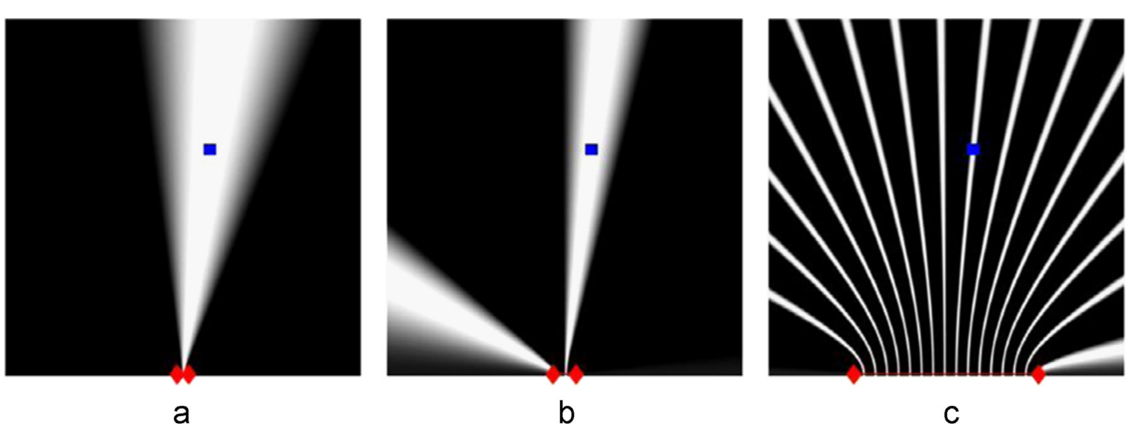

Fig. 7 Tradeoff between resolution and unambiguity [61]: (a) $\lambda/2$ separation, (b) λ separation and (c) 8λ separation.

5. Other radio based activity recognition

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

Scholz et al. [64,65] place two USRP software defined radio (SDR) devices with 900 MHz transceiver to both sides of a door to detect the door state, talking on mobile phone and walking activity. Sigg et al. [66] deploy several USRP SDR devices on the ground in indoor environments to distinguish five activities (walking, crawling, standing, lying and empty) conducted simultaneously by two subjects.

Sekine et al. [67] utilize Doppler Effect of 24.1 GHz microwave for activity monitoring. One hundred and one features in time domain, frequency domain and time-and-frequency domain are extracted to recognize eight daily human activities. Adib et al. [68] present a wireless breath monitoring system, Vital-Radio, which detects the reflections of low-power wireless signal off the human body and identifies the minute chest motion due to the inhale and exhale process (as shown in Fig. 9).

6. Comparison of radio based activity recognition methods

Each method introduced above does have its advantages and disadvantages, and only suits for specific application scenarios. We select some representative methods from four categories and give a qualitative comparison, based on technical metrics such as coverage, activity type, accuracy, existing infrastructure usage, system deployment cost, on-body device, etc. *Coverage* indicates the scope of valid recognition area. *Activity types* include body motion, home activity, gesture, etc. *Accuracy* shows the experimental recognition performance reported in the paper, which is roughly divided into three grades: high ($\geq 80\%$), middle ($< 80\%$ and $\geq 60\%$), and low ($< 60\%$). *Existing infrastructure usage* means whether the recognition system can (partially) utilize existing infrastructure in our daily living such as FM broadcast station, WiFi access point (AP), smart TV, desktops, etc. *System deployment cost* indicates the labor cost of recognition system construction. *On-body device* means whether the user needs to wear on-body device or not. The comparison results are shown in Tab.2, which contains 10 aforementioned activity recognition methods.

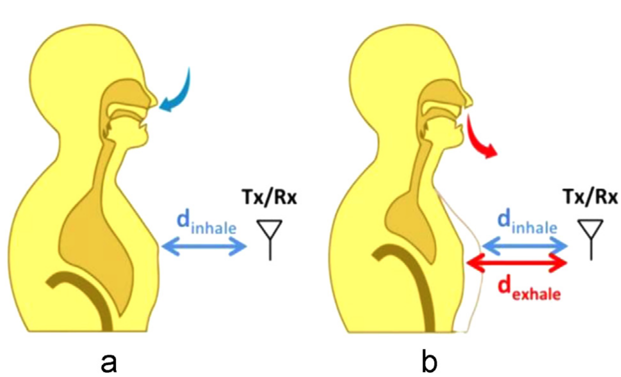

Fig. 9 Chest motion due to breathing: (a) inhale motion and (b) exhale motion [68].

7. Future research directions

Although there has been some related work in radio based activity recognition, this new research topic is still at its initial development stage. There are a lot of potential research questions that need to be answered. We list and discuss a few directions at follows:

1) *Free infrastructure based recognition methods*: As we introduced above, different radios can be used for activity recognition. However, in a specific application environment, there are some existing radios that can be used for free, such as WiFi radio in an office room. Taking full advantage of free infrastructure will eliminate the burden of specific device deployment, decrease system cost, and increase user acceptance. Besides, free infrastructure based recognition methods are easier to be widely spread. Except WiFi, there are some other free radios that have not been explored yet. For example, the BlueTooth radio in wearable device network.
2) *Multi-radio fusion based recognition methods*: Sometimes, an application requires high recognition accuracy, which is out of reach for single radio based recognition. Then, one possible way is to combine two or more types of radios and implement recognition tasks simultaneously and cooperatively. As different radios have different transmission characters, their fusion will certainly improve the recognition performance. However, how to define the best radio combination and how to fusion multiple radios are still under exploration and need further research.
3) *Combining radio sensing with conventional sensors*: Another way to improve recognition accuracy is to combine radio sensing with conventional sensors, especially in body sensor network based activity recognition. Because traditional recognition methods need collect physical sensor data and send it to an aggregator or base station using wireless communication, the conventional sensor data and the radio features are available at the same time. Combining radio sensing with conventional sensors can enhance the performance and stability of recognition system especially when the wireless data transmission is not adequately stable. But, on the other hand, the combination brings extra computation cost. Therefore, a strategy is necessary to balance the gain and cost and assist decide when to combine these two information sources. In addition, the combination algorithm should adapt to different application requirements to minimize system cost.
4) *Interference impact analysis*: As radio based methods utilize the body attenuation and/or channel fading of

Tab. 2 Comparison results of radio based activity recognition methods.

Category	Method	Comparison metrics					
		Coverage	Activity type	Accuracy	Existing infrastructure usage	System deployment cost	On-body device
ZigBee based	Qi et al. [40]	Body	Body motion	High	Yes	Low	Yes
	Ekure et al. [51]	Body	Body motion	Middle	Yes	Low	Yes
	Scholz et al. [53]	Room	Body motion	High	No	High	Yes/No
WiFi based	Wang et al. [41]	Room	Home activity	High	Yes	Low	No
	Adib et al. [57]	Room	Location tracking /gesture	High	No	Low	No
	Pu et al. [58]	Room	Whole-body gesture	High	Yes	Low	No
RFID based	Kellogg et al. [42]	Near receiver	Gesture	High	Yes	Low	Yes/No
	Wang et al. [61]	Room	Trajectory tracing/word input recognition	High	No	High	Yes
Others	Shi et al. [63]	Near receiver	Body motion	Middle	Yes	Low	No
	Adib et al. [68]	Near transceiver	Breath monitoring	N/A	No	Low	No

wireless radio to recognize human activities, radio interference can change the radio communication patterns and, thus, affect the recognition performance. Some interference may come from the same type of radio. For example, ZigBee communication of nearby sensor nodes will interfere with packet reception of a body sensor network. Some other interference may be caused by different types of radios, such as WiFi and BlueTooth that also operate in the same 2.4 GHz ISM band. In this subtopic, we foresee two research questions: (1) How to evaluate the interference impact on the recognition performance? (2) How to mitigate the impact of radio interference?

5) *Context-aware recognition strategy*: As activity recognition algorithm might be used in different scenarios, the application layer contexts (accuracy requirements, difference in human subjects, etc.) and the lower layer contexts (power left, device availability, network condition, etc.) may be different or change dynamically. Fixed recognition strategy may not obtain the maximum system performance. Therefore, context-aware recognition strategy is necessary. For example, with the consideration of difference in human subjects, a self-adaptive strategy could be designed to evolve fixed recognition model to personal recognition model. The context-aware recognition strategy would take one or more contexts into consideration, according to the application requirements. Normally, the more contexts a strategy includes, the more complex it will be.
6) *Energy efficiency issue*: Radio sensing is based on wireless communication, which consumes much energy. The most direct way for energy saving is to reduce the sending rate of wireless packets. But it accordingly decreases the recognition accuracy and increases the recognition delay. One research question here is how to locate the break-even between gain and cost. In addition, human activity status tracking and prediction is helpful to further decrease packet sending rate and, hence, improve energy efficiency. Therefore, another potential research question to answer is: how to accurately predict human activity status based on the recognition history?
7) *Parameter optimization*: As shown in [40], a recognition algorithm may contain several parameters, such as transmission power level, packet sending rate and smoothing window size. Each parameter may have a big impact on the final recognition results. The situation becomes worse when the parameters are correlated with each other. It is very hard to optimize all the parameters through manual adjustment. Therefore, one research question to answer is: how to optimize all algorithm parameters simultaneously and automatically? To deal with this problem, some existing theories may be helpful, such as control theory in the field of automation.
8) *Theory basis for radio based activity recognition*: Almost all aforementioned related works demonstrate the effectiveness of radio sensing through real world experiments. There may be some bias as the dataset is limited and often collected under control. Up till now, there is no theory basis for radio based activity recognition, which can mathematically model and analyze the relationship between human activities and corresponding radio transmission features or system parameters. Information theoretic analysis may gain fundamental insights to guide the optimal design of radio based recognition system.

9) *Privacy issue*: Compared with traditional recognition methods, radio based approaches have no physical sensing components and are more suitable for privacy protection. However, private information may also be digged out from wireless radio features. How to keep user's privacy during recognition is another important research topic.

8. Conclusion

This paper gives a brief review on radio based activity recognition, a new research topic in the field of ubiquitous computing. Different with traditional activity recognition methods that rely on specifically physical sensors, radio based recognition methods take advantage of body attenuation and/or channel fading of wireless radios. This paper introduces and compares some existing work in ZigBee, WiFi, RFID and other radio based activity recognition. In addition, some directions for future research are provided and discussed.

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References

[1] E. Kim, S. Helal, D. Cook, Human activity recognition and pattern discovery, IEEE Pervasive Comput. 9 (2010) 48-53.
[2] Q. Li, G. Zhou, J.A. Stankovic, Accurate, fast fall detection method using posture and context information, in: Proceedings of the 6th ACM International Conference on Embedded Networked Sensor Systems, 2008, pp. 443-444.
[3] Q. Li, J.A. Stankovic, M.A. Hanson, A. Barth, J. Lach, G. Zhou, Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information, in: Proceedings of the Sixth International Workshop on Wearable and Implantable Body Sensor Networks, 2009, pp. 138-143.
[4] T. Hao, G. Xing, G. Zhou, iSleep: unobtrusive sleep quality monitoring using smartphones, in: Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems, 2013.
[5] X. Qi, Y. Li, M. Keally, Z. Ren, G. Zhou, AdaSense: adapting sampling rates for activity recognition in body sensor networks, in: Proceedings of the 2013 IEEE 19th Real-Time and Embedded Technology and Applications Symposium, 2013, pp. 163-172.
[6] Y. Tang, S. Wang, Y. Chen, Z. Chen, PPCare: a personal and pervasive health care system for the elderly, in: Proceedings of the 9th International Conference on Ubiquitous Intelligence and Computing, 2012, pp. 935-939.
[7] L. Hu, Y. Chen, S. Wang, Z. Chen, b-COELM: a fast, lightweight and accurate activity recognition model for mini-wearable devices, Mob. Comput. 15 (2014) 200-214.
[8] T.V. Duong, H.H. Bui, D.Q. Phung, S. Venkatesh, Activity recognition and abnormality detection with the switching hidden semi-Markov model, in: Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2005, pp. 838-845.
[9] Y. Jia, Diatetic and exercise therapy against diabetes mellitus, in: Proceedings of Second International Conference on Intelligent Networks and Intelligent Systems, 2009, pp. 693-696.
[10] J. Yin, Q. Yang, J. Pan, IEEE Trans. Knowl. Data Eng. 20 (2008) 1082-1090.
[11] M. Keally, G. Zhou, G. Xing, J. Wu, A. Pyles, PBN: Towards Practical activity recognition using smartphone-based body sensor networks, in: Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems, 2011, pp. 246-259.
[12] M. Keally, G. Zhou, G. Xing, J. Wu, Remora: sensing resource sharing among smartphone-based body sensor networks, in: Proceedings of 2013 IEEE/ACM 21st International Symposium on Quality of Service, 2013, pp. 1-10.
[13] S. Wang, Y. Chen, Z. Chen, Recognizing transportation mode on mobile phone using probability fusion of extreme learning machines, Int. J. Uncertain. Fuzz. Knowl. Based Syst. 21 (2013) 13-22.
[14] L. Hu, Y. Chen, S. Wang, L. Jia, A nonintrusive and single-point infrastructure-mediated sensing approach for water-use activity recognition, in: Proceedings of the 11th IEEE/IFIP International Conference on Embedded and Ubiquitous Computing, 2013, pp. 2120-2126.
[15] T.L. Kasteren, G. Englebienne, B. Kröse, An activity monitoring system for elderly care using generative and discriminative models, J. Pers. Ubiquitous Comput. 14 (2010) 489-498.
[16] M. Buettner, R. Prasad, M. Philipose, D. Wetherall, Recognizing daily activities with RFID-based sensors, in: Proceedings of the 11th international conference on Ubiquitous Computing, 2009, pp. 51-60.
[17] P. Hevesi, S. Willea, G. Pirkl, N. Wehn, P. Lukowicz, Monitoring household activities and user location with a cheap, unobtrusive thermal sensor array, in: Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing, 2014, pp. 141-145.
[18] C.R. Wren, A. Azarbayejani, T. Darrell, A.P. Pentland, Pfinder: Real-time tracking of the human body, IEEE Trans. Pattern Anal. Mach. Intell. 19 (1997) 780-785.
[19] J. Shotton, A. Fitzgibbon, M. Cook, T. Sharp, M. Finocchio, R. Moore, A. Kipman, A. Blake, Real-time human pose recognition in parts from single depth images, in: Proceedings of the 2011 IEEE Conference on Computer Vision and Pattern Recognition, 2011, pp. 1297-1304.
[20] F. Huo, E. Hendriks, P. Paclik, A.H.J. Oomes, Markerless human motion capture and pose recognition, in: Proceedings of the 10th IEEE Workshop on Image Analysis for Multimedia Interactive Services, 2009, pp. 13-16.
[21] R. Mehran, A. Oyama, M. Shah, Abnormal crowd behavior detection using social force model, in: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, 2009, pp. 935-942.
[22] A.T. Campbell, S.B. Eisenman, K. Fodor, N.D. Lane, H. Lu, E. Miluzzo, M. Musolesi, R.A. Peterson, X. Zheng, CenceMe: injecting sensing presence into social network applications using mobile phones (Demo Abstract), in: Proceedings of the Ninth ACM International Symposium on Mobile Ad Hoc Networking and Computing, 2008.
[23] Y. Ke, R. Sukthankar, M. Hebert, Spatio-temporal shape and flow correlation for action recognition, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2007, pp. 1-8.
[24] W. Lu, J.J. Little, Simultaneous tracking and action recognition using the PCA-HOG descriptor, in: Proceedings of the 3rd Canadian Conference on Computer and Robot Vision, 2006, pp. 6.

[25] Y. Ohgi, M. Yasumura, H. Ichikawa, C. Miyaji, Analysis of stroke technique using acceleration sensor IC in freestyle swimming, in: A.J. Subic, S.J. Haake (Eds.), The Engineering of SPORT, Blackwell Science, Oxford, 2000, pp. 503-511.
[26] O.D. Lara, M.A. Labrador, A survey on human activity recognition using wearable sensors, IEEE Commun. Surv. Tutor. 15 (2013) 1192–1209.
[27] H.T. Cheng, F.T. Sun, M. Griss, P. Davis, J. Li, D. You, NuActiv: recognizing unseen new activities using semantic attribute-based learning, in: Proceeding of the 11th Annual International Conference on Mobile Systems, Applications, and Services, 2013, pp. 361–374.
[28] K. Aminian, F. Dadashi, B. Mariani, C.L. Hoskovec, B.S. Eggimann, C.J. Büla, Gait analysis using shoe-worn inertial sensors: how is fot clearance related to walking speed? in: Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing, 2014, pp. 481–485.
[29] T. Maekawa, Y. Kishino, Y. Sakurai, T. Suyama, Activity recognition with hand-worn magnetic sensors, Pers. Ubiquitous Comput. 17 (2013) 1085–1094.
[30] O. Yürüten, J. Zhang, P.H.Z. Pu, Predictors of life satisfaction based on daily activities from mobile sensor data, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2014, pp. 497–500.
[31] D. Schuldhaus, H. Leutheuser, B.M. Eskofier, Classification of daily life activities by decision level fusion of inertial sensor data, in: Proceedings of the 8th International Conference on Body Area Networks, 2013, pp. 77–82.
[32] F.O. Mokaya, B. Nguyen, C. Kuo, Q. Jacobson, A. Rowe, P. Zhang, MARS: a muscle activity recognition system enabling self-configuring musculoskeletal sensor networks, in: Proceedings of the 12th International Conference on Information Processing in Sensor Networks, 2013, pp. 191–202.
[33] S. Ke, L.U.T. Hoang, Y. Lee, J. Hwang, J. Yoo, K. Choi, A review on video-based human activity recognition, Computers 2 (2013) 88–131.
[34] X. Ren, C. Gu, Figure-ground segmentation improves handled object recognition in egocentric video, in: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, 2010, pp. 3137–3144.
[35] R. Messing, C. Pal, H. Kautz, Activity recognition using the velocity histories of tracked keypoints, in: Proceedings of IEEE 12th International Conference on Computer Vision, 2009, pp. 104-111.
[36] I. Oikonomidis, N. Kyriazis, A.A. Argyros, Efficient model-based 3D tracking of hand articulations using kinect, in: Proceedings of the 22nd British Machine Vision Conference, 2011.
[37] K. Lai, L. Boa, X. Ren, D. Fox, A scalable tree-based approach for joint object and pose recognition, in: Proceedings of Twenty-fifth Conference on Artificial Intelligence, 2011.
[38] J. Lei, X. Ren, D. Fox, Fine-grained kitchen activity recognition using RGB-D, in: Proceedings of the 2012 ACM Conference on Ubiquitous Computing, 2012, pp. 208–211.
[39] P. Rashidi, D.J. Cook, Mining sensor streams for discovering human activity patterns over time, in: Proceedings of the 2010 IEEE International Conference on Data Mining, 2010, pp. 431–440.
[40] X. Qi, G. Zhou, Y. Li, G. Peng, RadioSense: exploiting wireless communication patterns for body sensor network activity recognition, in: Proceedings of the 2012 IEEE 33rd Real-Time Systems Symposium, 2012, pp. 95–104.
[41] Y. Wang, J. Liu, Y. Chen, M. Gruteser, J. Yang, H. Liu, E-eyes: device-free location-oriented activity identification using fine-grained WiFi signatures, in: Proceedings of the 20th Annual International Conference on Mobile Computing and Networking, 2014, pp. 617–628.
[42] B. Kellogg, V. Talla, S. Gollakota, Bringing gesture recognition to all devices, in: Proceedings of the 11th USENIX Conference on Networked Systems Design and Implementation, 2014, pp. 303–316.
[43] ⟨http://en.wikipedia.org/wiki/ZigBee⟩ (cited November 2014).
[44] G. Zhou, T. He, S. Krishnamurthy, J.A. Stankovic, Models and solutions for radio irregularity in wireless sensor networks, ACM Trans. Sens. Netw. 2 (2006) 221–262.
[45] G. Zhou, C. Wan, M.D. Yarvis, J.A. Stankovic, Aggregator-centric QoS for body sensor networks, in: Proceedings of the 6th International Symposium on Information Processing in Sensor Networks, 2007, pp. 539–540.
[46] G. Zhou, J. Lu, C. Wan, M.D. Yarvis, J.A. Stankovic, BodyQoS: adaptive and radio-agnostic QoS for body sensor networks, in: Proceedings of the 27th Conference on Computer Communications, 2008.
[47] G. Zhou, Y. Wu, T. Yan, T. He, C. Huang, J.A. Stankovic, T. F. Abdelzaher, ACM Trans. Embed. Comput. Syst. 9 (2010).
[48] G. Zhou, Q. Li, J. Li, Y. Wu, S. Lin, J. Lu, C. Wan, M.D. Yarvis, J.A. Stankovic, Adaptive and radio-agnostic QoS for body sensor networks, ACM Trans. Embed. Comput. Syst. 10 (2011).
[49] I. Guyon, A. Elisseeff, J. Mach. Learn. Res. 3 (2003) 1157–1182.
[50] A. Fort, C. Desset, J. Ryckaert, P.D. Doncker, L.V. Biesen, S. Donnay, Ultra wide-band body area channel model, in: Proceedings of the 2005 IEEE International Conference on Communications, 2005, pp. 2840–2844.
[51] I. Ekure, S. Wang, G. Zhou, A Theoretical Analysis of path loss based activity recognition, in: Proceedings of 11th IEEE International Conference on Mobile Ad hoc and Sensor Systems, 2014.
[52] Y.I. Nechayev, P.S. Hall, C. Constantinou, H. Yang, A. Alomainy, R. Dubrovka, C.G. Parini, On-body path gain variations with changing body posture and antenna position, in: Proceedings of IEEE Antennas and Propagation Society International Symposium, 2005, pp. 731–734.
[53] M. Scholz, T. Riedel, M. Hock, M. Beigl, Device-free and device-bound activity recognition using radio signal strength, in: Proceedings of the 4th Augmented Human International Conference, 2013, pp. 100–107.
[54] S. Sigg, U. Blanke, G. Troester, The telepathic phone: frictionless activity recognition from WiFi-RSSI, in: Proceedings of IEEE International Conference on Pervasive Computing and Communications, 2014, pp. 148–155.
[55] S. Sigg, M. Hock, M. Scholz, G. Troester, L. Wolf, Y. Ji, M. Beigl,Passive, Device-free recognition on your mobile phone: tools, features and a case study, in: Proceedings of the 10th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, 2013, pp. 435–446.
[56] K. Wu, J. Xiao, Y. Yi, M. Gao, L.M. Ni, FILA: fine-grained indoor localization, in: Proceedings of IEEE INFOCOM, 2012, pp. 2210–2218.
[57] F. Adib, D. Katabi, See through walls with Wi-Fi! in: Proceedings of the ACM conference on SIGCOMM, 2013, pp. 75–86.
[58] Q. Pu, S. Gupta, S. Gollakota, S. Patel, Whole-home gesture recognition using wireless signals, in: Proceedings of the 19th Annual International Conference on Mobile Computing & Networking, 2013, pp. 27–38.
[59] Z. Chen, S. Wang, Y. Chen, Z. Zhao, M. Lin, InferLoc: calibration free based location inference for temporal and spatial fine-granularity magnitude, in: Proceedings of the 15th International Conference on Computational Science and Engineering (CSE), 2012, pp. 453-460.
[60] Y. Wang, J. Yang, Y. Chen, H. Liu, M. Gruteser, R.P. Martin, Tracking human queues using single-point signal monitoring, in: Proceedings of the 12th Annual International Conference on Mobile Systems, Applications, and Services, 2014, pp. 42–54.

[61] J. Wang, D. Vasisht, D. Katabi, RF-IDraw: virtual touch screen in the air using RF signals, in: Proceedings of the 2014 ACM Conference on SIGCOMM, 2014, pp. 235–246.
[62] Y. Liu, L. Chen, J. Pei, Q. Chen, Y. Zhao, Mining frequent trajectory patterns for activity monitoring using radio frequency tag arrays, in: Proceedings of the Fifth IEEE International Conference on Pervasive Computing and Communications, 2007, pp. 37–46.
[63] S. Shi, S. Sigg, Y. Ji, Joint localization and activity recognition from ambient fm broadcast signals, in: Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication, 2013, pp. 521–530.
[64] M. Scholz, S. Sigg, G. Bagschik, T. Guenther, G.V. Zengen, D. Shiskova, Y. Ji, M. Beigl, SenseWaves: radiowaves for context recognition, in: video Proceedings of the 9th International Conference on Pervasive Computing, 2011.
[65] M. Scholz, S. Sigg, H.R. Schmidkte, M. Beigl, Challenges for Device-free radio-based activity recognition, in: Proceedings of the 3rd Workshop on Context Systems Design Evaluation and Optimisation (CoSDEO), 2011.
[66] S. Sigg, S. Shi, Y. Ji, RF-based device-free recognition of simultaneously conducted activities, in: Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication, 2013, pp. 531–540.
[67] M. Sekine, K. Maeno, Activity recognition using radio doppler effect for human monitoring service, J. Inf. Process. 20 (2012) 396–405.
[68] F. Adib, Z. Kabelac, H. Mao, D. Katabi, R.C. Miller, Real-time breath monitoring using wireless signals, in: Proceedings of the 20th Annual International Conference on Mobile Computing and Networking, 2014, pp. 261–262.