Wireless Pers Commun (2018) 101:775–797
https://doi.org/10.1007/s11277-018-5715-4

Comparison Analysis of Radio_Based and Sensor_Based Wearable Human Activity Recognition Systems

Hamed Rezaie[1] · **Mona Ghassemian**[1]

Published online: 18 April 2018

Abstract Human activity recognition (HAR) systems aim to provide low-cost, low-power, unobtrusive and non-invasive solutions to monitor and collect data accurately for human-centric applications, such as health monitoring, assisted living and rehabilitation. Although wearable sensor_based HAR systems have been demonstrated to be effective in the literature, they raise various concerns such as energy consumption and hardware cost. In this work, we examine the pattern of radio signal strength variations in different activity classes in absence of sensor hardware. We present a performance comparison analysis by setting up two testbeds to compare a sensor_based with a radio_based HAR system over a range of variable metrics such as the number of sensor nodes, and the nodes and the sink node placement with respect to the accuracy and the energy efficiency. Wearable HAR datasets are constructed based on our reported testbeds. The main contributions of this work are in two folds: (1) when eliminating the use of accelerometers in the radio_based system, beside the reduced hardware cost, prolonged lifetime of the HAR system by nearly 30% can be achieved while maintaining the accuracy. The impact of the selected overlapping window size (WS) is also investigated with respect to the accuracy level in both systems over a range of activity classes. (2) The impact of the node placement on the accuracy indicates a higher dependency to the number of nodes, the nodes and the sink node placements in the radio_based system due to the dependency of the results to the distance.

Keywords Human activity recognition systems · Energy efficieny · Accuracy · Radio_based · Sensor_based · Accelerometer · Testbed

✉ Mona Ghassemian
mona.ghassemian@kcl.ac.uk

1 School of Computer Science and Engineering, Shahid Beheshti University, Tehran, Iran

1 Introduction

In recent years, we have witnessed a rapid surge in assisted living technologies due to an increasing aging population which motivates developments of new ubiquitous health monitoring systems. One of the important services that can be offered is monitoring the physical well-being of humans remotely and continuously for early and quick detection of anomalies.

The human activity recognition (HAR) systems can be implemented using either ambient or wearable sensor nodes. In the former case, the ambient HAR system utilises information collected from either sensor node attached to various objects (such as passive infrared or ultrasound sensor nodes placed on beds and doors) or camera systems capturing video from living spaces. In the latter case, the HAR system can be fulfilled by inferring information that is gathered from a set of wearable sensor nodes that are placed on the human body. Incorporating ambient sensor nodes, specifically video cameras, for HAR systems are extensively studied [1]. The downsides of such techniques are the costly video processing power, privacy issues, and limited indoor operational site [2].

The aforementioned limitations motivate the use of wearable sensor nodes that can be employed to provide inexpensive and wearable HAR systems. These systems can be trained to recognise specific predefined activities or movements such as fall detection [3] to overcome the privacy issue. Wireless body area networks (WBANs) use a set of miniaturised and wearable battery operated sensor nodes which consist of sensing, processing, and transmission units [4]. The successful implementation and realisation of WBAN for remote activity monitoring depends on numerous rising challenges. Among these challenges, recognition accuracy and system lifetime of at least 1 week are the most important ones.

In this paper, we aim to investigate the possibility of eliminating the sensor board to increase the system lifetime and reduce the hardware cost while maintaining the recognition accuracy. Therefore, we demonstrate how to establish a pattern of the radio signal strength to determine the activity classes which is the basis of the radio_based HAR system.

The rest of this paper is organised as follows: Related works for sensor_based and radio_based HAR systems are reviewed in Sect. 2. The HAR system framework is described in Sect. 3. Section 4 describes our experimental testbed to evaluate and compare the radio_based with the sensor_based HAR system. Collected results and analysis from our HAR system testbeds are presented in Sect. 5. Finally, Sect. 6 concludes the paper and highlights future research directions.

2 Related Work

In the context of the HAR for healthcare applications, there are a number of low-cost and non-invasive solutions for a continuous all-day and anyplace activity monitoring using wearable sensor nodes. There are two main approaches identified for the wearable HAR systems: Sensor_based and radio_based HAR systems. In this section we address challenges for HAR systems, present existing solutions for each category and link them with the aims and contributions of this work.

The main challenges for the HAR wearable systems are the system lifetime and the recognition accuracy. Increasing system lifetime can be realised by optimising the sampling rate in the sensing, processing and transmission process which may impact on the recognition accuracy [54]. Additionally, the number and node placements, processing power, extracted features, and battery type can affect the system lifetime and the accuracy. Previous research has mainly focused either on energy efficiency [7–13, 69] or the recognition accuracy [14–20]. Rezaie and Ghassemian [21] showed the trade-off between the main two challenges which delivered a more thorough performance analysis of the HAR systems. In this work, we also consider both challenges to evaluate the two HAR systems in our analysis.

In sensor_based solutions, the sampling rate of the sensor nodes (e.g. accelerometers) is often considered to be fixed. For instance, Yan et al. [22] proposed an activity-based strategy for continuous HAR system, namely adaptive accelerometer-based activity recognition (A3R), considering a fixed sampling rate and classification features which were adapted in real-time. The collected data using a single mobile handset showed that an ideal conditional activity-based strategy could achieve an energy saving of about 50%. French et al. [23] focused on the impact of the sampling rate. They evaluated different selected sampling strategies including a baseline uniform sampling strategy and a probability based sampling when a transition occured. This method required a prior dataset including activities similar to A3R method to be collected and processed in order to calculate the probability of transitions. Rezaie and Ghassemian [48] proposed a feedback controller algorithm for dynamically adjusting the sampling rate. Their proposed algorithm nearly doubled the lifetime of the HAR system under study while the accuracy of detection was maintained at the same level. Ghasemzadeh et al. [24] formulated coverage problem in the context of activity monitoring. Their method focused on the minimum number of sensor nodes that produced full activity coverage set. This solution reduced the number of sensor nodes while maintaining an acceptable accuracy for the HAR system.

The position and the number of sensor nodes were thoroughly studied by Atallah et al. [30] and Yang et al. [31] which showed that the recognition accuracy was decreased by using smaller subsets of sensor nodes and the position depends on the class and the level of activities under study. Studies conducted by Zhang et al. [32], Chavarriaga et al. [33], and Kale et al. [34] highlighted the impact of misplacement of sensor nodes with respect to (w.r.t) the degree of rotation. Kale et al. [34] confirmed that $-\ 15°$ to $+\ 15°$ misplacements in each axis could be tolerated in the HAR systems.

Beside the HAR systems utilising the accelerometer information, sensor-free solutions exist where the HAR systems rely on the radio signal strength to detect the activities. For this purpose low power/low range wireless technologies such as Zigbee (based on the IEEE 802.15.4), WiFi (IEEE 802.11), Bluetooth (IEEE 802.15.1), and RFID (IEEE 802.15.4f) can be employed [25]. Compared to the discussed sensor_based HAR systems [26], radio_based HAR systems only exploit wireless communication features. Thus, no physical sensing module (e.g. accelerometer) is needed, which relaxes the device deployment requirement, reduces the energy consumption for the sensing and the data transmission, and better protects the users' privacy.

Based on different radio parameters, measurements, characteristics and processing requirements, we divide the published radio_based HAR systems to the ZigBee radio_based, and other radio_based HAR systems. Geng et al. [27] used a measurement system that consisted of a vector network analyser (VNA, Agilent E8363), a pair of low-loss wired cable, and a pair of small size ISM quarter wavelength antenna to recognise a set of activities for firefighters. Their selected features [27] were based on the characteristics of the on-body RF signal propagation channel. While they analysed an in-house-made radio_based system measuring the movements of four places on the body, we have conducted a comparison study of the radio_based and the sensor_based HAR system in this work. Scholz et al. [28] also detected activities (i.e. standing, sitting, lying, walking and empty room) from radio signal strength indicator (RSSI) using sophisticated software defined radio devices in order to obtain frequency domain features using IEEE 802.15.4 wireless technology. They investigated three methods; device-free, device-bound and ambient monitoring and only employed one sensor on the body and eight transceivers were placed in the room. Qi et al. [29] presented another on-body RSSI measurement system using the IEEE 802.15.4 nodes placed on the wrist and the ankle of case studies. They reported system performance in terms of the accuracy, latency, and battery lifetime w.r.t packet delivery ratio, delay and power consumption over different overlapping WSs and the tenfold cross-validation technique.

In this paper, we have also applied smoothing windows; however, we have applied overlapping windows to investigate the recognition accuracy. We have applied a more realistic validation process to improve our work by applying more number of nodes and investigating the sink node position. Furthermore, the improvements investigated in the radio_based HAR system, are deployed and compared with the sensor_based HAR system.

3 Har System Framework

The sensor_based HAR system works based on measuring the acceleration variation of different body parts which are collected from the sensor nodes placed on the case study. A sample of such variations collected from acceleration of the right wrist over different activities is depicted in Fig. 1a. The variation of the x-axis accelerometer information depicted in Fig. 1a can highlight how different activity levels are captured: The signal variations in activities such as lying down and sitting (for the sensor node on the right

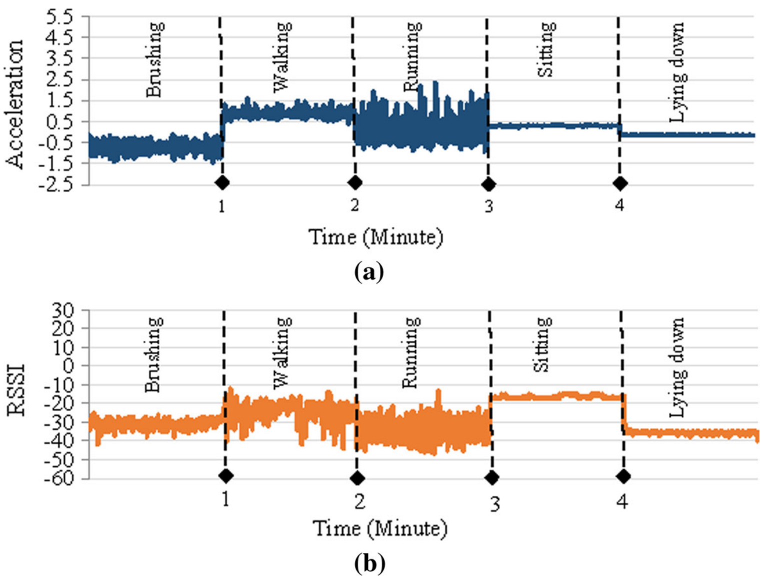

Fig. 1 **a** Acceleration and **b** RSSI variation collected from node placed on the right wrist over different activities

wrist) are relatively lower than in the case of brushing. For other activity classes such as running, the signal fluctuations are relatively higher compared to activities such brushing and walking.

The radio_based HAR system establishes a pattern of the radio signal strength which indicates the activity classes. The variation of the distance between the wireless transmitter and receiver nodes placed on the body results in variation of the received signal strength which is the basis of the radio_based HAR system. In the radio_based HAR system, a periodical signal is being transmitted to measure the radio signal strength. Depending on the communication technology in use, existing signals in the standard such as synchronisation messages or periodical beacons can be considered to avoid injecting additional signaling overhead. Link Quality Indicator (LQI) and RSSI parameters can be derived from the received signal to build the signal pattern and extract required features. A sample of RSSI variation over different activities collected from the right wrist is demonstrated in Fig. 1b. The signal strength variations depend on the distance between nodes; i.e., signal strength gets higher when the node placed on the right wrist gets closer to the sink node on the waist. The signal variations can be used to recognise the class of the activities as in the sensor_based HAR system. In the following, we describe the framework of the system in more detail.

The HAR system framework comprises components for data acquisition, preprocessing, segmentation, feature extraction and selection, training and classification, decision fusion, and performance evaluation. In this section we present two phases of the HAR system framework, i.e., training and recognition in details and describe functional stages as depicted in Fig. 2. In the first stage of training of the sensor_based HAR system, raw acceleration signals are acquired using multiple sensor nodes placed on different parts of the body which later be processed in the sink node to extract the features. The function of the second stage of HAR system, the preprocessing stage, is to synchronise and remove artifacts to prepare the acquired signals for feature extraction. Preprocessing of

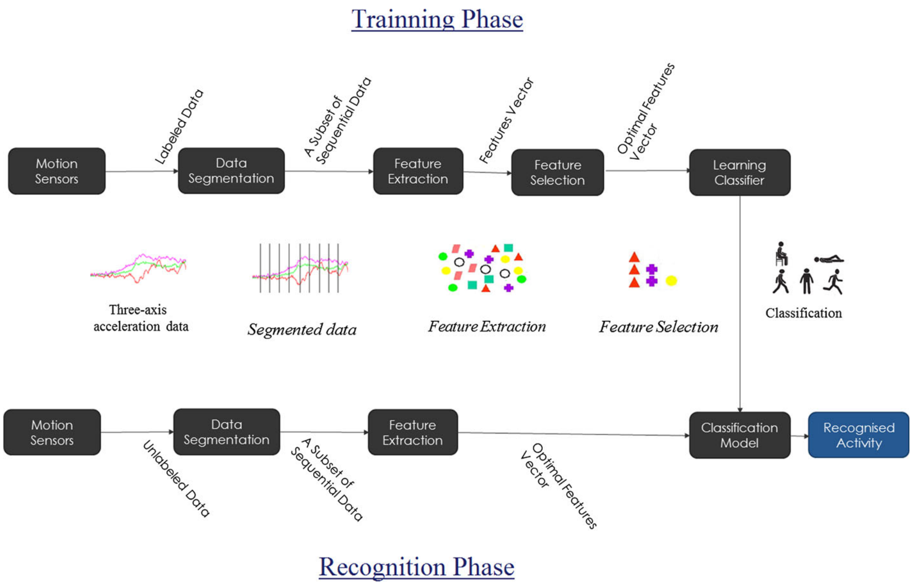

Fig. 2 General HAR system framework

acceleration signals include calibration, normalisation, and synchronisation. Preprocessed data along with its activity class (the associated ground truth) constitutes a data sample. The *data segmentation* stage identifies the preprocessed data samples that are likely to contain information about activities (often referred to as activity detection or spotting). In this work, we use the sliding window approach [35] in the data segmentation stage. In this approach, a window slides over the time series of data samples to extract a data segment which is subsequently used for the *feature extraction stage*. Length of the sliding window determines the number of data samples that contributes in the feature extraction stage. In the HAR context the size of the window is determined by varying the WS and analyzing the performance based on the tested WS values [29, 36–40]. Three approaches exist for feature extraction from segmented time series data: Intuitional [41], statistical and wavelet [42]. We use a commonly used statistical approach and derive features directly from the time-varying data (e.g., accelerometer, RSSI or LQI) signal. The *feature selection* stage employs wrappers, embedded or filter based methods [43] to select features from the derived ones in the previous stage. We apply a filter feature selection method to select the most relevant features which contain useful information about the different classes in the data. The set of selected features extracted from our testbed (as listed in Table 1) as well as the associated activity classes (as listed in Table 2) which form the training set are then fed to a *classification algorithm*. The degree of complexity of classification algorithms varies from a threshold-based algorithm to more advanced algorithms, such as decision tree, hidden Markov models, neural networks and machine learning techniques [44]. We employ C4.5 decision tree classifier [45] which builds a hierarchical model in which features are mapped to tree nodes, and edges represent the possible features' values. C4.5 is the most widely used decision tree classifier and is based on the concept of Information Gain (IG) to select the features that should be placed in the higher tree nodes (i.e., closest to the root). Feature f IG measures the amount of information that the feature reveals about the activity classes. IG is measured by the entropy reduction and defined as follows:

$$IG(f) = E(T) - E(T|f)$$

where T is the training samples that remains in the training set by traversing the decision tree from the root node down to the node f, $E(T)$ is the entropy of T and $E(T|f)$ is the entropy of T conditioned on the f and are calculated as follows:

Table 1 Features extracted from the data collected by each node

Feature	Description
Amp	Amplitude of signal segment
Med	Median of signal segment
Mean	Mean value of signal segment
Max	Maximum amplitude of signal segment
P2P	Peak to peak amplitude
Var	Variance of signal segment
Std	Standard deviation
RMS	Root mean square power
S2E	Start to end value

Table 2 List of activity classes and their durations

Activity	Duration (min)	Activity group
Standing	3	Very low level activity
Sitting	10	Very low level activity
Lying down	12	Very low level activity
Brushing	1	Low level activity
Eating	2	Low level activity
Walking	1	Medium level activity
Running slowly	1	High level activity

$$E(T) = \sum_{c \in C} P(c) Log_2 P(c)$$
$$E(T|f) = \sum_{i=1}^{n} P(f_i) E(T|f_i)$$
$$E(T|f) = \sum_{i=1}^{n} P(f_i) \sum_{c \in C} P(c|f_i) Log_2 P(c|f_i)$$

where n is the number of different values for the feature f, $P(f_i)$ and $P(c)$ are the probability of having value f_i and c for the feature f and activity classes C, respectively, and C is the set of activity classes in the T.

If the feature f is a continuous feature, C4.5 splits training set based on a threshold (t_f) into two subsets $T_{left}(t_f)$ and $T_{right}(t_f)$, where feature f in in $T_{left}(t_f)$ training set has a value less than or equal to (t_f) and in $T_{right}(t_f)$ training set has a value greater than (t_f). C4.5 selects the threshold values in such a way that minimises the entropy of data. The entropy of data for feature f and threshold (t_f) is calculated as following:

$$H(T|f_i) = \frac{|T_{left}(t_f)|}{|T|} E(T_{left}(t_f)) + \frac{|T_{right}(t_f)|}{|T|} E(T_{right}(t_f))$$

The produced decision tree created based on the measured IG is then constructed by a set of rules which classify the training set. Once the training phase is completed, to detect the activities, same set of functionalities (i.e., data acquisition, preprocessing and data segmentation) are performed over similar data collected from cases under study. The selected features in the training phase are extracted in the recognition phase to classify the activities based on the classification technique used in the training phase. In our testbed, each of test data samples is classified using the set of rules constructed in training phase.

4 HAR System Testbeds

To evaluate the described HAR systems in Sect. 3, we set up two testbed experiments. In this section, we provide the testbed details w.r.t the hardware specifications of the deployed nodes, data collection process, and ethical considerations.

4.1 Testbed Setup

In this work, we investigate and compare two HAR systems, i.e., (1) a radio_based HAR system using the RSSI and the LQI and (2) a sensor_based HAR system using accelerometer sensory data. To achieve these goals, radio_based and sensor_based systems are implemented in our research lab in the form of a WBAN based wearable HAR system.

General description of the above mentioned testbeds are as following: The WBAN based HAR system is comprised of Sun SPOT [46] nodes manufactured by Oracle (formerly Sun Microsystems), as shown in Fig. 3. The Sun SPOT nodes are either in form of a sensor or a sink node. While sensor nodes contains a processor, radio, sensor board, and battery, and the sink node only contains processor and radio board. Both sensor and sink nodes use a 32 bit ARM9 micro-processor running the Squawk VM and the IEEE 802.15.4 compliant radio unit. IEEE 802.15.4 radio unit provides information about the received signal. The effect of distance on the radio signal strength can be measured by the packet success rate, the RSSI, and the LQI provided by the radio board. The LQI is a metric introduced in IEEE 802.15.4 that measures the error in the incoming modulation of successfully received packets (i.e. packets that pass the CRC criterion). The LQI metric characterises the strength and quality of a received packet and is provided by CC2420 [47]. Each sensor node can be embedded in an environment and perform sensing tasks and communicate with the sink node over wireless links. The sink node can be connected to an external server such as a smart phone or a laptop through a USB interface to collect the information transmitted by the sensor nodes. In our testbed, we place four nodes on the body of a case study; two nodes on the right and the left wrists, one on the chest and the last one on the left thigh as illustrated in Fig. 3. These nodes communicate with the sink node placed within the sensor nodes transmission range. We have selected this setup based on the investigation of the related works (as described in Sect. 2) which lead us to the suggested configuration by Atallah et al. [30] for the wearable accelerometers framework. For short range WBAN communication systems to achieve a signal strength greater than − 80 dB over a distance of 5 m, the radio transmission power is set to level 7 (defined in the Sun SPOT radio) where the radio power transmission is equal to − 15 dBm and consumes current out 9.9 mA based on Mallinson et al. experiments [48].

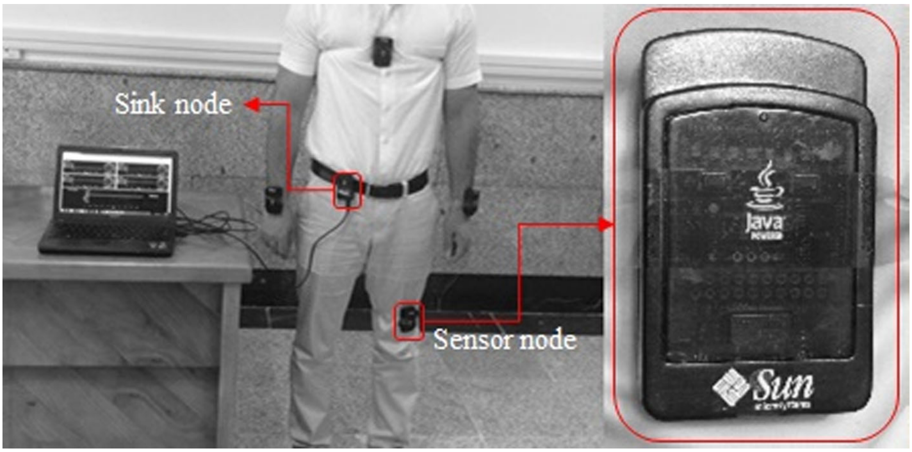

Fig. 3 The Sun SPOT nodes placement

Beside the described general testbed setup, the specific setup for the radio_based and the sensor_based HAR testbed are highlighted as followings:

In radio_based HAR testbed each node contains a battery, a processing, and a radio board. In this testbed, a periodical signal with 12 Hz frequency is being transmitted to measure the radio signal strength based on the RSSI and LQI. Built in sensor units are switched off for this testbed.

In sensor_based HAR system, each node requires an additional sensor board (i.e. an accelerometer). Each sensor node senses accelerometer data with a 12 Hz sampling rate and transmit the sensed data to the sink node.

In experiments conducted for both the sensor_based and the radio_based testbeds, we aim to identify seven activities (as listed in Table 2) that represent both activity intensive and non-intensive scenarios. The level of activities can be categorised based on the rates associated to them. We also categorised the level of activities based on the activity levels described by Atallah et al. [30] to capture a range of activities of daily living. The selected duration of each activity set proportionally to the normal daily activity duration of the elderly activities as shown in Table 2.

We have performed a set of controlled experiments using five average height case studies out of which there are two healthy females and three healthy male subjects. All case studies are right handed subjects. Although significant care is taken to place all the sensor nodes at similar positions for all case studies, there are some inevitable variations during the sensor nodes placement phase which can be overcomed by running the test for a numbers of trials. Case studies are given predetermined sequences of the seven aforementioned activities to follow for a predefined period of time as presented in Table 2. The length of each daily activity is scaled down to 30 min and each repeated five times by five case studies participated in experiments to maintain a 95% confidence interval. Each of the seven activities are detected using a set of features which are listed in Table 1. To evaluate the recognition accuracy, we temporally correlate activities with the sequence provided to the case studies and employ the J48 decision tree classifier of the Weka toolkit [49] as the selected classifier.

4.2 Data Collection Protocol

The data collection requirements on the accuracy, reproducibility and feasibility according to the quality of experience of users have led us to the selected number of subjects and the length of activity classes. The quality of experience of the users depends on the size, number and the position that the nodes are placed. Limited power supply of the nodes is the main restriction to allow nodes to run for couple of days as preferred. Furthermore, related published works are summarised in Table 3 which includes our testbed parameters (last row) for better comparison of results.

4.3 Testbed Experiments

We conduct three sets of experiments to analyse the radio_based HAR system to: (1) demonstrate the system performance w.r.t the accuracy of the pattern recognition and evaluate the trade-off with the power consumption of wireless wearable sensor nodes and (2) investigate the impact of sink node position on the recognition accuracy.

The location of the sink node (either on the waist or on the desk) does not have any impact on the results of the sensor_based HAR system. Hence, a set of data is collected for the sensor_based and two sets of data are collected for the radio_based HAR system to

Table 3 Example of HAR system acceptable accuracy based on accelerometers data

References	Sensor placement	# of activity classes	Average classification accuracy (%)	# of case studies	Data collection time
Bao et al. [50]	Wrist, ankle, thigh, elbow, hip	20	84	20	24 h
Mathie et al. [51]	Waist	5	98.9	26	65 min
Karantonis et al. [52]	Waist	2	90.8	6	NA
Olgun et al. [53]	Wrist, chest, hip	6	92.13	3	81 min
Parkka et al. [54]	Wrist, chest	5	83.3	17	34 h
Pirttikangas et al. [55]	Thigh, necklace, wrists	5	91.5	13	585 min
Minnen et al. [56]	Chest, right thigh, on the barrel of the field weapon, wrists, right hip	14	90	1	3.3 h
Salarian et al. [57]	Trunk, shanks (IMU sensor)	14	–	9	NA
Chen et al. [58]	Wrist	8	93	7	112 min
He et al. [59]	Pocket	4	92.25	11	44 min
Yang et al. [60]	Wrist	8	95	7	112 min
Yeoh et al. [61]	Thigh, waist	4	100	5	NA
Bonomi et al. [62]	Lower back	7	93	20	NA
Hanai et al. [63]	Chest	5	93.91	1	2 h
Altun et al. [64]	Knees,wrists, chest	19	87–99	8	32 h
Cheng et al. [65]	Neck, chest, leg, wrist (electrodes)	11	77	3	33 min
Gjoreski et al. [66]	Thigh, waist, chest, ankle	5	91	11	825 min
Chamroukhi et al. [67]	Chest, thigh, ankle	7	90.3	6	30 min
Bayat et al. [68]	Pocket, hand	6	91.15	4	~ 19 min
Gao et al. [69]	Chest, waist, thigh, side	5	96.4	8	NA
Gupta et al. [70]	Waist	7	98	7	~ 126 min
Moncada-Torres et al. [71]	Chest, thigh, ankle	16	89.08	6	67.46 min
Mass et al. [72]	Trunk (IMU and barometric pressure sensor)	4	90.4	12	360 min

Table 3 continued

References	Sensor placement	# of activity classes	Average classification accuracy (%)	# of case studies	Data collection time
Rezaie and Ghassemian [73]	Chest, right-wrist, left-wrist, thigh	7	99	20	250 h
Our testbed	Chest, right-wrist, left-wrist, thigh	7	Reported in Sect. 5	5	12 h

explore the impact of the sink node position. In the first round the sink node placed on the desk and in the second round on the waist. The average distance when the sink node is on the desk varies between 2.5 ± 2 m and the average is reduced to 60 ± 50 cm when the sink node is placed on the waist. We firstly investigate the impact of the radio_based HAR system on energy consumption. To reduce the cost and size of the wearable HAR system, we investigate the recognition accuracy when placing the radio board on the body to measure RSSI and LQI. Then a discussion on the results of recognition accuracy analysis is presented.

4.4 Ethical Considerations

The research protocol is approved by the ethical committee of Shahid Beheshti university. Case studies have signed an informed consent form to reflect their agreement to participate in the study. For privacy preservation, the demographic data is recorded not to reveal the identity of the case studies.

5 Experimental Results and Analysis

For wearable HAR systems, three sources of energy consumption are identified, i.e. sensory, processing and radio boards power consumption. In this section, we aim to look at the sensory board energy consumption. Furthermore, we have compared the performance of the radio_based and the sensor_based HAR systems w.r.t the the recognition accuracy and the energy consumption.

5.1 Performance Metrics

We define the main performance metrics in this subsection, namely energy and accuracy.

Energy consumption metric Due to the limited energy in the battery operated wireless nodes, energy consumption is one of the main bottlenecks, hence calculated to evaluate the performance of the proposed methods. We measure the energy consumption of nodes as the result of sensing, processing and transmission [3] by utilising the sun SPOT API which provides us the remaining battery charge of nodes in milliAmpere-hours. We calculate the energy that is consumed during each experiment as follows:

$$e = Q * V * 3.6$$

where Q is the depleted battery charge in milliAmpere-hours during experiment and V is the battery voltage of nodes in Volts.

Recognition accuracy metric We use accuracy and true positive rate (TPR) as performance metrics to evaluate the decision tree ability to classify each of the activities. The *accuracy* is computed as ratio of sum of the true positives and the true negatives to the total number of samples in the training set. The *TPR* is computed as the ratio of the true positives to the total number of samples in the training set. Based on the example of multi-class confusion matrix shown in Table 4, the recognition performance metrics are calculated as follows:

$$Accuracy(a_k) = \frac{N_{kk} + \sum_{i=1, i \neq k}^{n} \sum_{j=1, j \neq k}^{n} N_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} N_{ij}}$$

$$Overall\ Accuracy = \frac{1}{n} \sum_{i=1}^{n} Accuracy(a_i)$$

$$TPR(a_k) = \frac{N_{kk}}{\sum_{i=1}^{n} N_{ki}}$$

where N_{ij} is the number of data samples using label a_i but recognised as activity class of a_j, and classified as activities a_j and n is the number of activity classes.

5.2 Energy Consumption Analysis

As discussed before, the radio_based HAR system is investigated due to lower hardware and energy cost. In this subsection, we examine the trade-off parameters for the reduced energy level in the radio_based HAR system. Table 5 shows the amount of energy consumption saved in the radio_based HAR system. An overall 30% energy consumption improvement is achieved in the expense of 1.5% reduction in the recognition accuracy rate for the 30 min experiments. This shows that the radio_based HAR system can achieve a longer lifetime with a similar accuracy level considering a scenario where four nodes are placed on the body and the sink node is on the case study's waist. While the energy consumption should be improved, the impact of the solutions on other performance metrics such as accuracy needs to be explored.

5.3 Sliding Window Size Selection

To size of sliding window is one of the influencing factors that affects the overall HAR system accuracy. We explore the impact of the sliding WS on our analysis to select a

Table 4 An example of confusion matrix used in this work

Actual activities	Classified activities			
	a_1	a_2	$\cdots$	a_n
a_1	N_{11}	N_{12}	$\cdots$	N_{1n}
a_2	N_{21}	N_{22}	$\cdots$	N_{2n}
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
a_n	N_{n1}	N_{n2}	$\cdots$	N_{nn}

Table 5 Energy consumption comparison and measurement confidence level

HAR system	Energy evaluation		
	Energy consumption (J/min)	Confidence level (99%)	Average lifetime (h)
Sensor_based	16.329	0.057	9.84
Radio_based	11.441	0.13	13.97

suitable WS for the rest of our analysis. In our testbed, based on sampling frequency and the duration of the activity classes, a range of sliding WS should be selected between 2 and 720 samples (1 min as the minimum activity duration sampled with 12 Hz) so that it extracts the features for HAR system. We have taken a range of 5–300 for the sliding WS to select one which the accuracy does not improve much after this point. As discussed in Sect. 4, in the radio_based measurements, the sink node once placed on the desk and once on the case study's waist, which impacts on the accuracy due to the relative distance of the nodes during the activities. As shown in Fig. 4, when the sink node is placed on the desk, the accuracy of the radio_based HAR system degrades. However, it is still above the acceptable accuracy range of 95%. Since the sensor_based HAR system utilises the accelerometers information it shows an overall higher accuracy rate compared to the radio_based HAR system. Furthermore, the performance of the sensor_based HAR system remains almost the same over the applied range of WS. However, the impact of WS variation on the radio_based HAR system is significant. Improved accuracy rates for larger WSs result in higher processing power consumption as well as an additional delay. As overlapping window is applied in our analysis, different size of the sliding window does not impact on the average delay and only influences on the initial recognition time. The 5 s

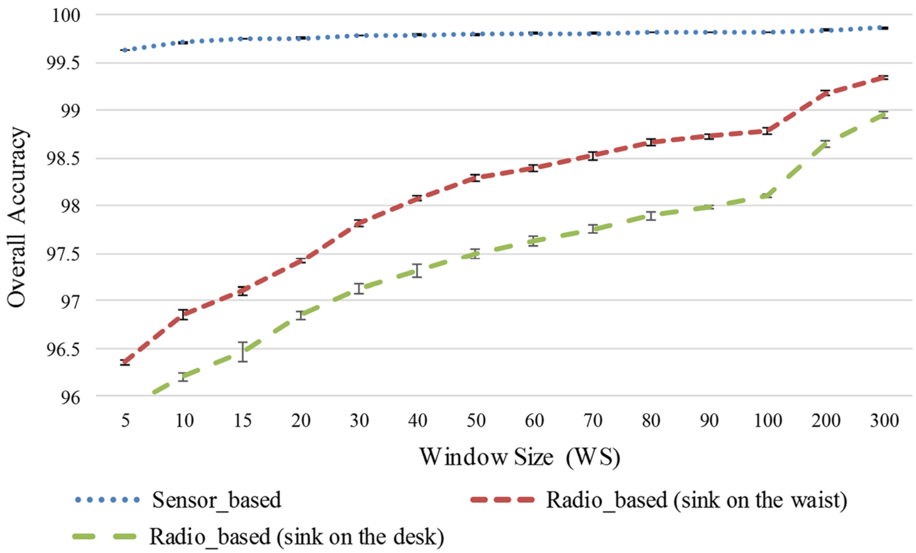

Fig. 4 Comparative analysis of the HAR system overall accuracy for the radio_based versus the sensor_based HAR systems over different WS values

initial delay corresponds to the WS of 50 samples per window and is acceptable for HAR applications [74]. Considering the radio_based HAR system (when the sink node is placed on the waist), the impact of WS for each activity is illustrated in Fig. 5. Moving from the very low level to low level activities demonstrates a lower recognition accuracy rate compared to the mid to high level activities. This observation can be justified due to the lower number of changes in the signal strength in low level activities. As shown in Fig. 4, since the overall accuracy improvment increases linearly till the WS equal to 50, we use this value for the rest of our analysis. This results in a minimum accuracy of 97% and 5 s initial delay in the HAR system.

5.4 Impact of Sensor Nodes Placement and the Sink Node Position

Considering the sliding window of 50 samples, we have further studied the impact of the sink node placement as demonstrated in Fig. 6. Since the sensor_based HAR system benefits from the features driven from the accelerometers, the accuracy level for the sensor_based outperforms the radio_based HAR system for all activity classes. Furthermore, considering the standard deviation depicted in Fig. 6, the sensor_based system confirms a higher confidence interval compared to the radio_based HAR system. For the radio_based HAR system, the accuracy also depends on the sink node position, i.e. where the sink node is placed on the body or placed on the desk. As shown in Fig. 6, when the sink node is placed on the waist, the distance between the node placed on the body and the sink node is less than when the sink is placed on the desk which results in higher sensitivity to distance changes. In other words, the relative body movements are measured based on the RSSI, can better distinguish the movements when sink is placed on the waist. This can justify the higher accuracy level in our results when the sink node moves relative to the nodes placed on the body for all activity classes.

We also examine the recognition accuracy with less number of measurement points on the body to decrease the cost and the energy consumption. Figure 7 shows three scenarios; i.e., 2, 3 and 4 measurement points on (a) the chest and tight, (b) the chest, thigh and right wrist, and (c) the chest, thigh, right and left wrists, respectively for both sensor_based and

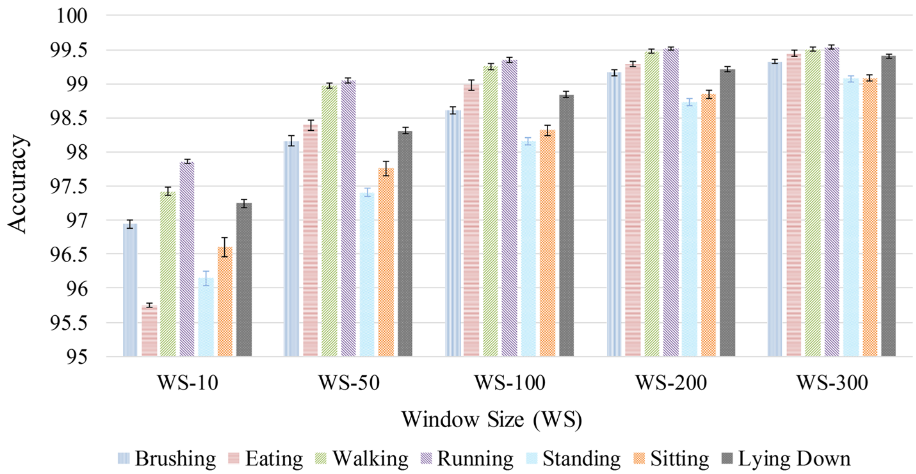

Fig. 5 Accuracy analysis for the radio_based HAR system (sink node on the desk) over different WS values for different activity classes

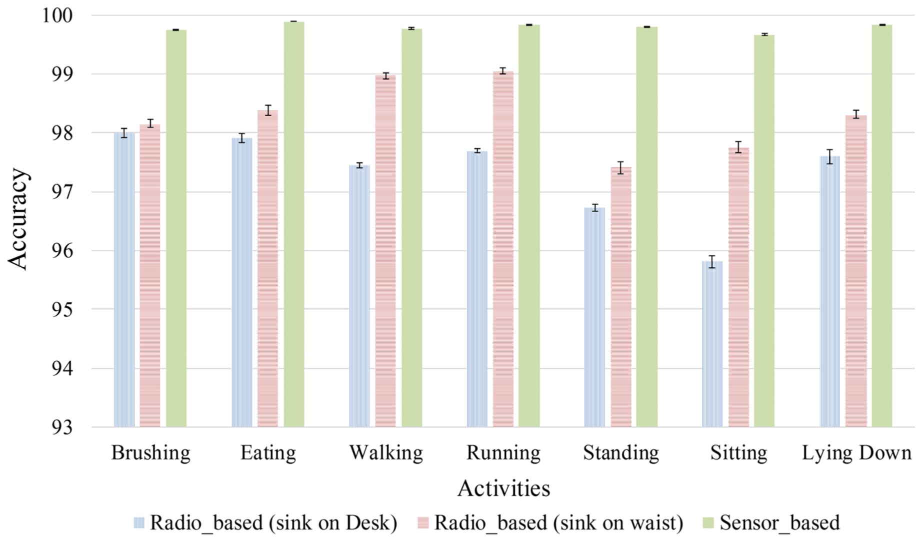

Fig. 6 Comparative analysis of the sensor_based and the radio_based (with different sink node positions) HAR systems with WS = 50

radio_based HAR systems. The recognition accuracy comparison of the radio_based HAR system is presented in Fig. 7 for a combination of the sensor nodes placed on the body and for all the activity classes. As shown in Fig. 7, in comparison with the sensor_based system for all activities using four nodes, an average accuracy degradation of 1.5 and 2.5% is observed when the sink node is placed on the waist and on the desk, respectively. The recognition accuracy further degrades when less number of nodes are utilised for the HAR systems. Nevertheless, for all cases are above 93%.

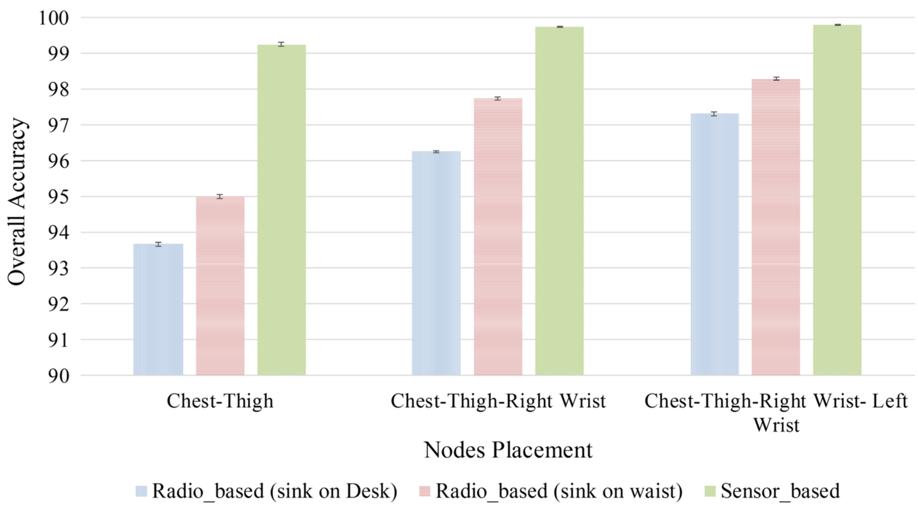

Fig. 7 Impact of node placement on the overall accuracy analysis

5.5 Activity Class Analysis

As the overall accuracy level, achieved in Sect. 5.4, shows higher performance where the sink node is placed on the waist in the radio_based HAR system, we have further explored this scenario in more details. Table 6 shows the true positive rate for different activities for the three nodes placement scenarios. In very low level activities such as standing and lying down, adding more than three nodes increases the true positive rate from 95.83 to 96.75% and from 97.16 to 97.74%, respectively. However, in low level activities such as brushing, this varies from 62.67 to 71.08%. Therefore, the additional hardware cost to place more number of nodes impacts on the accuracy in higher activity classes in the radio_based systems. For brushing, our experiments show that beside the number of nodes, the node placement on the right hand wrist is required to capture the wrist movements. Therefore, better node placements acquire a higher ratio of engaged nodes over the total number of the placed nodes.

5.6 Impact of Radio Indicators

We have also explored the impact of radio signal indicators. Results presented in Fig. 8, show that using LQI information results in a lower accuracy rate even with higher number of measurement points. On the other hand, using RSSI or combining RSSI with LQI measurements result in a similarly higher recognition accuracy level. Since LQI information is also derived from RSSI measurement, feeding this parameter to the system does not increase the accuracy in different node placements. LQI exhibits a very good correlation with packet loss and is therefore a good link quality indicator. However, one of the contributions of this paper is to show RSSI as an important metric if interference can be distinguished from noise. Given that LQI is a supplementary metric, we should bear in mind that it is only made available in IEEE 802.15.4-compliant devices. Therefore, the RSSI which can be calculated based on the received signal strength in wireless technologies is advised to be exploited in the radio_based HAR systems.

To summarise the experimental observations discussed in this work, we have compared the possibility of eleminating the commonly used accelerometer sensor in HAR systems and observe the system performance in absence of the sensory information when using the radio signal strength measurements. In the radio_based system, we observe that beside the reduced hardware cost of the sensor considering a system with four nodes, sink node on the waist, and WS 50, the lifetime of the systems is prolonged nearly 30% due to lower amount of processing (sensing part) as well as lesser number of transmissions. While the energy consumption is the main challenge of the wearable systems, the accuracy of the recognition is of importance. Our investigations also show that an approximate recognition accuracy degradation of 1.5% is negligible and acceptable compared to the energy consumption gain (Table 7).

Furthermore, we have investigated the node placement impact on the accuracy and reported a higher sensitivity to the number of nodes, node placements as well as sink node placement in the radio_based system which is due to the dependency of the results on the distance. Another influencing variable is the sliding WS for feature extraction and the IG impact on the accuracy which is demonstrated to be higher in the radio_based system. Therefore, while reducing the hardware and processing load helps the HAR system perform significantly better with respect to the energy efficiency, careful selection of the WS and node placement is suggested in the radio_based HAR system.

Table 6 Classification of selected human activities based on different number of nodes and their placement

	Nodes placement	True positive rate						
		Brushing (%)	Eating (%)	Walking (%)	Running (%)	Standing (%)	Sitting (%)	Lying down (%)
Brushing	Chest-thigh	38.78	22.84	1.03	1.42	8.84	22.51	4.58
	Chest-thigh-right wrist	62.67	19.15	1.58	1.19	3.77	7.02	4.63
	Chest-thigh-right wrist-left wrist	71.08	12.44	1.32	1.22	3.89	6.3	3.74
Eating	Chest-thigh	4.77	81.42	0.59	0.93	3.01	8.59	0.69
	Chest-thigh-right wrist	7.02	87.82	0.92	0.76	1.64	1.25	0.59
	Chest-thigh-right wrist-left wrist	2.85	92.61	0.66	0.84	1.48	1.03	0.52
Walking	Chest-thigh	1.03	3.23	69.98	22.4	1.65	0.64	1.07
	Chest-thigh-right wrist	0.85	3.02	83.02	9.72	1.91	0.65	0.84
	Chest-thigh-right wrist-left wrist	0.9	2.52	85.92	8.27	1.08	0.53	0.77
Running	Chest-thigh	0.64	2.48	25.02	69.72	0.89	0.55	0.7
	Chest-thigh-right wrist	0.57	2.39	10.03	85.98	0.4	0.14	0.49
	Chest-thigh-right wrist-left wrist	0.55	2.34	7.97	87.93	0.42	0.22	0.57
Standing	Chest-thigh	1.4	3.26	1.21	1.39	60.09	19.26	13.39
	Chest-thigh-right wrist	1.73	1.97	1.09	0.94	80.8	8.2	5.27
	Chest-thigh-right wrist-left wrist	1.56	1.91	0.64	0.98	85.63	5.57	3.71
Sitting	Chest-thigh	1.14	1.75	0.13	0.19	3.46	85.14	8.19
	Chest-thigh-right wrist	0.82	0.55	0.23	0.03	1.88	95.53	0.96
	Chest-thigh-right wrist-left wrist	0.60	0.55	0.18	0.04	1.29	96.75	0.6
Lying down	Chest-thigh	0.31	0.26	0.14	0.15	2.42	3.91	92.8
	Chest-thigh-right wrist	0.31	0.15	0.17	0.13	1.29	0.78	97.16
	Chest-thigh-right wrist-left wrist	0.2	0.18	0.17	0.13	1	0.57	97.74

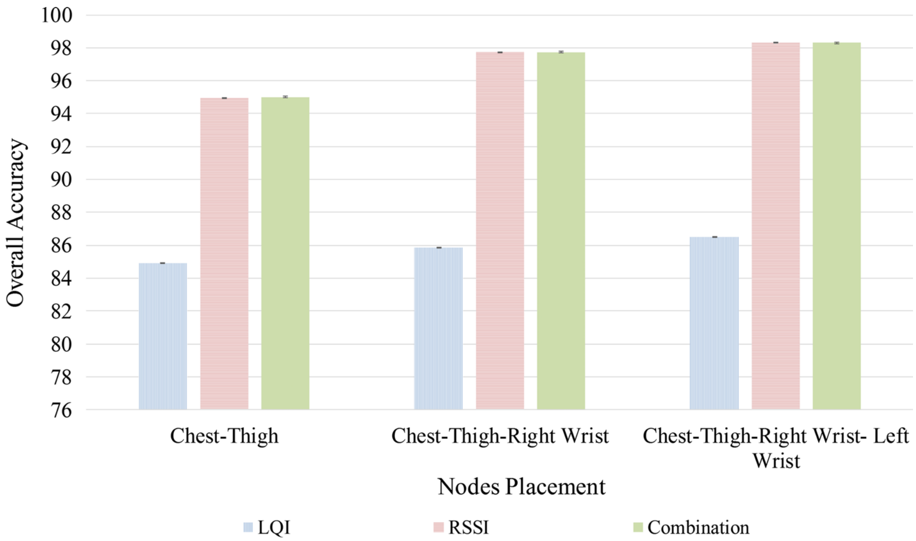

Fig. 8 Overall accuracy rate for different combination of RSSI and LQI information in the radio_based HAR system

Table 7 Summary of the experimental observations

			Sensor_based system	Radio_based system	
Variables	Hardware Requiremen		Processing, sensing and radio modules	Radio module	
	Measured input signals		Acceleration	RSSI	
	Size of sliding window		5 to 300	5 to 300	
	# of placed nodes		2 to 4	2 to 4	
	Sink node position		Fixed	On the desk-On the waist	
Performance metrics		# of placed nodes	Overall accuracy	Overall accuracy	
				Sink node on the desk	Sink node on the waist
	Recognition accuracy	2	~99.2%	~97.7%	~95%
		3	~99.7%	~96.3%	~97.7%
		4	~99.8%	~97.4%	~98.5%
	Transmission load		~6500 bps	~1500 bps	
	Lifetime (Hours)		9.84	13.97	
	Sensitivity to the number of nodes		Low	High	
	Sensitivity to the size of sliding window		Low	High	
	Dependency to the sink position		No	Yes	

6 Conclusion and Future Work

In the wearable human activity recognition systems, multiple wearable nodes are used to form a wireless body area network. System lifetime and recognition accuracy are the most important challenges. We first set up a sensor_based HAR testbed for activity recognition using accelerometer. Additionally, we investigate the impact of the radio pattern variation in the absence of the sensor board for the HAR systems and compare the collected results with the sensor_based HAR testbed. In this work, we use a sliding window rather than a distinct window to allow a precise feature extraction. We demonstrate that larger WSs result in a higher delay and processing complexity and improves the accuracy level. Furthermore, we have investigated the use of IEEE 802.15.4 radio signal indicators (i.e., LQI and RSSI) for HAR systems for different activity levels. We show the HAR system accuracy depends on the number of nodes, position of the nodes, and the sensory information. Our implementation and analysis of both sensor_based and radio_based HAR systems report a trade-off between energy-cost and accuracy. Our results show a comparable recognition accuracy of 1.5% lower level and 30% reduced energy consumption rate for the radio_based HAR system compared with the sensor_based one.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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Hamed Rezaie received his Master degree in Software Engineering at the University of Isfahan in 2009. He is currently a Ph.D. student at the Department of Computer Science and Engineering, Shahid Beheshti University (SBU). His research interests are wearable activity recognition systems and WBAN MAC layer design.

Mona Ghassemian received her Ph.D. in "Mobile and Personal Communications" research from King's College London in 2006 with NTT DoCoMo scholarship. After completion of her Ph.D. she continued at King's College London as a research associate in E-Sense (a project of the 6th Framework Programme of the European Commission). She worked at University of Greenwich as a senior lecturer and PG programme leader in computer networking 2007–2012. She visited a number of universities; namely UoT, TU, and SUT and collaborated with their research groups. She is a faculty member at SBU and a visiting research associate at King's College London. Her research interest is mainly on issues related to Wireless Sensor Networks with a focus on Smart Health and well-being. She served as IEEE UK & Ireland Secretary and IEEE Region 8 Student Activities Committee March 2012–March 2015 and Jan 2016–Dec 2017, respectively.