A review of sensor selection, sensor devices and sensor deployment for wearable sensor-based human activity recognition systems

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Abstract—**Data preprocessing, feature selection and classification algorithms usually occupy the bulk of surveys on human activity recognition (HAR). This paper instead gives a brief review on the data acquisition which is a critical stage of the wearable data-driven-based HAR. The review focuses on the determination of sensor types, modality of sensor devices, sensor deployment and data collection. The work aims to provide a comprehensive and detailed guidance for the fundamental part in HAR, also to highlight the challenges related to the topics reviewed.**

Keywords- wearable sensors; sensor device; sensor deployment; data collection; daily activity recognition

I. INTRODUCTION

According to the 2015 world population report, over the next decades, the number of older people is expected to grow faster, which is projected to more than double its size, reaching nearly 2.1 billion in 2050 from 901 million in 2015 [1]. Ageing population has caused many potential impacts on families, communities as well as societies, e.g. the increasing expenditure on healthcare. Additionally, 48% of the retirement-age pupation does not receive a pension [1]. More solutions are therefore needed to assist elderly people's daily life.

As one of the most promising assisted technologies, Home-based HAR aims at recognizing users' specific activities or discover long-term patterns from a series of observations in real life settings. The relationship between daily activities and the corresponding health status has been well aware. For example, long-term sedentary activities may imply that one person is suffering certain cognition problems or having early dementia symptoms; more sleep at daytime or less sleep at night may indicate insomnia or other medical and psychiatric problems; too frequent use of the toilet or frequent drinking are probably associated with diabetes or kidney diseases. Changes in routines prompt us some disorder is happening compared with the normal patterns, on the other hand, regular eating, regular exercise and other well organized daily activities will suggest the person is leading a healthy lifestyle. The above-mentioned conditions can be detected by HAR-based technologies. As a consequence, HAR has found a wide range of applications, including surveillance, assistance and care giving, home rehabilitation, and so on [2]–[4].

Wearable-sensors-based HAR (WSHAR) infers a user's activities by means of the data mining techniques based on the acquired data from on-body sensors. It has attracted much interest during the past two decades due to its strengths such as high recognition performance, flexibility and practicability [5]–[7]. Data-driven-based WSHAR systems basically share a similar procedure, as presented in Fig.1. Surveys in [8]–[10] talked more about data preprocessing, feature selection, classification and the corresponding challenges. Data acquisition, as the fundamental material for HAR, however, has not been given more attention in other reviews. Properly and strategically obtaining the wearable information is critical for further learning in WSHAR, this survey consequently highlights the key questions at data acquisition stage (Fig.1) and the challenges for each topic reviewed.

The rest of the paper is organized as follows. The popular sensors used in WSHAR are presented in section II. The sensor devices and the communication techniques are discussed in section III. Section IV details the different sensor deployments. Activity definition and data collection protocol are discussed in section V. The final section comes to the conclusion with several open issues.

II. WEARABLE SENSORS

These years, the advances in sensors make it possible and feasible to explore assisted living in healthcare and wellbeing. Wearable sensors, different from common industrial sensors, are designed to meet some specific requirements: high integration density, small size, low power consumption as well as high measurement accuracy, etc. The sensors are usually integrated into a

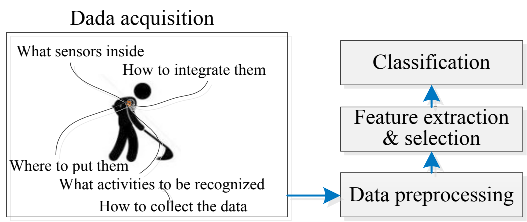

Fig.1. Procedure of WSHAR

TABLE I. MAJOR MANUFACTURES AND THEIR TYPICAL WEARABLE PRODUCTS

Manufacturers	Mainstream sensors	Typical Models
Freescale	Accelerometers	MMA8451Q
	Magnetometers	MAG3110
	Gyroscopes	FXAS21002
	Pressure Sensors	MPXHZ6130A
BOSCH	Accelerometer	BMA280
	Environmental Sensors	BME280
	Gyroscope	BMG160
Sitronix	Accelerometer	STK8312
MEMSIC	Accelerometer	MXR9150MZ
	Tilt sensor	CXTA02-T
	IMU	MMC3316xMT
Kionix	Accelerometer	KXTH9-2083
	Combo Parts	KXG02
	Gyroscopes	KGY23
MCUBE	Accelerometer	MC3210
	Magnetic Sensors	MC6470
	Gyroscope	MC7010
DMT	Accelerometer	DMARD06
TI	Temperature sensor	TMP006
InvenSense	IMU	MPU-9255
	Accelerometer.	MPU-3050
	Gyroscope	MPU-6500
ST	Accelerometer	LIS344ALH
	Gyroscope	L3GD20
	Humidity sensor	HTS221
	Inertial module	LSM6DB03
	Proximity sensor	VL6180X
	Temperature sensor	LM135
	Pressure sensor	LPS25H
Neurosky	Body and mind biosensors	Chips+
	ECG biosensor	Algorithms+
	EEG biosensor	Applications
ADI	Heart rate monitor	AD8232
	Accelerometer	ADXL362
	Gyroscope	ADXRS290
	Temperature sensor	ADT7420
	MEMS IMU	ADIS16485

IMU-Inertial Measurement Unit

small-size device for conveniently being attached to user's body parts. Microelectromechanical systems (MEMS) integrate very small sensors. These sensors merge at the Nano-scale, thereby generating the very-small-size devices. The sensors in MEMS gather information from the environment through measuring biological, mechanical, magnetic phenomena, chemical, thermal, and optical, etc. [11]. The main manufacturers which provide the leading wearable sensors, especially MEMS sensors, are shown in table I.

Wearable sensors available generally involve inertial sensors, physical health sensors, environmental sensors, camera, microphone, etc. Table II lists some popularly-used sensors through many references. More motion-based inertial sensors have been well applied, like the accelerometer, gyroscope or magnetometer, which can detect and measure acceleration, angular velocity, magnetic fields, tilt, shock, vibration, rotation, and multiple degrees-of-freedom motion. These observations vary sensitively according to a wearer's movements or body postures. Paper [12] developed a fast and accurate recognition model based on the accelerometer and gyroscope, aiming to avoid the data distribution variations caused by different users. Guo et al. [13] used an accelerometer, a magnetometer, and a gyroscope built in a smartphone for patients' activity recognition. Although motion-based sensors have been widely applied in WSHAR systems, they still suffer from some limitations, e.g. the calibration for effective measurements, battery life due to continuous logging, or arbitrary signals produced when performing activities.

Physical health sensors, including heart rate (HR), oxygen saturation (SpO2), blood pressure (BP), electrocardiogram (ECG), blood glucose (BG), respiratory rate (RR), etc., are sometimes used with motion sensors to detect the activities of patients for rehabilitation purpose or capturing their vital signals for health condition evaluation. Study in [29] developed a framework for detecting epileptic seizure by EEG sensors. Researchers in [4] proposed a practical activity recognition system by combining a heart rate sensor attached on chest with other six sensors worn on wrists. Physical sensors have been unable to obtain large-scale application in HAR due to the problems of size, precision, price, etc.

With respect to environmental sensors, only the temperature sensor, barometer as well as light sensor can be seen often. Maurer U et al. [30] implemented a multi-sensor platform embedded with a light sensor, the platform was attached on five different positions to explore the best location on body achieving highest accuracy. A barometer built in a smart phone [31] was used to help detect a total of 15 activities with other sensors inside.

III. SENSOR PLATFORMS

The wearable sensors (one or more) are usually integrated into one device carried by the users when they perform activities. In order to minimize the obtrusiveness during use, the sensor devices are usually seen in the following modalities: smart phones, smart watches, inertial units and specific-designed platforms, as shown in Fig. 2.

Nowadays, most **smart phones** are equipped with a variety of sensors, e.g. temperature, accelerometer, barometer, gyroscope, etc. Fusing the data gathered from these sensors could enable many potential applications in recognizing human activities, referring to the work in [13], [32]–[34], etc. The main problems when using smart phones for HAR, however, are the fact that the phones normally can be placed in pockets, which might not

TABLE II. WEARABLE SENSORS USED IN HAR

Inertial sensors	Accelerometer [4], [14], [15], [13]
	Gyroscope [16]–[18]
	Magnetometer [16], [17]
Physical health sensors	Electrocardiogram (ECG) [19]
	Skin temperature [20]
	Heart rate (HR) [4], [21]
	Electroencephalograph (EEG) [22]
	Electromyogram (EMG),etc. [23]
Environmental sensors	Temperature [4], [24]
	Humidity [25]
	Light sensor [4]
	Barometer, etc. [5]
Others	Camera [26]
	Microphone [27]
	GPS, etc. [28]

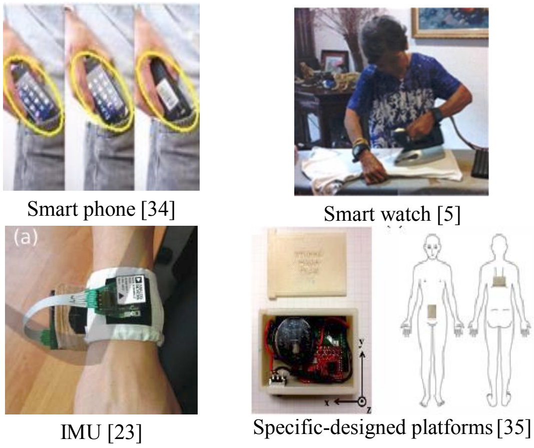

Fig.2. Typical wearable platforms in HAR

suitable for everyday use when the phone carrier performs daily activities at home.

Smart watches, similar to smart phones, are designed with integrated sensors that enable a connection to a PC via Bluetooth or Internet. The typical examples of using smart watches to identify daily activities can be seen in [4], [6], [36], etc. A smart watch is more convenient and less obtrusive for the user to wear compared with carrying a smart phone all the time, and both of them do not need more hardware cost. However, smart phones and smart watches share a same problem that the sensors inside are fixed and sometimes not the exact ones required for a specific research. In some cases, the data from the commercials might not be open-source.

An **inertial measurement unit** (IMU) is an electronic device that integrates an accelerometer, a magnetometer, a gyroscope and sometimes with a barometer. IMU typically measures and reports a craft's velocity and orientation. One or some combinations of IMU sensors are often employed to detect human gestures or activities in different applications, referring to [7], [10], [23], etc.

As for the **specific-designed devices**, they are specifically designed for one research or common research purposes, in which the sensors exactly required for a specific task are integrated. Paper [37] designed a flexible sensing device with multiple sensors built in. They evaluated the device's capabilities, including kinematic sensing, physiological sensing, ambient sensing, external hardware integration and so on; [38] presented a framework with a wrist-worn-9-axis-sensors device. They verified the feasibility of the device based on two activities: hands washing and drinking; Paper [19] designed an open-source, wearable, eight-channel bio-potential data collection platform integrated with an ECG and an accelerometer sensor, which was used to record health related information. Developing a specific sensor device can meet the exact sensor requirements for a task while for some research it may mean the increase in hardware cost and research period.

The communication techniques are used to transfer the collected data from on-body sensors to the processing center (such as a laptop or a mobile phone) in a wired or wireless way. The widely used wireless technologies are ZigBee [39], WiFi [40], Bluetooth [10], and other wireless modes [41]. The biggest advantage of Bluetooth is no wires or cables required, but the limitation is that it can only function effectively within a maximum distance of 10 meters. ZigBee is another such technology that is used to communicate and transmit data between two or more devices. The mainstream wireless communication techniques used in wearable device in terms of data rate, standard, diffraction, safety and so on, are listed in table III.

IV. SENSOR DEPLYMENT

Where to place the sensors selected in a specific task is a key problem in WSHAR, since different body parts deliver diverse sensitivity to different activities, thereby causing different performances. The most potential body positions have been explored to deploy sensor(s): hands [10], arms [10], wrists [38], chest [42], pockets [33], head [43], feet [44], shank [45], thighs [46], trunk [45], vest [47], waist [48], ankles [41], belt [49], pelvic [50],

TABLE III. KEY ENABLING TECHNOLOGIES FOR WIRELESS COMMUNICATION

	ZigBee	**2.4G Wireless**	**Bluetooth**	**UWB**	**Wi-Fi**	**NFC**
Price	low	low	low	moderate	moderate	low
Safety	high	high	high	high	low	Very high
Data rate (max)	250Kb/s	2Mb/s	3Mb/s	480Mb/s	54Mb/s	420Kb/s
Max Range	75m	50m	10m	10m	100m	20cm
Frequency	2.4GHz 915Mhz (Americas) 868Mhz (Europe)	2.4GHz	2.4GHz	3.1GHz-10.6GHz	2.4/5GHz	13.56MHz
Power consumption	30mW	low	2.5-100mW	30mW	1W	low
IEEE Standard	IEEE 802.15.4	Self-defined	IEEE 802.15.1x	IEEE 802.15.4a	IEEE 802.11	ISO/IEC 18092
Diffraction, penetrating barriers	not good	not good	not good	not good	not very good	not good
Applications	low data rate, low bandwidth, high-capacity network	data transmission	point to point, small-data transmission	high speed communication for short range	data transmission	Near Field Communication

UWB- Ultra wideband; NFC- Near-field communication

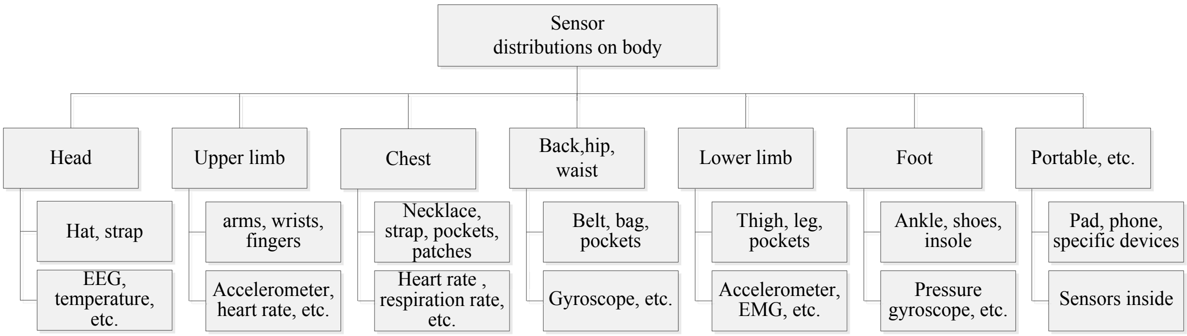

Fig.3. Typical distributions on body of wearable sensors in WSHAR

hip [46], legs [51], abdomen [52], back [43], knees [53], ears [54], neck [27], etc.

Take the accelerometer as an example, placing them on the ankle is expected to detect the motion information caused by legs or feet, such as running, on the arm for identifying exercise activities. The sensors attached on the chest might not measure the movements of arms. Based on the above discussed, typical sensor positions on body with the commonly used sensors are presented in Fig.3. According to the sensor device deployment, we divide WSHAR into four groups: the basic way is placing one single sensor on one single body part (One to One); the second approach is attaching one single type of sensor on multiple body parts to gain complementary signals from different positions (One to Multi); the third one is putting a sensor device with more than one type of sensors built-in on one body part, aiming to capture diverse-source information from different sensors (Multi to One); the last scenario is placing multiple devices, each embedded with one or more types of sensors, on multiple body parts (Multi to Multi) to combine the advantages of the aforementioned three situations. The four sensor deployments are presented in Fig.4. The following section then details and compares certain case studies on the four situations.

A. *One to One*

This sensor deployment aims to build a basic network for activity recognition. In this scenario, the sensor's location may vary with the task, from the head to the feet. The study in [55] focused on recognizing the transition-related postures for the patients with Parkinson or stroke only using a single 3-axis accelerometer attached to users' waist (Fig.5). They proposed a hierarchical

Fig.5. An accelerometer located at the waist in [49]

recognition algorithm to detect a total of 11 activities including lying from sitting, walking, sitting to standing, bending up/ down, etc. The models were evaluated using the data sets gathered from 31 healthy volunteers and 8 people with Parkinson's disease, respectively. They obtained the results with the sensitivity of 97% and specificity of 84% in posture recognition from the former dataset, and the results with sensitivity of 98% and specificity of 78% in postural transition detection from the latter data set. The on-line monitoring applications had been implemented using the proposed algorithm.

B. *One to Multi*

Intuitively, only one sensor placement position might deliver limited information from the activities, for example, a waist-attached sensor offers less information about the motions related to head movements. Consequently, some researchers explored to place the accelerometers to more body parts with the aim of evaluating the contributions of different sensor positions in recognition performance. Paper [44] designed an experiment system in which six wireless tri-axis accelerometers were deployed on the participants' foot, thigh, hip, lower back, wrist and chest (see Fig.6) to collect the data from activities of walking, standing, walking up/down stairs, etc. The experimental results

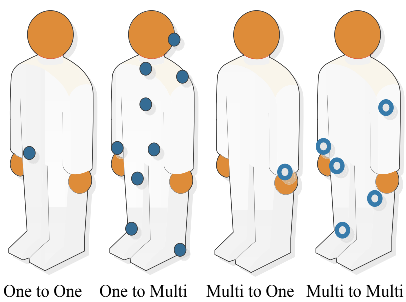

Fig.4. Deployment of wearable devices

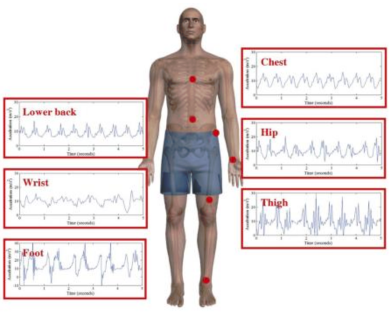

Fig.6. The accelerometer placed on the chest, lower back, wrist, hip, thigh and foot in [38]

indicated the data gathered from hip gave the best accuracy for detecting the activities among all six locations. The authors further studied the effect of combining multiple accelerometers from different positions and they concluded that increasing sensing locations from one to two or more could achieve small but significantly better accuracy.

C. Multi to One

An alternative strategy to acquire diverse-source data related to the activities is to integrate multiple sensors but not from the same type, and place them on one body part. By doing this, combined information from different types of sensors will be obtained without increasing the obtrusiveness and complexity in sensor deployment. [6] proposed a system to explore the only best single axis for each activity aiming at reducing computational load in repetition counting. They used a gyroscope and an accelerometer embedded in Samsung Galaxy Gear collecting 5 exercise routine activities (bicep curls, crunches, jumping jacks, etc.) from12 subjects (Fig.7). In order to evaluate their hypothesis, they tried 4 data sets derived from different sensor combinations. The corresponding average recognition accuracies given by the random forest classifier were 92%, 85%, 93%, and 90%, respectively.

D. Multi to Multi

Compared with the above discussed three frameworks, Multi to Multi is expected to be the most comprehensive structure to achieve higher performance in WSHAR. The authors in [4] proposed a practical home-based HAR, which used multiple on-body sensors on multiple body positions. They investigated the contributions of seven sensors (an altimeter, an accelerometer, a heart rate monitor, a barometer, a gyroscope, a light and a temperature sensor) towards activity classification. A ground-truth data set including 13 daily activities was collected through a group of elderly people. The heart rate sensor was attached to the chest using an elastic stretching band and other sensors were distributed on two wrists, shown in Fig.8. The experimental results showed their proposed system was superior to the earlier studies, achieving the accuracy of 97%.

People have been exploring to deploy the sensors on different body positions targeting different aims and applications. Generally, the scenario of One to One is more suitable for those basic tasks, such as step counting. Placing more sensors on more body parts is intuitively beneficial for improving the performance and robustness, while coupled with increasing complexity in deployment and higher computational cost. Also, the sensors equipped over the human body may hinder the wearer doing everyday activities, thus leading to the user rejecting to wear them. Consequently, exploring the way with less obtrusiveness, affordable cost as well as higher accuracy becomes more important.

V. DATA COLLECTION

Data is the first material for activity recognition after determining sensor types and sensor deployment. Data collection can be a tedious and cumbersome work. Researchers may face a serial of problems when collecting data, such as obtrusiveness, ease of using sensors, time arrangement, experiment environment, cost for participants, annotation, etc. Although there have been some benchmark data in HAR, in most cases, the specific tasks require the ground truth from the different target population over the different time periods.

A comprehensive study should involve as more as possible target population with diverse age, gender, weight, height and health conditions. Whilst due to the time cost and the subjects' will, the number of recruited subjects were highly limited, varied from 1 [40] to 45 [58], and most fell in the interval of 2 to 20 [27] [54], apart from some special benchmark datasets. As for the elderly participants, the number was usually no more than 12 [5], [60], etc.

The protocol of data collection directly affects the recognition performance, and the factors are like the number of activities, the number of subjects, performing activities in a natural way or a constrained way, a controlled environment or a real-home setting, and so on. Several studies collected data based on the predefined activities under controlled environment. In [56], the volunteers were asked to perform the same activity in approximate frequency and intensity or repeat one single activity in one minute or longer time, thereby achieving high accuracy due to the high intra-class similarity under this protocol. While data collection in [57] was in more natural settings. With respect to annotation, most studies, such as [12], supervised the data collection process, labeled the data by themselves or recorded the process with a camera to avoid mislabeling. To provide a more natural environment for participants and minimize the burden of annotation, some utilized semi-automatic approach [32], and other researchers labeled the activities using certain specific applications developed by themselves [47].

Fig.7. Device worn on wrist in [6]

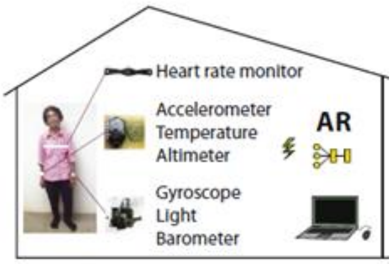

Fig.8. Sensors spreading over body in [4]

VI. CONCLUSION

The wearable sensor-based HAR systems have been proved to be the most promising way for activity recognition. This paper presents a short review on the fundamental part of the procedure to realize WSHAR. Below are some discussions according to the review questions.

Choosing the most appropriate sensor set highly depends on the problem at hand. The following factors could be referred to explore the optimal sensors for a specific study: i.e. the inherent characteristic of a sensor, the target application, the cost, the expected accuracy, the easy accessibility of a sensor on the market, etc. A physical health sensor, for example, allows to obtain vital signals, which is usually used for health condition detection. Initial sensors are well suited for capturing motion information instead. Some case studies with their fundamental materials are listed in table IV, in which [21] utilized a heart rate sensor to help identify an activity' intensity; [53] combined a wearable camera on ear to help improve activity recognition accuracy compared with using traditional wearable sensors alone.

When it comes to the integration of the selected sensors, the commercials, like smart phones and smart watches, can be chosen first if only the following requirements are met simultaneously: 1) the device exactly has the sensors required for a specific application; 2) it can be conveniently attached to the body part as designed for the problem at hand; 3) the data can be easily obtained from the commercial. Otherwise, self-developed or custom-designed sensor platforms will be necessary options.

The motivation behind the choice of positions to place sensors can be very intuitive and straightforward. For instance, arm-equipped inertial sensors are more sensitive to upper-limb-caused motions, like the arm rehabilitation, and the chest- or back-attached inertial sensors are more capable of detecting the tilt of the body. Intuitively, only one body part with wearable sensors might obtain less sufficient information than putting them on multiple body parts. Complex sensor deployment benefits improving the performance, whilst also bringing high cost, obtrusiveness and cumbersomeness. A practical system thus should consider the tradeoff between the performance and the user acceptance.

With respect to the size of collected data, generally, larger data size facilitates improving the generalization of the trained classification models, while there is a practical limitation on availability of collecting as more as possible data due to the cost, participants recruiting, device limitation, etc. Different studies define their activity types according to the applications, such as, the specific activities performed by some special patients [55], sports activities [6], normal daily activities [4], abnormal daily activities [35] and so on. Most studies only recognize the predefined activities, which means the system cannot do anything when it encounters undefined activities in real use. Meanwhile, it is unpractical to recognize all activities in most applications due to technology limitations, privacy concerns and diverse types of activities to be identified. The challenge is how to deal with the unknown activities which are not seen by the model in the training stage.

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TABLE IV CASE STUDIES IN TERMS OF THE FUNDAMENTAL MATERIALS

Sensor deployment	Study	Sensor types	Sensor positions	# of activities	# of participants	Application
One to One	[55]	Accelerometer	Waist	9	31/8	Recognizing physical activity and posture transition especially for the patients with Parkinson
One to Multi	[44]	Accelerometer	Chest, thigh, foot, lower back hip, wrist	7	8	Exploring the optimal placement of accelerometers for detecting daily activities
	[32]	Accelerometer	Front pocket of their shirt	6	5	Identifying daily activities in terms of duration, type, intensity, etc.
Multi to One	[18]	Accelerometer gyroscope	Wrist	3	4	Recognizing upper limb movements
	[35]	Accelerometer gyroscope	Belt/upper end of the pelvis	15	2	Fall and daily activity detection
	[17]	Accelerometer gyroscope magnetometer	Chest, ankle right, thigh right	7	11	Identifying daily activity and postures with varied sensor locations
	[21]	Accelerometer heart rate	Wrist, thigh, ankle, chest, hip, arm	30	21	Recognizing certain physical activities and their intensities

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