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Examining sensor-based physical activity recognition and monitoring for healthcare using Internet of Things: A systematic review.

Examining Sensor-based Physical Activity Recognition and Monitoring for Healthcare Using Internet of Things: A Systematic Review

Jun Qi[a,b], Po Yang[b], Atif Waraich[b], Zhikun Deng[c], Youbing Zhao[c], Yun Yang[a]

[a] *School of Software, Yunnan University, Kunming, China*

[b] *Department of Computer Science, Liverpool John Moores University, Liverpool, L3 3AF, UK*

[c] *Department of Computer Science, University of Bedfordshire, Luton, LU1 3JU, UK*

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Due to importantly beneficial effects on physical and mental health and strong association with many rehabilitation programs, Physical Activity Recognition and Monitoring (PARM) have been considered as a key paradigm for smart healthcare. Traditional methods for PARM focus on controlled environments with the aim of increasing the types of identifiable activity subjects complete and improving recognition accuracy and system robustness by means of novel body-worn sensors or advanced learning algorithms. The emergence of the Internet of Things (IoT) enabling technology is transferring PARM studies to open and connected uncontrolled environments by connecting heterogeneous cost-effective wearable devices and mobile apps. Little is currently known about whether traditional PARM technologies can tackle the new challenges of IoT environments and how to effectively harness and improve these technologies. In an effort to understand the use of IoT technologies in PARM studies, this paper will give a systematic review, critically examining PARM studies from a typical IoT layer-based perspective. It will firstly summarize the state-of-the-art in traditional PARM methodologies as used in the healthcare domain, including sensory, feature extraction and recognition techniques. The paper goes on to identify some new research trends and challenges of PARM studies in the IoT environments, and discusses some key enabling techniques for tackling them. Finally, this paper consider some of the successful case studies in the area and look at the possible future industrial applications of PARM in smart healthcare.

1. Introduction

A World Health Organization (WHO), survey of has identified physical inactivity as the fourth leading risk factor for global mortality causing an estimated 3.2 million deaths. Low levels of physical activity (PA) are detrimental to the health and functioning of older people [1], and may cause many chronic diseases [2], [3] such as diabetes, obesity, cancers, etc. Effective long-term observation of PA has significance on promoting diagnosis and treatment of these chronic diseases, monitoring PA we can also promote a healthier lifestyle for elderly people and potentially provide a substantial reduction in healthcare costs. Due to these potentially beneficial effects, and rendering assistant services such as falls detection for older people and functional loss prevention in many rehabilitation programs. By promoting, recognizing and numerous studies over recognition and monitoring (PARM) solutions for the last few decades have focused on research aiming to deliver accurate and robust physical activity clinical use. Recently, advances in Internet of Things have enabled PARM as a key paradigm in many fields including Smart Health, Smart Rehabilitation and Ambient Assisted Living (AAL).

* Corresponding authors at: School of Software, Yunnan University, Kunming, China; Department of Computer Science, Liverpool John Moores University, 3 Byrom St, Liverpool, L3 3AF, UK.
E-mail address: ruth1012@live.com (Jun Qi), p.yang@ljum.ac.uk (Po Yang)

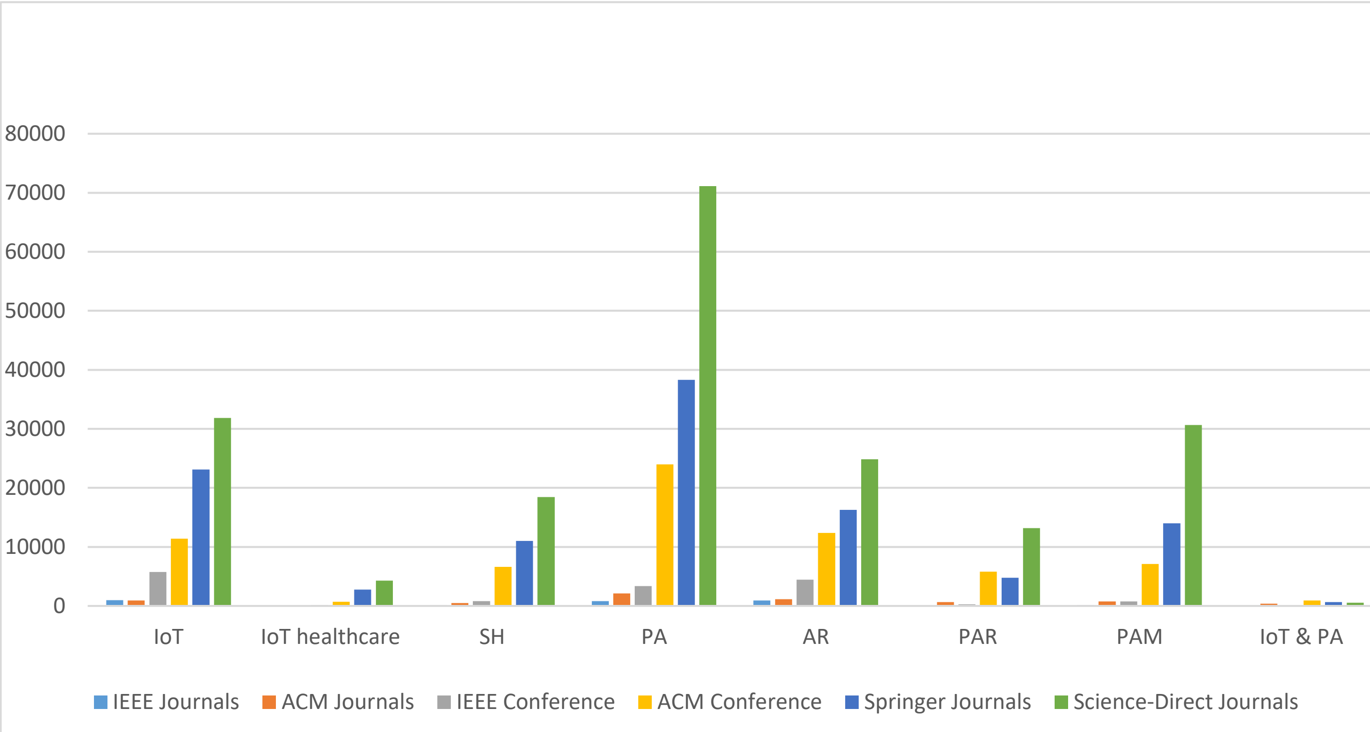

Fig. 1 Number of Journal and Conference articles related to IoT and PARM from 2008 to 2018 (IoT-Internet of Things, SH-Smart Home, PA-Physical Activity, AR-Activity Recognition, PAR-Physical Activity Recognition, PAM-Physical Activity Monitoring)

Table 1. Activity categories and examples

Category	Subcategories	Examples
Simple physical activities	Aerobic exercises	Walking, jogging, climbing, descending, running, swimming
	Transportation	Driving, cycling, taking a bus
	Sedentary postures	Sitting, lying, standing, tilting
	Transitional activities	Sit-to-stand, stand-to-walk, walk-to-run, run-to-walk
Complex physical activities	ADL	Cooking, brushing teeth, cleaning, eating, dressing, having a party
	Ball sports	Playing football, playing tennis

Traditionally, PARM studies focus on the discovery of PA patterns or subject's, accurate recognition of PA itself and robustness of monitoring PA in a controlled environment, such as clinics or labs. These are based on either designing standalone novel wearable sensors to achieve highly accurate recognition of human movements, or investigating advanced machine learning algorithms for training features from observed wearable sensory data from human body positions into specific several activity types. Also, some researchers have investigated how to attach wearable sensors for optimal accuracy or have utilized body area networks for energy-efficient PA monitoring. While these conventional state-of-the-art PARM technologies enable achieving PARM for recognition of 10-20 activity types with accuracy ranging up to 100%, one major challenge limiting their usefulness and efficiency in practice is that the emergence of Internet of Things (IoT) enabling technology is transferring PARM studies from traditional hubs of healthcare to personalized, open and connected uncontrolled healthcare environments [4]. This trend leads to a number of key obstacles on the adoption and utilization of existing PARM studies for delivering holistic, mobile, energy-efficient PARM solutions that provide accurate state detection and monitoring with moderate to complex implementation in an IoT environment [4]–[6]. For instance, how to address the sheer volume of information and the heterogeneous-devices used to capture long-term PA information; how do we estimate and measure uncertainties of PA with varied human behaviour patterns; how do we maintain the recognition accuracy of PA with the use of moderate low-cost wearable devices; etc. In this respect, little is known about whether traditional PARM solutions can address these issues, and in particular how to harness and improve their utilization in IoT environments.

In an effort to better understand the advance of IoT technologies in PARM studies, this paper aims to provide a systematic review of current researches of PARM from an IoT layer-based perspective. As shown in Fig.1. We undertook an extensive literature review by examining relevant articles from major academic databases (IEEE Xplore, ACM, Springer digital library and Science-Direct). Search terms include the key words 'Internet of Things', 'Activity Recognition', 'Activity

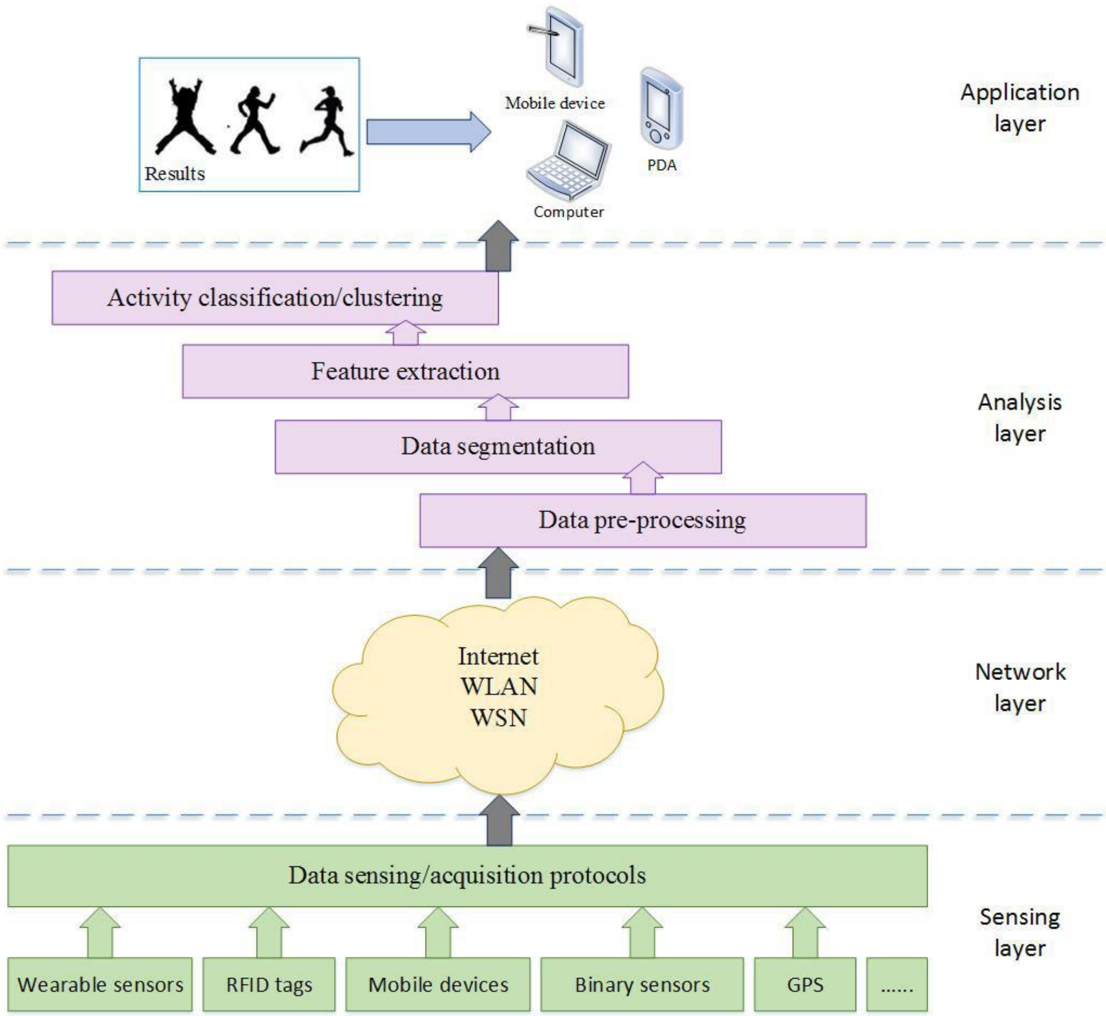

Fig. 2. Examining PARM from an IoT layer based perspective

Table 2. IoT-based layers and descriptions for PARM

Layers	Description
Sensing layer	The layer detects and collects signals from a variety of sensors on human body or in environment.
Network layer	The layer is responsible for transferring signal data from sensing layer to analysis layer over wired, wireless sensor or actuator networks,
Processing layer	The layer processes and analyses raw signals, and classifies/clusters into different PA types.
Application layer	The layer provides applications that interacts with users.

Monitor' and 'Physical Activities'. In addition, we reviewed research projects related to IoT, e- health, smart healthcare, etc, by searching from EU, TSB and EPSRC funded projects. As a result, we found a large number of journal articles and conference papers related to PARM studies and IoT enabled healthcare respectively, and identified a number of opportunities for future researchers. A main contribution of this review paper is that it is a first attempt to categorise classic PAMA technologies into an IoT architecture systematically and it reviews the current research on IoT, key enabling technologies, major PARM applications in healthcare, and identifies research trends and current challenges.

The rest of this paper is structured as follows. Section 2 presents the description of the IoT-based PARM architecture. Section 3 and 4 demonstrates a variety of sensors and devices used in the sensing layer and technologies in network layer respectively. Section 5 gives a PARM implementation procedure ranging from data processing up to PARM algorithms in the analysis layer. Section 6 reports some applied cases in application layer. Section 7 examines future trends in PARM area, and section 8 is the conclusion.

2. IoT-based PARM system architecture

The concept of Internet of Things (IoT) encompasses a set of technologies that enable a wide range of devices and objects to connect, communicate and interact using networking technologies. Initially, Radio Frequency Identification (RFID) technology was considered a fundamental solution to implement IoT based systems. In the last few years, advances in sensing technologies have promoted more cost-effective wearable devices connecting in an IoT environment. The concept of IoT based personalized healthcare systems was established and become increasing popular. These systems uses a set of interconnected devices to create an IoT network devoted to healthcare assessment, patients.

Four IoT-based layers are involved in the PARM system structure, as shown in Figure 2 and Table 2. The general system collects personalized health information from different wearable sensing devices through a middleware that provides the interoperability and security needed in the context of IoT for healthcare. These wearable devices are capable of recording multiple types of health data, including lung function [7], [8], sleep duration [7], [9], heart rate [10], blood pressure [11] and user-context information [12]. Rapid development in microelectromechanical (MEMS) accelerometer technology and global positioning system (GPS) has increased the accuracy of observing PA. Utilizing IoT to monitor low level PA has become popular, and easily accessible to normal users. Wired or wireless networks (e.g., Bluetooth, Wi-Fi or ZigBee) are normally adopted in the network layer. As the raw data usually contains redundant information that needs to be filtered, it is processed in the analysis layer and sub-categorized into four phases form pre-processing up to activity type classification/clustering. Data pre-processing is used to clean the data and reduce dimensions, which are subsequently divided into equal or non-equal time windows for the specific recognition. Key signal features using time-domain, frequency-domain or other techniques are collected in the feature extraction phase in order to provide more useful and robust representation. The activity classification/clustering step eventually categorizes these features into different basic PA types. Combination with user context information (e.g., user's location, object's state) can be used to infer high-level daily activities such as *eating*, *cooking* or *dressing* listed in the table 1. The application layer provides user interface to interact with patients or caregivers to present PARM results and treatments.

3. Sensing layer

The sensing layer is used for the identification of objects and gathering information from sensors, tags, etc. The development of low-cost and small-in-size wearable sensor such as inertial sensors (e.g., accelerator, gyroscope or barometric pressure sensors) and physiological sensors (e.g., spirometer, skin temperature sensor or blood pressure cuff), as well as wearable devices (e.g., fitness band or mobile phone) has facilitated the process of measuring attributes related to individuals and their soundings in recent years. Fig.3 presents some typical wearable devices. GPS localization, Bluetooth and so on are also incorporated into the devices. As physical inactivity is often a major risk factor for chronic diseases, daily PARM with wearable sensors is being investigated by a number of researchers. Table 3 shows a variety of wearable sensor categories.

3.1 On-body sensors

3.1.1 Inertial sensors

An accelerometer is a small-scale MEMS device that is the current leader for PARM, they are widely used for monitoring dynamic activities. When distinguishing static postures (e.g., laying, standing, sitting), it needs to be placed on a specific part of the body [13] and a threshold or value has to be set to discriminate them [14]. Gyroscopes are generally used as an additional method for measuring rotational movements. Detecting behaviours like falling [15] by measuring patient's angular velocity of movement such as bending knees, descending stairs [16], ascending stairs [12] or turning [20]. Likewise, a Barometric pressure sensor, along with an accelerometer is also useful in monitoring stairs behaviours [21] and fall detection [22] owing to the relationship between sensory readings and altitude. Magnetic field sensors can be placed close to the measurement location and thus achieve higher spatial resolution to detect a subject's direction. When recognizing "watching TV", for instance, a magnetometer can tell that the subject is facing the direction of the television whilst combining accelerometers and indoor localization information [23]. It is not essential to use magnetic field sensors to detect activities measuring altitudes or angles such as fall [8], [9].

3.1.2 Physiological sensors

Physiological these can be used for monitoring patients in and out-of-hospital conditions. They are ordinarily used in combination to observe other types of medical health data. Among these sensors, are heart rate monitors such as Electrocardiogram (ECG) which has been used for PARM for healthy subjects [27] as well as for patients [28] in daily lives. It is believed that there is a distinct relationship between heart rate and PA. For example, when a subject starts performing intensive activities such as running or swimming, their heart rate will increase. Nevertheless, it is difficult for such sensors to precisely determine activity transitions for a very short period as when a subject stops running, his/her heart rate will remain the same level for a while [29]. To overcome this issue, special feature extraction methods have been applied in some studies. This will be discussed in section 5.

3.1.3 Wearable/mobile devices

Recently, many commercial wearable products and mobile applications have been developed for the long term recording and collection of personal lifelogging physical activity. The most famous mobile apps, such as *Moves* [31], which is based on smartphone 3D accelerometer data and GPS information allow tracking of user movement activities including location, distance and speed. The wearable products are often wristband devices that record step counts, distance, and calories burnt. These wearable devices communicate with a mobile phone via Bluetooth employing relevant mobile applications. Also, smart watch and mobile phones, are now replacements for conventional wearable sensors.

3.1.4 Discussion

Accelerometers, gyroscopes, barometric pressure sensors and magnetic field sensors, due to issues with their integration, are normally used with accelerometers. Inertial sensors can be attached over an individual's body [34]–[39]. Despite this many studies conclude that multiple sensor fusion can achieve highly accurate PA recognition results [28], [35], while such methods are obtrusive, uncomfortable, impractical and expensive. Therefore, many studies have used applications with only one wearable sensor attached on a specific part of the body [37]–[44], such as the hip [16], [17], back [40], wrist [43], chest [43], waist or thigh [14]. Some work has investigated the best performance placement with various algorithms and activities. For example, Purwar et al [48] found that placement on the chest is better than the wrist in fall detection. Others has no requirement for specific placement. Khan et al [49] allowed subjects to put an accelerometer in any pocket on their body and achieved 94% accuracy in ambulation and static posture recognition.

Although inertial sensors have made great progress in the last decade, they have limited use for long-term activity monitoring in a free living environment, as even only a small single sensor attached on a specific part of the body is still uncomfortable for permanent monitoring. On the other hand, physiological datasets are rarely used in PARM as a consequence of the time-delay and obscure signal features, they do not play a vital role but simply act as supplements for inertial sensors in static and ambulatory activity detection, and almost none appeared as a single sensor for discriminations of PA. Wearable and mobile devices have proven popular among general users owing to their portability and relatively low cost. However, because of diversity of life pattern and environmental impacts, personal PA data from individual wearable device exhibits remarkable uncertainty in the natural environment such as battery, capacity issues and placed positions. The results are widely divergent when the mobile phone is put in the pants pocket from handbags. Particularly that inertial sensors are sensitive to any changes in position and orientation. Despite some studies tried training data from different orientations [50] or positions [51], the issue is not fully and largely resolved. Therefore, validating of these PA data in longitudinal healthcare cases is very challenging.

3.2 On-object sensors

Subject's interaction with objects need to be assessed for composite activity recognition like watching TV, preparing a meal or washing clothes. For these purposes, low-cost, easy-to-install on-object sensors (e.g., environment sensors, binary sensors or RFID) are able to provide this data in an unobtrusive and private way. Environmental sensors are used for measuring indoor environmental conditions such as humidity, temperature and energy [52], [53]. Binary sensors can sense an object's state with a digit of 0 or 1, representing on/off, open/close [53] . Indoor localization sensors including Bluetooth, Radio-Frequency Identification (RFID) [57], [58] and outdoor localization such as GPS [59], [60] can be used in information acquisition, they are effective for complex activity recognition without using a large number of on-object sensors. RFID tags and readers to detect human object interactions in the matter of motion and touch [61]. It uses wireless electromagnetic fields to transfer data and can be, exploited as on-object sensors for automatically identifying and tracking tags attached to specific objects [62], [63].

3.3 Discussion

In order to accurately capture complex PA in context-aware environment, a majority of sensors are required to be installed in each object even on the cups and cans. The study in [53] presents hundreds of on-object sensors installed in the laboratory. As such, maintenance costs for such a large amount of sensors are fairly high. Furthermore, large number of sensors also suffer from potential issues during data acquisition including transmission errors, low battery and asynchrony.

4. Network layer

The networking layer for PARM is responsible for connecting all the devices in the sensory layer together and allowing personalized health data to be collected, stored, transmitted, shared and aggregated under IoT infrastructures. Typically, this layer contains a wide range of concepts and techniques, such as communication and location technologies, topologies, architecture, security and privacy, etc.

Body Area Networks (BANs) are ad hoc sensor networks and tags attached to an individual's body, constituting inertial sensors, biological sensors, RFID tags, etc.

IoT networks cover a range of PARM use cases that scale from a single constraint sensor to dozens of cross-platform real-time technologies. There are numerous communication protocols from legacy, contemporary to emerging that govern the sensors and server communication. This section is mainly with the network stack, the communication / transport layer.

4.1 Bluetooth

Bluetooth is a wireless technology standard for exchanging data among devices within a short distance. It has been widely used in PARM studies. Chen et al. [64] created a framework, MoGATU which abstracts all devices in the environment as a collection of information managers, information providers, and information consumers with several communication interfaces for supporting ad-hoc IEEE 802.11 and Bluetooth like networks.

Table 3. Sensor categories, examples and descriptions

Sensor category	Sensor subcategories	Sensor examples	Description
On-body sensors	Inertial sensors	Accelerometer	Measures linear acceleration of movement
		Gyroscopes	Measures the angular rotational velocity
		Pressure sensors	Measures object's altitude
		Magnetic field sensors	Measures location for higher spatial resolution
	Location sensors	GPS	Tracks outdoor locations
	Physiological sensors	Blood pressure cuff	Measures human systolic and diastolic blood pressure
		Electrocardiogram (ECG)	Test and records the rhythm and electrical activity of the heart.
		Spirometer	Measures respiration, flow rate and lung volume
		Electrooculography (EOG)	Measures eye movement.
		Skin temperature sensor	Measure subject temperature on surface of the skin
On-object sensors	Environment sensors	Thermometer	Measures indoor/outdoor temperature
		Hygrometer	Measures indoor/outdoor humidity
		Energy sensors	Measures object's energy usage
	Binary sensors	Window contact	Detects window open/close state
		Door contact	Detects door open/close state
		Light switch	Detects light on/off state
	Location detectors	Remote control switch	Detects remote control on/off state
		Infra-red	Detects human indoor localization
		Active RFID	Detects human indoor localization
	Tags	RFID tags	Detects objects individual interaction with
		NFC tags	Detects objects individual interaction with

Table 4. Network protocols used in PARM

	Traditional PARM	IoT Suit
Application Layer	HTTP/FTP etc.	CoAP
Transport Layer	TCP/UPD	UDP
Network Layer	IPv4/IPv6	6LoWPAN
Link Layer	IEEE 802.3 Ethernet / 802.11 Wireless	IEEE 802.15.4e

4.2 Zigbee

The ZigBee protocol uses the 802.15.4 standard and is capable of data rates of 250 kbps and operates in the 2.4 GHz frequency range. Zigbee allows encryption with 128-bit AES and works with node up to 200 meters in range. Zigbee sensor networks applied to PARM can be referred in [65].

4.3 Near field communication (NFC)

NFC is based on the ISO/IEC 18092:2004 standard, using inductive coupled devices at frequency centre of 13.56 MHz, allows short range to communicate with a data rate of up to 424 kbps. NFC allows automatic storing and launching smartphone apps though tapping the NFC tag on various objects [66], [67].

4.4 Wireless local area networking (Wi-Fi)

Wi-Fi is an IEEE 802.11 standard network. Wi-Fi is able to provide indoor localizations for PARM using Received Signal Strength Indicator (RSSI) [68] as well as wireless transmission of PA signals among sensors, mobile devices and servers [69].

4.5 Cellular

Mainly used for mobile phones GPRS/2G/3G/4G cellular is currently in use. Mobile phones are often used by research projects as monitoring devices, the multiple sensor nature of mobile phones and their direct internet connection makes these devices especially useful in PARM solutions. Examples can be seen in [70] and [71].

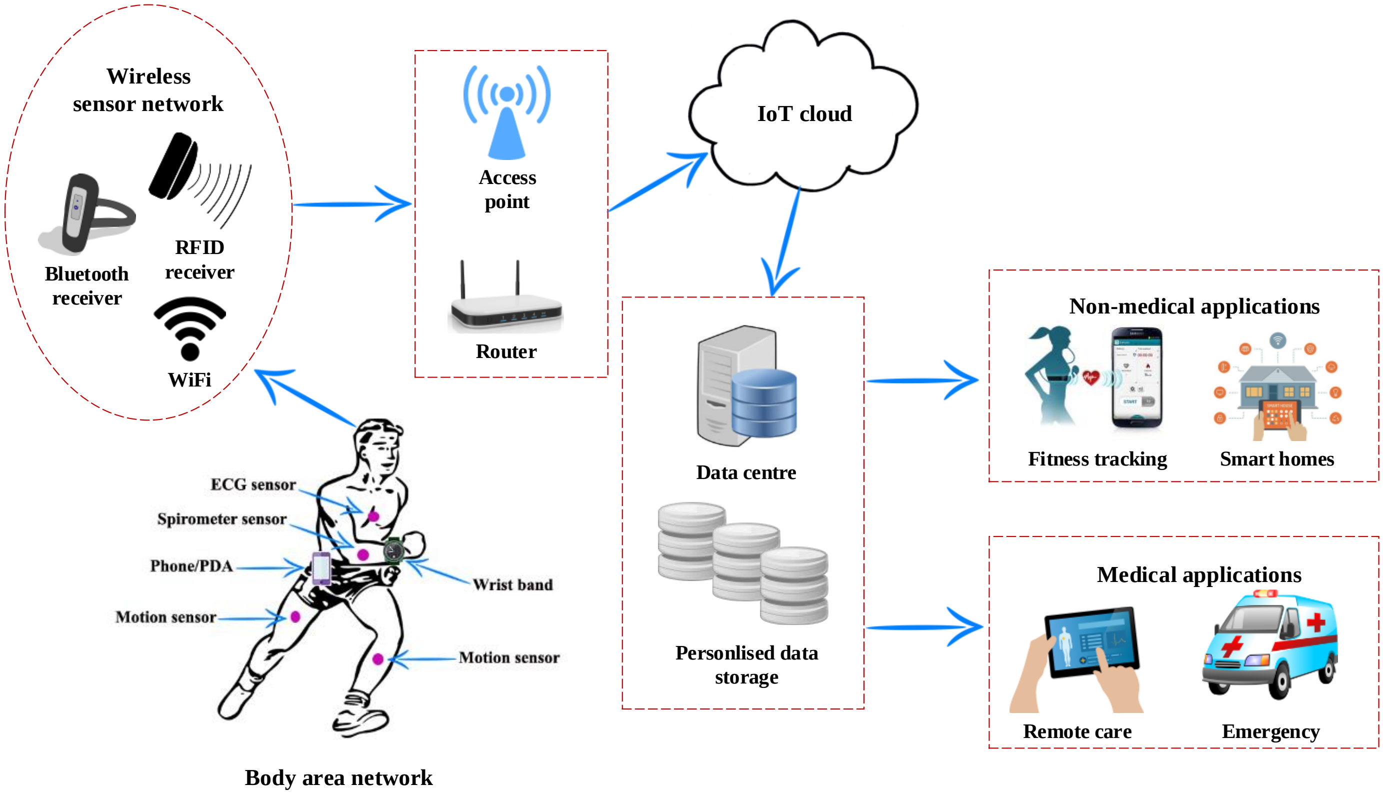

Fig.3 wireless sensor network in physical activity recognition and monitoring

Table 5. Comparison of popular wireless radio communication technologies in PARM

Standard	**Zigbee /802.15.4**	**Bluetooth**	**Wifi**	**NFC**	**Cellular (4G)**	**RFID**
Frequency	868/915 MHz, 2.4 GHz	2.4 – 2.5 GHz	2.4, 5 GHz	13.56 MHz	450 MHz - 2.6 GHz	125 kHz-2.45 GHz
Data Rate	250 Kbps	723 Kbps	11 - 1730 Mbps	424 Kbps	1 Gbps	40 kbps-640 kbps
Range	10 – 300m	50m	10 – 100m	20m	70km	30cm-100m
Power	Very Low	Low	High	Low (active)	High	Low
Battery Life	Months to years	Days to weeks	Hours	Days to weeks	Days	Months to years

5. Processing layer

The processing layer stores and analyzes the signal information received from the network layer. Data pre-processing, feature extraction and classification/clustering are the three main steps for PARM.

5.1 Data pre-processing

5.1.1 Time-series segmentation

Temporal segmentation methods are typically used for PARM. In order to match PA patterns, sensor data sets need to be segmented to accommodate consecutively activated sensors either on a subject's body or in an environmental context. Such data sets are broken down in a temporal series using time windows. Generally, time-series segmentation methods applied in PARM are categorised into two types. These are the sliding window method, and sliding-window and bottom-up algorithm (SWAB) method [72]. The sliding window, has outstanding online performance in time point clustering and sub-series clustering. It is simple, intuitive and has thus become the most broadly used method for feature extractions and classifications [73]–[80]. As presented in Fig.4, the static sliding windows uses fixed temporal length with overlapping [73], [74] and non-overlapping instances [81], [82] and has been extensively adopted in most studies. Inappropriate lengths of non-overlapping time window will split an activity instance with continuous sensor signals and potentially cause incorrect recognition outputs, while a high percentage (e.g., 50% [74], 70%, 90% [83]) of overlapping time windows would lead to excessive time and resource consumption. Dynamic sliding window, as a non-fixed length segmentation, enables extraction features when the specific events are detected via sensors [76], [77]. This tends to be more energy-efficient for the long-term activity monitoring. Heuristics, probability approaches [75] or user-specific thresholds [77], are commonly exploited for dynamic length partition. The SWAB segmentation method is able to produce better results but is more complicated since it combines the sliding window and bottom up approaches, allowing the algorithm to be used online while keeping a global view of the data. It has been successfully applied in gesture identification with a continuous signal stream from accelerometers, gyroscopes or ECG [84]–[88].

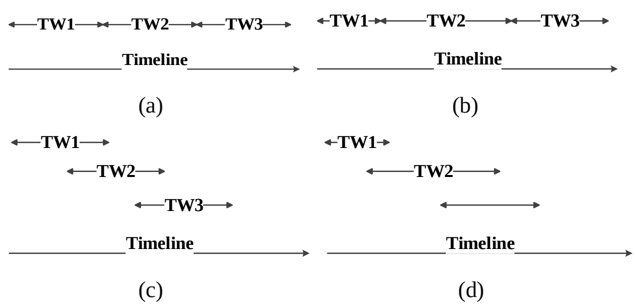

Fig.4. Time window segmentation (a) fix-sized non-overlapping; (b) dynamic-sized non-overlapping; (c) fix-sized overlapping; (d) dynamic-sized overlapping

5.1.2 *Discussion*

The key challenge of temporal segmentation is, how to determine a suitable window length at the runtime? Various defined sizes in the literature are based on different signal's attributes or the application environments. Short window size (e.g., 6.7s [74], 1s [43], 0.25s [73]) may improve the efficiency of classification algorithms but dissipates too much energy for current sensing devices. A long window size (e.g., 30s [89]), on the contrary, could conserve energy but tends to bring more redundant information; there also might be more than one activity leading to spurious features. However, almost all the existing work focuses on the online precise time series segments with high classification accuracy, for life-logging PARM limited battery and capacity cannot support frequent seconds/minutes-based activation of such PARM algorithms.

5.2 *Feature extraction*

Feature extraction is a crucial procedure for PARM since any classification method can be appropriately selected if the features are robust. There are four major groups: time-domain, frequency domain, biometrical domain and other methods, as shown in Table 6.

Table 6. Feature extraction category and extracted features/techniques

Category	Extracted features/ techniques
Time domain	Mean, standard deviation(SD), magnitude, covariance, variance, min, max, Range, correlation, integration, cross-correlation, root mean square (RMS), signal magnitude area (SMA), signal magnitude vector (SMV)
Frequency domain	Coefficients sum, DC component, dominant frequency, spectral energy, entropy, spectrum centroid
Bio-metric features	Magnitude of change, trend of vital signs, cepstral feature
Feature selection	Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA)

5.2.1 *Time domain features*

Time domain features are mathematical and statistical metrics that present randomly continuous signal changes with time, and hence are suitable for discriminating signals of inertial sensors. The traditional features extracted from sensor signals are mean [74], variance [90] , standard deviation (SD) [46], root mean square (RMS) [33], covariance [75] and energy [74]. The mean, a basic statistical metric that measures different kinds of sensor types, is used to smooth signals. SD used to provide stable signals. Variance describes the distance to the expected output, and has been used to extract features from signals of static postures, walking and running [90]. RMS is a quadratic mean and is commonly known as wavelet classification and is sued to analyse both static and dynamic activity features [93].

5.2.2 *Frequency domain features*

These features are mostly extracted by using Fourier Transform (FT) such as Fast Fourier Transform (FFT) and Discrete Fourier Transform (DFT). DC component [74], spectral energy [57], entropy [31], [74], [84]are the popular features. The DC component is the average acceleration value of the input signal series during the time window. The energy is defined as the sum of the squared discrete component magnitudes of the signal. Entropy is the normalized information entropy of the FT components to distinguish different activities with similar energy values [74]. These features are normally related to specific activities such as walking or running [43], [74] and gestures [95]. On the other hand, FT supplements frequency domain information does not cover time information realting to where these frequency components occurred [96]. Wavelet transformation (WT), consisting of low-frequency components known as approximation and high-frequency components called the detail, takes advantage of both facets in time and frequency domain to analyse low frequency physiological sensors signals like ECG [97], and deal with high frequency accelerometer signals. Walking [98], descending, ascending stairs [32], [86], static postures [100] can all be detected using WT.

5.2.3 Biometrical features

Previous work suggests physiological sensors are problematic in PARM since traditional time and frequency domains have their limitations in the bio-feature discrimination, especially in recognizing transitional activities as was discussed in Section 3. Some work, however, disputes these conclusions and takes advantage of biometrical features or self-defined thresholds to overcome this issue. For example, Perriot et al. [40] proposed two new features called magnitude of change and trend of vital signs to extract effective information from ECG, skin temperature, respiration rate and heart rate sensor signals. The function of the proposed features are defined time series states and the extent of changes of ECG signals [97]. In order to strengthen the PARM model and improve accuracy, Liu et al. [34] used a biometric called cepstral features in conjunction with time-domain features from accelerometers. The cepstral features simplify the processing of ECG signals by pre-processing and time segmentation. Formula (1) defines the cepstral feature extraction method, where $\theta_i(t)$ represents the cardiac activity mean (CAM) which denotes the normal heartbeat signal, $x_{i,j}(t)$ is the additive motion artefact noise (MAN) of ith activity, and $\delta_{i,j}(t)$ is the ECG signal noise.

$$r_{i,j}(t) = \theta_i(t) + x_{i,j}(t) + \delta_{i,j}(t) \tag{1}$$

5.2.4 Others

Linear Discriminant Analysis (LDA) is a linear classifier that enables us to reduce the data dimensions through projecting a dataset onto a lower-dimensional space with good class separability [101]. Formula (2) defines the optimal discrimination projection matrix where D_{opt} comes from the maximum value of the ratio of within-class scatter matrix S_B and S_W, which can be used to discriminate transitional activities [42], static postures, running, walking, ascending and descending stairs [33]. Principal Component Analysis (PCA), similar to LDA, is also a dimensionality reduction approach that allows various signal data to be identified in the principal directions through computing the eigenvector of variance and covariance [32]. Mantyjarvi et al. [32] investigated the PCA, ICA and WT methods for different human ambulation activities, and concluded that the classification results of PCA and ICA outperformed WT, and PCA and achieved the highest recognition rate. PCA has an undesirable restriction that categorizes all data into one cluster. To overcome this restriction, Common Principal Component analysis (CPCA) has been proposed by Dolédec et al. [102] and adopted by Yang et al. [93] for determining a set of simple PA and complex PA.

$$D_{opt} = argmax_{\frac{D^T S_B D}{D_T S_W D} = [d_1, d_2, \cdots, d_t]}^{T} \tag{2}$$

5.2.5 Discussion

Although the general performance of frequency domain features like FFT exceeds time domain features [103], they require more algorithmic complexity and have consumption limits for long-term monitoring due to the battery and capacity issues [33]. This drawback also leads to the weakness of their employment in transitional activities (e.g., lie-to-sit, stand-to-walk). In contrast, traditional time domain features outweigh spectral methods in these circumstances [104]. Other straightforward metrics that directly process acceleration signals are also levered in transitional PARM. For example, Signal Magnitude Area (SMA) [42], [43], defined in formula (3) represents accelerometer signals from three axis x$(i), y(i), z(i)$ respectively. Likewise, Signal Magnitude Vector (SMV) shown in formula (4) provides a measurement of the degree of activity intensity, wherex_i, y_i and z_i are similar to (1). Apart from this, static postures, ambulation and falling can also can be detected by using SMA [42] and SMV metrics [43]. Furthermore, SMA enables the possibility of changing positions and orientations for mobile devices [105]. Using simple time domain features (e.g., mean, SD) is reported to achieve better outcomes than frequency domain features in static postures [106]. But this situation is restricted to multiple wearable sensors, when it comes to a single sensor, the frequency domain features play a greater role in such complicated scenarios [91].

$$\text{SMA} = \sum_{i=1}^{N}(|x(i)| + |y(i)| + |z(i)|) \tag{3}$$

$$\text{SMV} = \sqrt{x_i^2 + y_i^2 + z_i^2} \tag{4}$$

5.3 Classification and clustering

Classification and clustering are the two key techniques in machine learning, corresponding to supervised and unsupervised algorithms, respectively. Semi-supervised learning is a class of supervised learning but makes use of unlabeled data for training. Meanwhile, rule-based PARM approaches also appear frequently in some studies. Table 5 lists some typical methods and approaches.

5.3.1 Supervised learning methods

a) Artificial neural networks (ANNs) consist of interconnected artificial neurons structured into three parts: input layer, hidden layer and output layer. The lines between the nodes indicate the flow of information from one node to the next. From a PARM perspective, the input layer normally comes from vectors of feature extraction, sequentially duplicated and sent to all of the hidden nodes. One key issue for ANNs is how to decide on the size of hidden layers for the classification. A common approach is to try various sizes and then to choose the model with the best cross-validated estimate of performance, i.e., 5-fold cross validation [39] or 12-fold cross validation [38]. Compared with a higher number of neurons, fewer neurons are preferable as long as they can achieve a satisfactory results [39]. Generally, PARM performance tends to be more accurate with higher numbers of hidden nodes [107]. The other issue is the noise of activity signals which often influence convergence of the model, leading it to the partial minimal value. By choosing a high learning rate or integrating algorithms of global optimum, i.e., genetic algorithms, it is possible to avoid this issue. A drawback of ANNs is that of continuously selecting nodes which is fairly time-consuming, and they require a majority a large training data set.

b) Hidden Markov Models (HMMs) are tools for representing probability distribution over a sequence of observations [108]. They are utilised to represent and learn the sequential and temporal characteristics of activity sequences using the Baum-Welch algorithm where activities can be seen as the hidden states and the observable output; this is sensor data, and using the Viterbi algorithm in the recognizing the stage to calculate the maximum likelihood for each input vector. Using such characteristics, HMMs are suitable for sequence activities like eating [109]. Extensions of HMM include such approaches as the Hierarchical Hidden Markov model (HHMM) [110] and the Switching Hidden semi-Markov model (S-HSMM) [111], [112] and are carried out for the purpose of increasing accuracy as well as measuring some more complex PA (e.g., working or cooking). The structure of the extensions is normally divided into two layers: the top layer is the Markov chain of switching variables to detect simple physical activities or gestures, while parameters in the bottom layer combine the sub-activities from the top layer to infer more complex activities [110]–[112]. In addition to the requirement for prior knowledge of various facets of the model, the most overt limitation of HMMs is that they suffer from the sequence consistence of each activity; however, activities in real life would not always be constantly in the same order because of a variety of uncertainties.

c) Decision trees (DT) are multistage decision making algorithms used to classify data through a set of rules based on object's attributes [113]. A DT is built by using many leaf nodes and branches, which represent outcomes of the binary decision and classification rules, respectively. The rules can be set making use of domain knowledge and features of the signals [114]. Some studies compared different classifiers in Weka [115], a machine learning tool, showed that DT classifiers achieved the best performance in more than 20 activities including reading, using a computer, eating [53], [74], walking, sitting, stretching, vacuuming [74], static postures, transportation [114], descending, running [33] etc. Although DT has a highly effective learning method compared to ANN or Bayesian models, a large tree with a large number of branches, would be complex and time-consuming to process.

d) Support Vector Machine (SVM) is a statistical algorithm for both linear and non-linear classification by building a model to assign new data into one category or another [116]. For non-linear classification, it discriminates patterns and classes through constructing separating boundaries in a high-dimensional feature space with kernel functions. SVM is able to address the issue of either multiple wearable sensors data fusion for precise observing of ambulation and complex activities [31], or to process signals from a single inertial sensor for detecting ambulation and static postures [91]. Extensions of SVM are also applicable to other situations. For instance, Anguita et al. [117] exploited Hardware-Friendly SVM to address hardware-limited devices and Naik et al. [118] presented twin SVM as suitable for handling EMG signals to classify hand gestures.

e) Dynamic Time Warping (DTW) is an algorithm that measures the similarity of two time sequences. It aims at aligning two sequences of feature vectors by warping the time axis iteratively until an optimal match between the two sequences is found [119]. The distance is denoted as formula (5) and (6), where w_k represents the warp path of time series of i and j; $D(i,j)$ is the shortest warp path. DTW has been applied in a few recognizing daily activities for elderly and disabled people [119], hand gestures [120], ascending and descending stairs [121].

$$w_k = (i,j), w_{k+1} = (i',j')(i \le i' \le i+1,\ \ j \le j' \le j+1) \quad (5)$$

$$D(i,j) = Dist(i,j) + min[D(i-1,j), D(i,j-1), D(i-1,j-1)] \quad (6)$$

5.3.2 *Unsupervised and Semi-supervised learning methods*

Undoubtedly, supervised learning methods are able to achieve high accuracy for PARA, but in practice, labelling every sample is expensive and requires lots of effort. Also, some datasets provided by unknown third parties may not have user annotations; in such circumstances, some workers have explored semi-supervised classification and unsupervised clustering for detection of PARM with only a few or without any annotations.

a) Unsupervised methods: a few PARM studies investigated unsupervised clustering methods such as K-means cluster [46] and the Gaussian Mixture Model (GMM) [46], [122]. For example, Maekawa et al. [123] proposed a probabilistic model employing GMM to calculate the similarity of physical characteristics between a new user and source users and hence find the closest activity pattern. Alshurafa et al. [46] have pointed out that GMM is the better algorithm compared to K-means clustering when different levels of activity intensity are present which would benefit intersubject variability. In addition to these, minority unsupervised learning methods aid the analysis of Intermediary abundant data resources available from the web rather than directly labelling raw signals collected by the researchers. For example, the "bag-of-words" model [124] is a text processing technique, which Huỳnh et al. [125] employed in activity observation where a series of sensor data were converted into documentation for the inference of different types of activity. As such, sensor-based activity data is regarded as a stream of natural language terms to match objects for mining models from the web [126], [127].

b) Semi-supervised methods: are used to train a small amount of labelled data and a large number of unlabeled data in order to improve practical feasibility or to reduce cost. Co-training is a classic semi-supervised setting that takes advantage of two classifiers independently to train and update data from using unlabeled samples with a high degree of confidence [128]. Stikic et al. [129] made use of an accelerometer and an infra-red sensor, compare different semi-supervised techniques, and found that co-training and self-training methods are the most appropriate methods for activity models. En-Co-training is an improved version proposed by Guan et al. [130] which is more flexible for PA data classification, as compared to Co-training with only two separately strong classifiers, En-Co-training trains data as a whole without the requirement for the confidence of the labelling of each classifier. The study showed that with 40 wearable sensors on an individual's legs, the results of static postures and ambulation obtained were better than performance with supervised methods when 90% of samples are unlabeled.

Apart from the well-known semi-supervised techniques, the combination of supervision or semi-supervision with a fully supervised algorithm is another common approach for reducing labelled samples. For example, Huỳnh et al. [131] proposed a scheme of a mixture of unsupervised multiple eigenspaces with fully supervised SVMs, revealing that the recognition outcomes of static postures, stair activities, shaking hands and keyboard activities overweighs supervised naïve Bayes and an unsupervised eigenspaces method with 6 sensors on different parts of a subject's body. Similarly, Mathie et al. [132] presented the semi-supervised Virtual Evidence Boosting (sVEB) algorithm associated with unlabelled conditional entropy for training supervised Conditional Random Fields (CRFs) frame. In addition, multi-instance learning and SVMs have been integrated by Stikic et al. [133] to deal with different coarse-grained labels without the researcher's supervision. The approach has been verified with activities used by Bao et al. [74] and ultimately acquired high recognition rates.

5.3.3 Rule-based classification methods

Knowledge model construction and rule-based inference are two main stages for carrying out rule-based methods. The structure of models is built by a decision tree or ontology in a way that allows systems to automatically process reasoning, whilst the inference is made of a set of IF-THEN rules from training data or ontological instances. It is used for recognizing complex activities like activity in daily lives (ADLs) in context-aware environment.

The knowledge model is expressed in a knowledge representation language or data structure that enables the computer to execute the semantic rules. Knowledge-based approaches consist of syntax-based, logic-based and ontology-based approaches. Syntax-based approach make use of grammar that expresses the structure based on language modelling. It follows a hierarchical structure containing two layers which are HMMs (Hidden Markov Models) and BNs (Bayes Networks) on the bottom and CFGs (Context Free Grammars) on the top. Logic-based methods such as Description Logic (DL) describes entities and then make logical rules for high-level reasoning. Among knowledge-based approaches, ontology is the most flexible and widely used approach in IoT PARM due to its reusability, computational completeness, decidability and it is practical reasoning algorithms. The model is implemented in [81], [134]–[136] for context-aware activity recognition with the definition of concepts, properties, and relationships, as well as the support of instance-based reasoning.

W3C Web Ontology Language (OWL) is normally adopted for rule-based inference as it provides an expressive formalism for knowledge modelling and representation that supports computational completeness, decidability and practical reasoning algorithms. Each object in a context-aware environment can be regarded as a fact, and the relationships are represented between activities or objects for rule-based reasoning in the inference engine. A situation related to the environment is inferred through these relationships. Take "cooking" for example, the activity includes environmental information, i.e., location is the kitchen, objects are knife and pan, time period is an hour, and occupant's simple PA postures. The description logic (DL) is defined as:

$$COOKING \subseteq \forall HASACTOR.(PERSON1 \wedge PERSON2 \ldots) \wedge \exists HASLOCATION(KITCHEN) \wedge \forall HASTIMEPERIODE(1HOUR) \wedge \forall HASUTENSILS(PAN) \wedge \forall HASPOSTURE(STANDING) \quad (8)$$

Where the left of the arrow is termed conditions, and the right is called conclusions. ⊆ refers to concept inclusion; ∧ refers to intersection or conjunction of concepts; and ∀ is universal restriction. Formula (8) equals to DL-based rule defined as:

$$Person(?p1 \ldots ?p2), hasLocation(?kitchen), hasTimePeriode(?1hour), hasUtensils(?pan), hasPosture(?standing) \rightarrow hasKitchenActivity(?p1 \ldots ?p2, ?cooking) \quad (9)$$

Where the classes are defined as "Person", "Location", "TimePeriode", "Utensils", "Posture" and "KitchenActivity", the relationships between an individual and environment are defined as "hasLocation", "hasTimePeriode", "hasUtensils", "hasPostures" and "hasKitchenActivity". Instances defined inside brackets (e.g., (?p1…?p2) or (?kitchen), etc.) are for the purpose of conducting this reasoning.

5.4 Discussion

Supervised learning methods have mature and deep theoretical foundations, providing reliable and stable results for PAMR, and thus have been explored by a majority of studies. While the greatest weakness is to require a large number of samples and set appropriate categories ahead of time, statistical models like HMM must be trained on sufficiently massive samples. Also, each sample in supervised learning needs to be precisely labelled, which is a tedious and time-consuming procedure (it may take months depending on the size of the samples). In comparison across a diverse range of experiments and scenarios of supervised learning, PARM investigations in unsupervised and semi-supervised learning are relatively limited. Only a few studies are devoted to long-term PARM performance in naturalistic or semi-naturalistic environments by using multiple sensors [125], [133] or mobile phones [137]. Almost no studies on complex PA use context-aware applications. This is because of their intrinsic limitations where a big theoretical gap still exists. Firstly, it is difficult to know the correct classification boundaries when separating features into different PA groups. Secondly, most studies assume that the numbers of clusters is known, from extending PA types. Setting unknown numbers of clusters often leads to unstable consequences, so it is difficult to control the complexity of the algorithm when trying different initial selections. Nonetheless, semi-supervised and unsupervised approaches are more useful in practice when there are many uncertainties. Resolving the complexity and accuracy of the algorithms, or adding more complex PA types is a challenging topic that should be further investigated. On the other hand, rule-based inference has no requirement of any training samples. Using Knowledge representation is unambiguous, sharable and reusable. The significant drawback is that simple PA must be recognized in advance for further rule-based reasoning, yet rule-based methods can hardly be carried out if one lacks part of the conditions in a rule. Likewise, it is impossible to draw conclusions from rules in which there is missing data from the sensing layer. If the acquired sensor data is empty or inaccurate, the rules would fail to be executed or produce faulty results. Errors often occur due to sensor asynchronies or network transmission in practice. Thus, we suggest that rule-based systems still need to be further investigated.

6. Application layer

PARM has been applied in many healthcare relevant fields from activity tracking products (e.g., mobile app and wearable fitness bands) to medical interventions (e.g., monitoring daily living activities for the elderly and measuring chronic diseases). Some existing PARM applications are introduced in this section from aspects of fitness tracking and monitoring, remote AAL, remote health monitoring, diagnosis and rehabilitation, emergency alerts and smart biomedical sensing.

6.1 Mobile fitness tracking

PARM in fitness is a relatively mature and widely commercialized technique that is designed for various groups of people from elderly citizens, patients with chronic diseases to healthy sedentary and physically active adults. There are many popular mobile apps (i.e., Moves, Nike+ or Google fit) to fitness wearable devices (i.e., Fitbit or smart watches from some technology manufacturers); Automatic tracking with simple PA such as *walking, running, cycling, sleeping*, etc. have been integrated into the public's daily lives. On the other hand, there are some trade-offs between PA types, the position of devices and the recognition accuracy. Existing customer devices/apps are of limited use due to a number of uncertainties such as placement of the mobile devices on different parts of the body, battery consumption, capacity or manufacturer's intrinsic settings, whilst PA types are quite narrow; accuracy and precision are also challenged. Work has been continually carried out to improve all of these aspects.

WISDM (Wireless Sensor Data Mining) [70] is a typical platform that detects PA based on Android phone sensors placed in one's pocket. Data is taken from the accelerometer, some repetitive PA (e.g., *walking, jogging*, etc.) are investigated using supervised training algorithms like J48, logical regression, multilayer perceptron and straw man. The result exhibits that ascending and descending stairs are the most difficultly recognized PA. M. Shoaib et al. [138] offers a comprehensive review of the possibilities in mobile phone PARM. The experiment tests PA performance (e.g., *walking, running, etc.*) in position-aware, position-unaware and personlised evaluation scenarios with accelerometers, gyroscopes embedded in a smart phone. The comparison of results using some typical classifiers from signals from the upper arm, wrist, belt and right pocket through four groups of features extracted from the time and frequency domain in the three scenarios. Results suggest that each sensor takes a key role in different activities, and the positions only have a limited influence on classification results.

6.2 Ambient assisted living

AAL is applied in a person's daily living and working environment to enable them to stay active longer, remain socially connected and live independently into old age. It covers a range of research areas, particularly in ADL recognition with an individual's context and situation. AAL uses numerous ambient sensors and one or several wearable sensors to understand an individual's behaviours in a context-aware environment. For instance, E. M. Tapia et al. [139] installed 77 simple and low-cost environmental sensor in occupants' real homes for ADL detection (i.e., *cooking* or *eating*). Naïve Bayesian networks as a PA classifier is implemented for ADL recognition. One noteworthy point in the work is that the Experience Sampling Method (ESM) is used for labelling binary sensor data especially in an uncontrolled living environment, where self-reported diary entries in personal digital assistant (PDA) can be triggered when a user performs PA in successive time windows. However, the study also reports that the user's attitude towards ESM is that in daily life they are not very positive responding to the computer all the time and the monitoring does impact on their behaviours. Chernbumroong et al. [140] propose an ADL recognition method with feature combinations using small and low-cost wearable sensors on the wrist. The data is collected from a free living environment of elderly adults and points out that recognition accuracy can be improved by combining data from temperature sensors or altimeter sensors with accelerometer in the SVM model. On the other hand, *dressing* is not well detected with this model. IDSense [61] is a simple move and touch indoor human-object interaction applications with only RFID passive tags, developed by Li Hanchuan et al . The recognizing procedure is in accordance to the changes in the physical layer signals of the communication channel between the RFID reader and the passive tags. With over 90% precision and recall, the work indicates RFID sensor is a promising PA recognition tool.

6.3 Remote health monitoring

Special interest in home-based remote PARM is often of significance to seniors or people with chronic diseases as well as caregivers and physicians. PA patterns can reflect physical states of the patients and thus recording such PA data will provide physicians and caregivers with a useful method for accurate intervention and diagnosis. This work [43] presents an early online remote monitoring system for patients using wireless 3D accelerometers by recognizing simple PA, static PA, ambulation and abnormal PA, etc. The data processing and classification procedures are carried out on a small waist-worn unit where the battery and capacity would be constrained. Moreover, the classification method is implemented through the threshold of a straightforward SMA calculation. Hence the online system is low consumption cost, fast and more useful in a free living environment. Hynes et al. [141] implement a smartphone-based long-term remote monitoring system for both patients and caregiver that is capable to displaying PA states (*walking* or *resting*), levels (high, medium, low and inactive) and durations. The PA intensity is calculated from the Average Magnitude Difference Function (AMDF) and evaluated on the placement of jacket, belt and trousers. Resource consumptions are also considered in the work.

6.4 Diagnosis and rehabilitation

ICT technologies can be used to facilitate patients with chronic diseases through PA measurements in home or hospital environments. Compared with conventional questionnaires or manual exercise tests (i.e., 6 minute walk test), objective PA assessments by using smart monitoring and sensor technologies in diagnosis and rehabilitation systems will deliver particular information for physicians and carers and thus potentially assist self-management wellbeing, reduce healthcare cost, and avoid undesirable consequences, in a personalised manner for different patients in accordance with a period of behaviour analysis. Li et al. [45] combine ECG and accelerometer data to categorise PA for the purpose of health assessment, rehabilitation and intervention. A special feature extraction approach proposed in the integration of time domain and cepstral domain from two sensor signals respectively; this illustrates how to harness ECG in PARM. COPDTrainer [142] is a smartphone-based system of detection and monitoring of rehabilitation training exercises (e.g., arm extension, elbow circle, etc.) for COPD patients. With a holster carrying the phone on the wrist and ankle, the system provides real-time feedback regarding exercise performance and quality to users through comparison of a "teaching model" and "training model". Classification of exercises is determined by features, speed and range of motion. This work demonstrates that recognition of training exercises can be a possible way of using a single mobile phone. *mHealthDroid (Mobile Health Android)* [143] is an open source framework designed to facilitate the rapid and easy development of biomedical android applications. The platform is able to collect data from connecting heterogeneous commercial devices for both ambulation and biomedical signals. Healthcare interventions such as alerts and guidelines are also available. The most important aspect is its extensibility, which supports diverse modes and ways to facilitate new system implementation for time and cost savings. For instance, mDurance [144], a mobile healthcare support system for assessment of trunk endurance, is implemented in terms of the core functionalities of mHealthDroid.

6.5 Emergency system

Monitoring abnormal activities is a major issue in healthcare for elders particularly for those who are living independently. Falls are the greatest cause of emergency hospital admissions for older people, and delaying treatment and care would significantly influence long-term outcomes. Other abnormal activities such as going to the toilet too many times at night can predict some diseases like bladder inflammation or diabetes. Therefore, immediate emergency systems are essential to monitor and detect such abnormal PA and thus avoid adverse consequences.

Duong et al. [145] propose an effective scheme to detect ADL and abnormality through the use of two layers of switching hidden semi-Markov model (S-HSMM) where an ADL is divided into a series of atomic PA combinations, whilst abnormality detection is determined by the likelihood of a parameter of the normal model and abnormal model. The study is a typical time sequence application addressing complex PA recognition and abnormality detection. Another fall monitoring and rescue system is presented in [65] that employs a smartphone's built-in sensors in an elder's pocket and then information from GPS sent to a rescue centre via 3G communication networks in real-time once falling occurs. The mechanism of fall detection is through verifying a series of features in a sequential states and classifying them with SVM. Also the smartphone as the processing platform, well manages the consumption issues and recognition rate.

6.6 Smart biomedical sensing

Biomedical sensing and monitoring technologies play significantly supplementary roles in healthcare-related PARM. These vital signs may reflect human healthy states and thus are gradually provided by an alternative approach with mobile device built-in personalized self-management systems/apps. A variety of individuals' conditions can be handled with the smart monitoring and sensing technologies such as spirometry sensing [7], sleep apnea detection [9] and breathing and heart rate signs [10], etc. that may increase efficiency of recognitions and physical states in terms of the PA intensities from respirations and heartbeats. Vital-Radio [10] presents is a wireless and multi-user breathing and heartbeats monitor that can detect different type of PA in smart environments. Similar research is also investigated in the WiBreathe [8] that is competent to contactless measure respirations during *sleeping, reading, tying, watching TV* and *lying down*. SpiroSmart [7] shows a home-based spirometry by using low-cost mobile phone app with built-in microphone that user can exhale toward to the screen while the microphone records data and send it to be evaluated. The app may also useful and commonplace for PA monitoring.

7. Future research trends

PARM using sensing technologies has huge potential benefits in the healthcare field, yet it is still broadly agreed that IoT technologies are in their infancy and face many challenges in successfully applying them into PARM due to further requires of free living environment, lifelogging monitoring, scalability and extensibility, device cost and various PA types, etc. Future work is required to address these challenges and to examine the suitability of existing PARM technologies to ensure a good fit in the IoT environment.

7.1 Free living environment

It is reported in some work that the accuracy of PA recognizers drops dramatically from lab settings to free living environments where there are uncontrolled elements, such as short-battery life or poor capacity of devices and the requirement to run time-consuming machine learning algorithms. Another key issue is intersubject variability, which means different people perform the same behaviours differently. One reason is due to various physical characteristics like age or weight. More importantly, uncertainties normally occur from PA types especially in complex PA (i.e., ADL or playing balls). As a standalone mathematical model it is not highly effective when recognizing the changing time-sequence-based atomic simple PA due to inflexible patterns and templates. Optimizing existing algorithms/frameworks/platforms may improve the stability in free living environment.

7.2 Lifelogging PA data from customer devices/apps

The effective collection of measures of PA in the long term is beneficial to interdisciplinary healthcare research and collaboration from clinicians, researchers and patients. However, owning to heterogeneity of connected devices and rapid change of diverse life patterns, lifelogging PA information captured by third party devices/apps normally contains much uncertainty thereby limiting their adoption for healthcare studies. Many issues have been well addressed in customer devices/apps like storage, battery life and cost, especially mobile apps are cheap and even free. Nevertheless, PA recognition results offered by mobile devices are widely divergent so that making its information turn to be scattered, erroneous and limited for healthcare uses. Thus, handling with uncertainties and more effectively harnessing these data would be greatly beneficial for PARM in a long term.

7.3 Low-cost device

Most previous work on implementing PARM algorithms/frameworks with relatively precise and stable signals have used expensive devices/sensors for high recognition accuracy. Cheap mobile devices have also been obtained much attention both in the research and industrial fields in recent years. Due to their low-cost and portability, tracking everyone's daily PA becomes possible. One of the inevitable issues is resource consumption (i.e., memory and battery), especially in online PARM systems where the user may acquire immediate feedback. Most studies showed the accuracy under offline settings where data is processed remotely and feedback provided after. Few mobile online systems have reported their computational demands. Thus there might be a trade-off between recognition accuracy and processing requirements to be further investigated.

7.4 Physical activity types

PARM has been studied over several decades, yet a range of PA types that have not or have only been explored by a few studies exist. For example, weight training exercises are essential PAs that may bring considerable healthcare benefits for various groups of people. However, research work on such PARMs are very limited and immature. Also, some other fitness PA (i.e. *playing basketball* or *playing tennis*) are rarely involved. Compared with repetitive movements (i.e., *waking, running*) or sedentary actions (i.e., *standing, sitting*), the activities are relatively complex and thus require more effective techniques to implement. Moreover, in the AAL field, there is increasingly active researches on concurrent and interleaved activity recognition although it is still in its infancy and faces many challenges. For instance, a person may be *cutting food* while *boiling water* in an ADL *cooking*. Furthermore, multi-user and multi-activity recognition and monitoring also are in difficulty at the moment. While along the development of sensing technologies and the abilities, recognizing more complex PA types suggests promising opportunities. HMM and conditional random fields (CRF) [109] and knowledge-driven approaches [146] could be useful techniques in addressing such issues.

7.5 High volume of data

The heterogeneous devices connected in IoT environments and life-logging collection of physical activity data will be driving major expansion in big data of PA. These data contain not only a sheer volume of long-term PA information, but also complex, diverse and rich context of other health information. The uncertainty of these data will be much higher than physical activity data training by classic machine learning methods of PARM techniques. Effectively and efficiently improving validity of these PA data and exploring useful knowledge becomes a difficult task. Therefore, research work on how to explore these big PA data under IoT environments for bringing intelligence for more solid clinical decision-making and policy formulation will be significance.

8. Conclusion

Given the importance of Physical Activity Recognition and Monitoring (PARM) for healthcare support of a variety of chronic diseases, musculoskeletal rehabilitation, independent living of the elderly, as well as fitness goals for active life styles, a number of studies have been devoted to the crucial issues of PARM during the last two decades. The contribution of this work is from the perspective of Internet of Things (IoT) that sequentially covers the sensing layer, network layer, processing layer and application layer, distinctively and systematically summarizing existing primary PARM devices, methods, and environments. Wearable and portable sensors/devices, inertial signal data processing and classification/clustering approaches are described and compared in the light of physical activity types, subjects, accuracy, flexibility and energy. Typical research and project applications regarding PARM are also introduced. In the end, challenges and potential future trends have been analysed and those associated with IoT highlighted.

Appendix

Table 7. Studies of activity recognition and monitoring based on Internet of Things (IoT) structure (ACC-accelerometer; gyro-gyroscope; ECG-electrocardiography)

	Sensing layer		**Network layer**	**Processing layer**					**Application layer**
Works	Device/s	Placed position	Network	Segmentation /Features	Classifier/ Cluster	Subjects	Detected activities	Accuracy	
[39]	1 ACC	Waist	Not mention	Time-domain and frequency-domain features	SVM, ANN, DT	20 young healthy people	Postures, transitions, walk, run, cycle, football	In lab: 82%-99% Out of lab: 24%-83%	Compared PAR models in and out of the lab and proposed potential solutions
[37]	ACOR+ kinematic system (1 3D ACC, 1 microcontroller	day: belt; night: chest	Bluetooth	Not mention	DT	15 (9 COPD patients, 6 healthy people)	Postures, walk, read, exercises	77%-94%	Simple device and real-time PARM applied on COPD (chronic obstructive pulmonary disease) patients home monitoring.
[36]	1 3D ACC, 1 wearable camera	ACC on the belly; Camera hung over neck	ZigBee, Wi-Fi, Bluetooth	FFT (mean, energy, correlation)	SVM	Not mention	Run, go downstairs, go upstairs, take an elevator, walk forward, walk backward, stand, sit, turn	90%-99%	Apply in the context-aware environment for lifelogging health monitoring.
[31]	2 3D ACC, 1 ventilation sensor	Accelerometers : hip, wrist; ventilation sensor: abdomen	Not mention	Time-domain (mean value, SD, median, percentiles); frequency-domain (energy, entropy)	SVM	50 healthy people	Postures, vacuum, cycle, play balls, work	89.3% on average	Effectively and accurately assess PA energy expenditures using multi-sensor fusion technique.
[16]	1 gyro on shoe	Feet, knee	Not mention	Not mention	Knowledge-based algorithm	10 able body people, 6 people with impaired gait	Walk on level ground, walk up and down a steep cobblestone road, walk on grass, ascend and descend, stand up and down, bend knees, rotate	>96%	A system of controlling the gait cycle of a neuroprosthesis for walking in real time.

[147]	1 3D ACC, 1 3D gyro, 1 3D magnetic sensor.	Upper and lower limb	Bluetooth	Kalman-filtering	Kinematic modelling	8 healthy male people (24–40 years old)	circular, rectangular motion, reach, hand to mouth, flexion-extension, elevation	95%-98%	A low-cost human motion capture system used in the domain of home-based stroke rehabilitation for measure of different motion circumstances
[104]	A 3D seismic ACC，3 gyros	Belt on waist	Not mention	Statistics for each axis		15 older patients of a geriatric rehabilitation clinic (median age 81 years) , 10 young healthy people (median age 37 years)	lying-to-sit-to-stand-to-walk (LSSW) test	90%-100%	Detect falls at bedsides for elderly and patients in independent living environment with cost-effective method.
[148]	1 watch with 1 ACC, 1 gyro, 1 iPhone 4	Belt on waist, thigh, shank;	Not mention	self-defined features based on each interpeak segmented period	Bayes	49 people	Gestures, drinks, swallows, chews, bites	79%-95%	Detect energy intake for the study of obesity by the means of continuously and automatically detecting the periods of eating throughout the day.
[74]	5 biaxial ACCs	right hip, dominant wrist, non-dominant upper arm, dominant ankle, and non-dominant thigh	Not mention	Time-domain (sum, energy, mean,); FFT (DC component, entropy)	nearest neighbor algorithms; leave-one-subject-out training	20 people (age from 17 to 48)	ambulation, posture, stretch, laundry, brush teeth, ride lift eat, drink, bike, read, vacuum	43%-97%	First work of wireless accelerometers measuring PA in an uncontrolled environment for the purpose of assessing PA accuracy.
[84]	Inertial sensors	Arm	Not mention	SWAB segment; Euclidean distance	HMM		object interaction gestures, dietary intake gestures	97.4%-98.4%	Facilitate PA recognition and context applications in real life.
[43]	3D ACC unit	Wrist, arm	ZigBee	SMA, SVM	Calculate angle between the z-axis vector and the gravitational vector	6 people	Transitions, fall, walk, static postures, circuit	83.3%-95.6%	Assist remote supervision for healthcare monitoring in terms of promoting the longevity of battery life and thus enhancing the system’s usability in real life.
[149]	9 ACCs	Chest, waist, right thigh, left ankle	Not mention	Multiple HMM regression segmentation	Multiple HMM	6 healthy subjects with age 25–30	Stairs down, stand, sit down sit, from sitting to sitting on the ground, sit	82.3%-98.5%	Automatic recognition of PA without human efforts in a healthcare monitoring environment.

					regression (MHMMR)	years old, weight 55–70 kg.	on the ground, lie down, lie, from lying to sitting on the ground, stand up, walking, stairs up		
[45]	1 ECG, 1 ACC	Left hip	Bluetooth	Time domain and Cepstral features	SVM, GMM	5 young healthy people (ages 13-20 2 M, 3 F)	Postures, play games, brisk walk, slow walk, run	79.3%-97.3%	Healthcare assessment and rehabilitation intervention
[27]	5 ACCs, 1 ECG necklace	Chest, ankle, thigh, wrist, right hip	Wireless network		Activity-specific energy expenditure methods	15 young healthy people (11 M, 5 F)	Sedentary, lifestyle, sports, run	70%-98%	Compared sensor numbers and positioning to accurately measure PA types and energy expenditures for healthcare and wellbeing purpose
[150]	Gyros, ACCs	Shoulder, elbow	Not mention	Not mention	Kalman filtering	8 healthy people	Elbow and shoulder flexion/extension, forearm supination/pronation, shoulder abduction /adduction	95%-99%	Diagnosis of neurological movement disorders, rehabilitation from injury, and enhancement of athletic performance.
[151]	A watch with 1 ACC and 1 gyro	Wrist	Not mention	Not mention	HMM	23 subjects	Wave arms, watch check, drink, pick up phones from a table, shake hands, natural arm actions when walking	97.1% on average	Help people to achieve performance goals and reduce bad habits through arm motion recognition.
[46]	1 3D ACC, metabolic cart	Left hip	Not mention	Time-domain (mean, SD, variance)	K-means cluster, GMM	12 young healthy people	Walk, run	90.8%-94.3%	Measure PA intensity with intersubject variability.

REFERENCE

[1] C. J. Caspersen, K. E. Powell, and G. M. Christenson, "Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research.," *Public Health Rep.*, vol. 100, no. 2, pp. 126–131, 1985.

[2] M. A. Minor, J. E. Hewett, R. R. Webel, S. K. Anderson, and D. R. Kay, "Efficacy of physical conditioning exercise in patients with rheumatoid arthritis and osteoarthritis," *Arthritis Rheum.*, vol. 32, no. 11, pp. 1396–1405, 1989.

[3] G. H. Guyatt, M. J. Sullivan, P. J. Thompson, E. L. Fallen, S. O. Pugsley, D. W. Taylor, and L. B. Berman, "The 6-minute walk: a new measure of exercise capacity in patients with chronic heart failure.," *Can. Med. Assoc. J.*, vol. 132, no. 8, pp. 919–23, 1985.

[4] H. Amroun, "Recognition of Human Activity Using Internet of Things In a Non-Controlled Environment," vol. 2016, no. November, pp. 13–15, 2016.

[5] D. Castro, "Wearable-Based Human Activity Recognition Using an IoT Approach," *J. Sens. Actuator Networks*, vol. 6, no. 4, p. 28, 2017.

[6] C. Rodriguez, D. M. Castro, W. Coral, J. L. Cabra, N. Velasquez, J. Colorado, D. Mendez, and L. C. Trujillo, "IoT system for Human Activity Recognition using BioHarness 3 and Smartphone," *Proc. Int. Conf. Futur. Networks Distrib. Syst. - ICFNDS '17*, pp. 1–7, 2017.

[7] E. C. Larson, M. Goel, G. Boriello, S. Heltshe, M. Rosenfeld, and S. N. Patel, "SpiroSmart," *Proc. 2012 ACM Conf. Ubiquitous Comput. - UbiComp '12*, no. Figure 1, p. 280, 2012.

[8] R. Ravichandran, E. Saba, K. Chen, M. Goel, S. Gupta, and S. N. Patel, "WiBreathe : Estimating Respiration Rate Using Wireless Signals in Natural Settings in the Home," vol. 16, pp. 131–139, 2015.

[9] R. Nandakumar, S. Gollakota, and N. Watson, "Contactless Sleep Apnea Detection on Smartphones," *Proc. 13th Annu. Int. Conf. Mob. Syst. Appl. Serv. - MobiSys '15*, pp. 45–57, 2015.

[10] F. Adib, H. Mao, Z. Kabelac, D. Katabi, and R. C. Miller, "Smart Homes that Monitor Breathing and Heart Rate," *Proc. 33rd Annu. ACM Conf. Hum. Factors Comput. Syst. - CHI '15*, pp. 837–846, 2015.

[11] E. J. Wang, W. Li, D. Hawkins, T. Gernsheimer, C. Norby-Slycord, and S. N. Patel, "HemaApp," *Proc. 2016 ACM Int. Jt. Conf. Pervasive Ubiquitous Comput. - UbiComp '16*, pp. 593–604, 2016.

[12] F. Paganelli and D. Giuli, "An ontology-based context model for home health monitoring and alerting in chronic patient care networks," *Proc. - 21st Int. Conf. Adv. Inf. Netw. Appl. Work. AINAW'07*, vol. 1, no. Iccc, pp. 838–845, 2007.

[13] P. H. Veltink, H. J. Bussmann, W. de Vries, W. J. Martens, and R. C. Van Lummel, "Detection of static and dynamic activities using uniaxial\naccelerometers," *IEEE Trans. Rehabil. Eng.*, vol. 4, no. 4, pp. 375–385, 1996.

[14] G. M. Lyons, K. M. Culhane, D. Hilton, P. a. Grace, and D. Lyons, "A description of an accelerometer-based mobility monitoring technique," *Med. Eng. Phys.*, vol. 27, no. 6, pp. 497–504, 2005.

[15] M. Luštrek and B. Kaluža, "Fall Detection and Activity Recognition with Machine Learning," *Informatica*, vol. 33, no. 2, pp. 205–212, 2009.

[16] I. P. I. Pappas, M. R. Popovic, T. Keller, V. Dietz, and M. Morari, "A reliable gait phase detection system," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 9, no. 2, pp. 113–125, 2001.

[17] P. a. Costigan, K. J. Deluzio, and U. P. Wyss, "Knee and hip kinetics during normal stair climbing," *Gait Posture*, vol. 16, no. 1, pp. 31–37, 2002.

[18] B. Coley, B. Najafi, A. Paraschiv-Ionescu, and K. Aminian, "Stair climbing detection during daily physical activity using a miniature gyroscope," *Gait Posture*, vol. 22, no. 4, pp. 287–294, 2005.

[19] H. Dejnabadi, B. M. Jolles, and K. Aminian, "A new approach to accurate measurement of uniaxial joint angles based on a combination of accelerometers and gyroscopes," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 8, pp. 1478–1484, 2005.

[20] A. Salarian, H. Russmann, C. Wider, P. R. Burkhard, F. J. G. Vingerhoets, and K. Aminian, "Quantification of tremor and bradykinesia in Parkinson's disease using a novel ambulatory monitoring system," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 2, pp. 313–322, 2007.

[21] a Moncada-Torres, K. Leuenberger, R. Gonzenbach, a Luft, and R. Gassert, "Activity classification based on inertial and barometric pressure sensors at different anatomical locations," *Physiol. Meas.*, vol. 35, no. 7, pp. 1245–1263, 2014.

[22] F. Bianchi, S. J. Redmond, M. R. Narayanan, S. Cerutti, and N. H. Lovell, "Barometric pressure and triaxial accelerometry-based falls event detection," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 6, pp. 619–627, 2010.

[23] S. a. Lowe and G. ÓLaighin, "Monitoring human health behaviour in one's living environment: A technological review," *Med. Eng. Phys.*, vol. 36, no. 2, pp. 147–168, 2014.

[24] G. Wu and S. Xue, "Portable preimpact fall detector with inertial sensors," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 2, pp. 178–183, 2008.

[25] H. J. Luinge and P. H. Veltink, "Inclination measurement of human movement using a 3-D accelerometer with autocalibration.," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 12, no. 1, pp. 112–121, 2004.

[26] J. K. Lee, E. J. Park, and S. N. Robinovitch, "Estimation of attitude and external acceleration using inertial sensor measurement during various dynamic conditions," *IEEE Trans. Instrum. Meas.*, vol. 61, no. 8, pp. 2262–2273, 2012.

[27] M. Altini, J. Penders, R. Vullers, and O. Amft, "Estimating Energy

Expenditure Using Body-Worn Accelerometers: a Comparison of Methods, Sensors Number and Positioning.," *IEEE J. Biomed. Heal. informatics*, vol. 2194, no. c, pp. 1–8, 2014.

[28] J. P. Giuffrida, A. Lerner, R. Steiner, and J. Daly, "Upper-extremity stroke therapy task discrimination using motion sensors and electromyography," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 1, pp. 82–90, 2008.

[29] E. M. Tapia, S. S. Intille, W. Haskell, K. Larson, J. Wright, A. King, and R. Friedman, "Real-Time Recognition of Physical Activities and Their Intensities Using Wireless Accelerometers and a Heart Rate Monitor," *2007 11th IEEE Int. Symp. Wearable Comput.*, pp. 1–4, 2007.

[30] T. Choudhury, J. Hightower, A. Lamarca, L. Legrand, A. Rahimi, A. Rea, B. Hemingway, K. Koscher, J. a Landay, J. Lester, and D. Wyatt, "An embedded Activity Recognition system," *IEEE Pervasive Comput.*, vol. 7, no. 2, pp. 32–41, 2008.

[31] S. Liu, R. X. Gao, D. John, J. W. Staudenmayer, and P. S. Freedson, "Multisensor data fusion for physical activity assessment," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 3, pp. 687–696, 2012.

[32] J. Mantyjarvi, J. Himberg, and T. Seppanen, "Recognizing human motion with multiple acceleration sensors," *2001 IEEE Int. Conf. Syst. Man Cybern. e-Systems e-Man Cybern. Cybersp.*, vol. 2, pp. 2–7, 2001.

[33] U. Maurer, a. Smailagic, D. P. Siewiorek, and M. Deisher, "Activity recognition and monitoring using multiple sensors on different body positions," *Int. Work. Wearable Implant. Body Sens. Networks*, pp. 4–7, 2006.

[34] D. Minnen, T. Starner, J. a Ward, P. Lukowicz, and G. Troster, "Recognizing and Discovering Human Actions From On-Body Sensor Data," *IEEE Int. Conf. Multimed. Expo ICME*, pp. 1545–1548, 2005.

[35] J. a. Ward, P. Lukowicz, G. Tröster, and T. E. Starner, "Activity recognition of assembly tasks using body-worn microphones and accelerometers," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 10, pp. 1553–1566, 2006.

[36] Y. Nam, S. Rho, and C. Lee, "Physical activity recognition using multiple sensors embedded in a wearable device," *ACM Trans. Embed. Comput. Syst.*, vol. 12, no. 2, pp. 1–14, 2013.

[37] B. Perriot, J. Argod, J. L. Pepin, and N. Noury, "Characterization of Physical Activity in COPD Patients: Validation of a Robust Algorithm for Actigraphic Measurements in Living Situations," *IEEE J. Biomed. Heal. Informatics*, vol. 18, no. 4, pp. 1225–1231, 2014.

[38] M. Ermes, J. Pärkkä, J. Mäntyjärvi, and I. Korhonen, "Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions," *IEEE Trans. Inf. Technol. Biomed.*, vol. 12, no. 1, pp. 20–26, 2008.

[39] I. C. Gyllensten and A. G. Bonomi, "Identifying types of physical activity with a single accelerometer: Evaluating laboratory-trained algorithms in daily life," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 9, pp. 2656–2663, 2011.

[40] D. Naranjo-Hernández, L. M. Roa, J. Reina-Tosina, and M. Á. Estudillo-Valderrama, "SoM: A smart sensor for human activity monitoring and assisted healthy ageing," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 12 PART2, pp. 3177–3184, 2012.

[41] G. Spina, P. Casale, P. S. Albert, J. Alison, J. Garcia-aymerich, R. W. Costello, D. Leuppi, R. Mesquita, S. J. Singh, F. W. J. M. Smeenk, R. Tal-singer, E. F. M. Wouters, M. A. Spruit, and A. C. Den Brinker, "Identifying Physical Activity Profiles in COPD Patients Using Topic Models," vol. 19, no. 5, pp. 1567–1576, 2015.

[42] A. M. Khan, Y. K. Lee, S. Y. Lee, and T. S. Kim, "A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 5, pp. 1166–1172, 2010.

[43] D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, and B. G. Celler, "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring.," *IEEE Trans. Inf. Technol. Biomed.*, vol. 10, no. 1, pp. 156–167, 2006.

[44] a. Godfrey, a. K. Bourke, G. M. Ólaighin, P. van de Ven, and J. Nelson, "Activity classification using a single chest mounted tri-axial accelerometer," *Med. Eng. Phys.*, vol. 33, no. 9, pp. 1127–1135, 2011.

[45] M. Li, V. Rozgić, G. Thatte, S. Lee, A. Emken, M. Annavaram, U. Mitra, D. Spruijt-Metz, and S. Narayanan, "Multimodal physical activity recognition by fusing temporal and cepstral information," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 4, pp. 369–380, 2010.

[46] N. Alshurafa, W. Xu, J. Liu, M.-C. Huang, B. Mortazavi, C. Roberts, and M. Sarrafzadeh, "Designing a Robust Activity Recognition Framework for Health and Exergaming using Wearable Sensors.," *IEEE J. Biomed. Heal. informatics*, vol. 18, no. c, pp. 1–11, 2013.

[47] J. Merilahti, P. Viramo, and I. Korhonen, "Wearable monitoring of physical functioning and disability changes, circadian rhythms and sleep patterns in nursing home residents," *IEEE J. Biomed. Heal. Informatics*, vol. 2194, no. c, pp. 1–1, 2015.

[48] a. Purwar, D. D. J. D. Do Jeong, and W. Y. C. W. Y. Chung, "Activity monitoring from real-time triaxial accelerometer data using sensor network," *2007 Int. Conf. Control. Autom. Syst.*, pp. 2402–2406, 2007.

[49] A. M. Khan, Y. K. Lee, S. Lee, and T. S. Kim, "Accelerometer's position independent physical activity recognition system for long-term activity monitoring in the elderly," *Med. Biol. Eng. Comput.*, vol. 48, no. 12, pp. 1271–1279, 2010.

[50] A. Khan, M. Siddiqi, and S.-W. Lee, "Exploratory Data Analysis of Acceleration Signals to Select Light-weight and Accurate Features for Real-time Activity Recognition on Smartphones," *Sensors*, vol. 13, no. 10, pp. 13099–13122, 2013.

[51] H. Martín, A. M. Bernardos, J. Iglesias, and J. R. Casar, "Activity logging using lightweight classification techniques in mobile devices," *Pers. Ubiquitous Comput.*, vol. 17, no. 4, pp. 675–695, 2013.

[52] A. Environment and M. C. Mozer, "that Adapts to its Inhabitants," pp. 0–4, 1998.

[53] B. Logan, J. Healey, M. Philipose, E. M. Tapia, and S. Intille, "A Long-Term Evaluation of Sensing Modalities for Activity Recognition," *UbiComp 2007 Ubiquitous Comput.*, vol. 4717, pp. 483–500, 2007.

[54] D. Ding, R. a. Cooper, P. F. Pasquina, and L. Fici-Pasquina, "Sensor technology for smart homes," *Maturitas*, vol. 69, no. 2, pp. 131–136, 2011.

[55] K. Wongpatikaseree, M. Ikeda, M. Buranarach, T. Supnithi, A. O. Lim, and Y. Tan, "Activity Recognition Using Context-Aware Infrastructure Ontology in Smart Home Domain," *2012 Seventh Int. Conf. Knowledge, Inf. Creat. Support Syst.*, pp. 50–57, 2012.

[56] V. Guralnik and K. Z. Haigh, "Learning Models of Human Behaviour with Sequential Patterns," pp. 24–30, 2002.

[57] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of Wireless Indoor Positioning Techniques and Systems," *IEEE Trans. Syst. Man, Cybern. Part C Appl. Rev.*, vol. 37, no. 6, pp. 1067–1080, 2007.

[58] M. a. Stelios, A. D. Nick, M. T. Effie, K. M. Dimitris, and S. C. a. Thomopoulos, "An indoor localization platform for ambient assisted living using UWB," *Proc. 6th Int. Conf. Adv. Mob. Comput. Multimed. - MoMM '08*, p. 178, 2008.

[59] L. Liao, D. J. Patterson, D. Fox, and H. Kautz, "Learning and inferring transportation routines," *Artif. Intell.*, vol. 171, no. 5–6, pp. 311–331, 2007.

[60] M. Han, J. Bang, C. Nugent, S. McClean, and S. Lee, "A Lightweight Hierarchical Activity Recognition Framework Using Smartphone Sensors," *Sensors*, vol. 14, pp. 16181–16195, 2014.

[61] H. Li, C. Ye, and A. P. Sample, "IDSense," *Proc. 33rd Annu. ACM Conf. Hum. Factors Comput. Syst. - CHI '15*, no. c, pp. 2555–2564, 2015.

[62] M. Philipose, K. P. Fishkin, M. Perkowitz, D. J. Patterson, D. Fox, H. Kautz, and D. Hähnel, "Inferring activities from interactions with objects," *IEEE Pervasive Comput.*, vol. 3, pp. 50–57, 2004.

[63] J. Wu, a Osuntogun, T. Choudhury, M. Philipose, and J. M. Rehg, "A Scalable Approach to Activity Recognition based on Object Use," *Comput. Vision, 2007. ICCV 2007. IEEE 11th Int. Conf.*, pp. 1–8, 2007.

[64] H. Chen, F. Perich, T. Finin, and A. Joshi, "SOUPA : Standard Ontology for Ubiquitous and Pervasive Applications ∗."

[65] L.-J. Kau and C.-S. Chen, "A smart phone-based pocket fall accident detection, positioning, and rescue system.," *IEEE J. Biomed. Heal. informatics*, vol. 19, no. 1, pp. 44–56, 2015.

[66] J. Rafferty, C. N.-I. Member, L. C.-I. Member, J. Qi, R. Dutton, A. Zirk, L. T. Boye, M. Kohn, and R. Hellman, "NFC based provisioning of instructional videos to assist with instrumental activities of daily living," pp. 4131–4134, 2014.

[67] M. Kranz, A. Möller, N. Hammerla, S. Diewald, T. Plötz, P. Olivier, and L. Roalter, "The mobile fitness coach : Towards individualized skill assessment using personalized mobile devices," *Pervasive Mob. Comput.*, vol. 9, no. 2, pp. 203–215, 2013.

[68] C. Lu and L. Fu, "Robust location-aware activity recognition using wireless sensor network in an attentive home," *IEEE Trans. Autom. Sci. Eng.*, pp. 598–609, 2009.

[69] J.-L. Reyes-Ortiz, L. Oneto, A. Samà, X. Parra, and D. Anguita, "Transition-Aware Human Activity Recognition Using Smartphones," *Neurocomputing*, vol. 171, pp. 754–767, 2015.

[70] J. R. Kwapisz, G. M. Weiss, and S. a. Moore, "Activity recognition using cell phone accelerometers," *ACM SIGKDD Explor. Newsl.*, vol. 12, p. 74, 2011.

[71] H. E. Jian and H. U. Chen, "T ELECOMMUNICATIONS FOR R EMOTE M EDICINE A Portable Fall Detection and Alerting System Based on k-NN Algorithm and Remote Medicine," no. April, pp. 23–31, 2015.

[72] E. Keogh, S. Chu, D. Hart, and M. Pazzani, "Segmenting Time Series: A Survey and Novel Approach," *Data Min. Time Ser. Databases*, pp. 1–21, 2003.

[73] J. Lester and T. Choudhury, "A hybrid discriminative/generative approach for modeling human activities," *Proc. 19th Int. Jt. Conf. Artif. Intell.*, pp. 766–772, 2005.

[74] L. Bao and S. S. Intille, "Activity Recognition from User-Annotated Acceleration Data," *Pervasive Comput.*, pp. 1–17, 2004.

[75] D. Krishnan, Narayanan; Cook, "Activity Recognition on Streaming Sensor Data," vol. 13, no. 9, pp. 1133–1145, 2012.

[76] G. Okeyo, L. Chen, H. Wang, and R. Sterritt, "Dynamic sensor data segmentation for real-time knowledge-driven activity recognition," *Pervasive Mob. Comput.*, vol. 10, pp. 155–172, 2014.

[77] S. Kozina, M. Lustrek, and M. Gams, "Dynamic signal segmentation for activity recognition," *Proc. Int. Jt. …*, pp. 1–12, 2011.

[78] Z. Yan, V. Subbaraju, D. Chakraborty, A. Misra, and K. Aberer, "Energy-Efficient Continuous Activity Recognition on Mobile Phones: An Activity-Adaptive Approach," *2012 16th Int. Symp. Wearable Comput.*, pp. 17–24, 2012.

[79] C. Lombriser, N. B. Bharatula, D. Roggen, and G. Tröster, "On-body activity recognition in a dynamic sensor network," *Proc. ICST 2nd Int. Conf. Body area networks*, pp. 1–6, 2007.

[80] D. Roggen, K. Förster, A. Calatroni, and G. Tröster, "The adARC pattern analysis architecture for adaptive human activity recognition

systems," *J. Ambient Intell. Humaniz. Comput.*, vol. 4, no. 2, pp. 169–186, 2013.

[81] L. Chen, C. D. Nugent, and H. Wang, "A knowledge-driven approach to activity recognition in smart homes," *IEEE Trans. Knowl. Data Eng.*, vol. 24, no. 6, pp. 961–974, 2012.

[82] T. van Kasteren, A. Noulas, G. Englebienne, and B. Kröse, "Accurate Activity Recognition in a Home Setting," pp. 1–9, 2008.

[83] I. E. Achumba, S. Bersch, R. Khusainov, D. Azzi, and U. Kamalu, "Activity Classification," pp. 427–430, 2012.

[84] H. Junker, O. Amft, P. Lukowicz, and G. Tröster, "Gesture spotting with body-worn inertial sensors to detect user activities," *Pattern Recognit.*, vol. 41, no. 6, pp. 2010–2024, 2008.

[85] N. C. Krishnan, P. Lade, and S. Panchanathan, "Activity gesture spotting using a threshold model based on adaptive boosting," *2010 IEEE Int. Conf. Multimed. Expo, ICME 2010*, pp. 155–160, 2010.

[86] K. Van Laerhoven, E. Berlin, and B. Schiele, "Enabling efficient time series analysis for wearable activity data," *8th Int. Conf. Mach. Learn. Appl. ICMLA 2009*, pp. 392–397, 2009.

[87] D. Bannach, P. Lukowicz, and O. Amft, "Rapid Prototyping of Activity Recognition Applications," *Pervasive Comput. IEEE*, vol. 7, no. 2, pp. 22–31, 2008.

[88] K. Van Laerhoven and E. Berlin, "When else did this happen? Efficient subsequence representation for matching in wearable activity data," *Proc. - Int. Symp. Wearable Comput. ISWC*, pp. 101–104, 2009.

[89] K. Oh, H.-S. Park, and S.-B. Cho, "A Mobile Context Sharing System Using Activity and Emotion Recognition with Bayesian Networks," *2010 7th Int. Conf. Ubiquitous Intell. Comput. 7th Int. Conf. Auton. Trust. Comput.*, no. Im, pp. 244–249, 2010.

[90] N. Kern, B. Schiele, and a Schmidt, "Multi-sensor activity context detection for wearable computing," *Ambient Intell.*, p. pp 220-232, 2003.

[91] Z. He and L. Jin, "Activity recognition from acceleration data based on discrete consine transform and SVM," *Syst. Man Cybern. 2009. SMC 2009. IEEE Int. Conf.*, no. October, pp. 5041–5044, 2009.

[92] N. Ravi, N. Dandekar, P. Mysore, and M. M. L. Littman, "Activity Recognition from Accelerometer Data," *Proc. Natl. …*, pp. 1541–1546, 2005.

[93] J.-Y. Yang, J.-S. Wang, and Y.-P. Chen, "Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers," *Pattern Recognit. Lett.*, vol. 29, no. 16, pp. 2213–2220, 2008.

[94] Y.-J. Hong, I.-J. Kim, S. C. Ahn, and H.-G. Kim, "Mobile health monitoring system based on activity recognition using accelerometer," *Simul. Model. Pract. Theory*, vol. 18, no. 4, pp. 446–455, 2010.

[95] J. Wu, G. Pan, D. Zhang, and G. Qi, "Gesture recognition with a 3-d accelerometer," *Proc. 6th Int. Conf. Ubiquitous Intell. Comput.*, pp. 25–38, 2009.

[96] O. Rioul and M. Vetterli, "Wavelets and signal processing," *IEEE Signal Processing Magazine*, vol. 8, no. 4. pp. 14–38, 1991.

[97] E. Hankin, "Ambulatory cardiac monitoring.," *Conn. Med.*, vol. 41, no. 6, pp. 341–345, 1977.

[98] M. Sekine, T. Tamura, T. Togawa, and Y. Fukui, "Classification of waist-acceleration signals in a continuous walking record," *Med. Eng. Phys.*, vol. 22, no. 4, pp. 285–291, 2000.

[99] M. Sekine, T. Tamura, M. Akay, T. Fujimoto, T. Togawa, and Y. Fukui, "Discrimination of walking patterns using wavelet-based fractal analysis.," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 10, no. 3, pp. 188–96, 2002.

[100] B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C. J. Büla, and P. Robert, "Ambulatory system for human motion analysis using a kinematic sensor: Monitoring of daily physical activity in the elderly," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 6, pp. 711–723, 2003.

[101] S. Mika, G. Ratsch, J. Weston, B. Schölkopf, and K.-R. Muller, "Fisher discriminant analysis with kernels," *Ieee*, pp. 41–48, 1999.

[102] S. Dolédec and D. Chessel, "Between- and Within-Groups Principal Components Analyses," *Work. Pap.*, pp. 1–28.

[103] Z. He and L. Jin, "Activity recognition from acceleration data using AR model representation and SVM," *2008 Int. Conf. Mach. Learn. Cybern.*, no. July, pp. 12–15, 2008.

[104] F. Bagala, J. Klenk, A. Cappello, L. Chiari, C. Becker, and U. Lindemann, "Quantitative description of the lie-to-sit-to-stand-to-walk transfer by a single body-fixed sensor," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 4, pp. 624–633, 2013.

[105] S. Reddy, M. Mun, J. Burke, D. Estrin, M. Hansen, and M. Srivastava, "Using mobile phones to determine transportation modes," *ACM Trans. Sens. Networks*, vol. 6, no. 2, pp. 1–27, 2010.

[106] J. Fahrenberg, F. Foerster, M. Smeja, and W. Müller, "Assessment of posture and motion by multichannel piezoresistive accelerometer recordings.," *Psychophysiology*, vol. 34, no. 5. pp. 607–12, 1997.

[107] J. Staudenmayer, D. Pober, S. Crouter, D. Bassett, and P. Freedson, "An artificial neural network to estimate physical activity energy expenditure and identify physical activity type from an accelerometer," no. 17, pp. 1300–1307, 2009.

[108] a McCallum, D. Freitag, and F. Pereira, "Maximum Entropy Markov Models for Information Extraction and Segmentation.," *Icml*, pp. 1–26, 2000.

[109] E. Kim, S. Helal, and D. Cook, "Human Activity Recognition and Pattern Discovery," *Pervasive Comput. IEEE*, vol. 9, no. 1, pp. 48–53, 2010.

[110] Y. Lee, "Activity Recognition Using Hierarchical Hidden Markov

Models on a Smartphone with 3D Accelerometer," *Hybrid Artif. Intell. Syst.*, pp. 460–467, 2011.

[111] T. L. M. Van Kasteren, G. Englebienne, and B. J. A. Kröse, "Activity recognition using semi-Markov models on real world smart home datasets," *Environments*, vol. 2, pp. 311–325, 2010.

[112] P. Natarajan and R. Nevatia, "Coupled hidden semi Markov Models for activity recognition," *Proc. IEEE Work. Motion Video Comput.*, p. 10, 2007.

[113] R. S. Safavian and D. Landgrebe, "A survey of decision tree classifier methodology," *IEEE Trans. is Syst. man, Cybern.*, vol. 21, no. 3, pp. 660–674, 1991.

[114] J. Pärkkä, M. Ermes, P. Korpipää, J. Mäntyjärvi, J. Peltola, and I. Korhonen, "Activity classification using realistic data from wearable sensors.," *IEEE Trans. Inf. Technol. Biomed.*, vol. 10, no. 1, pp. 119–128, 2006.

[115] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA data mining software," *ACM SIGKDD Explor.*, vol. 11, no. 1, pp. 10–18, 2009.

[116] J. Vandewalle, "Least Squares Support Vector Machine Classifiers," *Neural Process. Lett.*, vol. 9, no. 3, pp. 293–300, 1999.

[117] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 7657 LNCS, pp. 216–223, 2012.

[118] G. R. Naik, D. K. Kumar, and Jayadeva, "Twin SVM for gesture classification using the surface electromyogram," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 301–308, 2010.

[119] S. Paiyarom, P. Tungamchit, R. Keinprasit, and P. Kayasith, "Activity monitoring system using Dynamic Time Warping for the elderly and disabled people," *2009 2nd Int. Conf. Comput. Control Commun.*, pp. 1–4, 2009.

[120] M. H. K. M. H. Ko, G. West, S. Venkatesh, and M. Kumar, "Online Context Recognition in Multisensor Systems using Dynamic Time Warping," *2005 Int. Conf. Intell. Sensors, Sens. Networks Inf. Process.*, vol. 00, pp. 283–288, 2005.

[121] R. Musculo, S. Conforto, M. Schmid, P. Caselli, and T. D'Alessio, "Classification of motor activities through derivative dynamic time warping applied on accelerometer data," *Annu. Int. Conf. IEEE Eng. Med. Biol. - Proc.*, pp. 4930–4933, 2007.

[122] A. Bulling, J. a. Ward, and H. Gellersen, "Multimodal recognition of reading activity in transit using body-worn sensors," vol. 9, no. 1, pp. 1–21, 2012.

[123] T. Maekawa and S. Watanabe, "Unsupervised activity recognition with user's physical characteristics data," *Proc. - Int. Symp. Wearable Comput. ISWC*, pp. 89–96, 2011.

[124] Y. Zhang, R. Jin, and Z. H. Zhou, "Understanding bag-of-words model: A statistical framework," *Int. J. Mach. Learn. Cybern.*, vol. 1, no. 1–4, pp. 43–52, 2010.

[125] T. Huỳnh, M. Fritz, and B. Schiele, "Discovery of activity patterns using topic models," *Proc. 10th Int. Conf. Ubiquitous Comput. (UbiComp '08)*, pp. 10–19, 2008.

[126] P. Palmes, H. K. Pung, T. Gu, W. Xue, and S. Chen, "Object relevance weight pattern mining for activity recognition and segmentation," *Pervasive Mob. Comput.*, vol. 6, no. 1, pp. 43–57, 2010.

[127] D. Wyatt, M. Philipose, and T. Choudhury, "Unsupervised activity recognition using automatically mined common sense," *Sensors*, vol. 20, no. 1, pp. 21–27, 2005.

[128] T. Mitchell and A. Blum, "Combining labeled and unlabeled data with co-training," *Proc. Elev. Annu. Conf. Comput. Learn. theory*, pp. 92–100, 1998.

[129] M. Stikic, K. Van Laerhoven, and B. Schiele, "Exploring semi-supervised and active learning for activity recognition," *2008 12th IEEE Int. Symp. Wearable Comput.*, pp. 81–88, 2008.

[130] D. Guan, W. Yuan, Y.-K. Lee, A. Gavrilov, and S. Lee, "Activity Recognition Based on Semi-supervised Learning," *13th IEEE Int. Conf. Embed. Real-Time Comput. Syst. Appl. (RTCSA 2007)*, no. 1, pp. 469–475, 2007.

[131] T. Huỳnh and B. Schiele, "Towards less supervision in activity recognition from wearable sensors," *Proc. - Int. Symp. Wearable Comput. ISWC*, pp. 3–10, 2007.

[132] M. Mahdaviani and T. Choudhury, "Fast and scalable training of semisupervised crfs with application to activity recognition," *Adv. Neural Inf. …*, pp. 1–8, 2007.

[133] M. Stikic and B. Schiele, "Activity recognition from sparsely labeled data using multi-instance learning," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 5561 LNCS, pp. 156–173, 2009.

[134] S. Knox, L. Coyle, and S. Dobson, "Using Ontologies in Case-Based Activity Recognition.," *FLAIRS Conf.*, pp. 1–6, 2010.

[135] G. Meditskos, S. Dasiopoulou, and I. Kompatsiaris, "MetaQ: A knowledge-driven framework for context-aware activity recognition combining SPARQL and OWL 2 activity patterns," *Pervasive Mob. Comput.*, 2015.

[136] S. McKeever, J. Ye, L. Coyle, and C. Bleakley, "Activity recognition using temporal evidence theory," *J. Ambient Intell. Smart Environ.*, vol. 2, no. 3, pp. 253–269, 2010.

[137] Y. Kwon, K. Kang, and C. Bae, "Unsupervised learning for human activity recognition using smartphone sensors," *Expert Syst. Appl.*, vol. 41, no. 14, pp. 6067–6074, 2014.

[138] M. Shoaib, S. Bosch, O. Durmaz Incel, H. Scholten, and P. J. M.

Havinga, *Fusion of smartphone motion sensors for physical activity recognition*, vol. 14, no. 6. 2014.

[139] E. M. Tapia, S. S. Intille, and K. Larson, "Activity Recognition in the Home Using Simple and Ubiquitous Sensors," *Pervasive Comput.*, vol. 3001, pp. 158–175, 2004.

[140] S. Chernbumroong, S. Cang, A. Atkins, and H. Yu, "Elderly activities recognition and classification for applications in assisted living," *Expert Syst. Appl.*, vol. 40, no. 5, pp. 1662–1674, 2013.

[141] M. Hynes, H. Wang, E. McCarrick, and L. Kilmartin, "Accurate monitoring of human physical activity levels for medical diagnosis and monitoring using off-the-shelf cellular handsets," *Pers. Ubiquitous Comput.*, vol. 15, no. 7, pp. 667–678, 2011.

[142] G. Spina, G. Huang, A. Vaes, M. Spruit, and O. Amft, "COPDTrainer : A Smartphone-based Motion Rehabilitation Training System with Real-Time Acoustic Feedback," pp. 597–606, 2013.

[143] M. D. Oresti Banos, Rafael Garcia, Juan A. Holgado-Terriza and and C. V. Hector Pomares, Ignacio Rojas, Alejandro Saez, "mHealthDroid: A Novel Framework for Agile Development of Mobile Health Applications," in *Ambient Assisted Living and Daily Activities*, Springer International Publishing, pp. 91–98.

[144] O. Banos, J. A. Moral-Munoz, I. Diaz-Reyes, M. Arroyo-Morales, M. Damas, E. Herrera-Viedma, C. S. Hong, S. Lee, H. Pomares, I. Rojas, and C. Villalonga, "MDurance: A novel mobile health system to support trunk endurance assessment," *Sensors (Switzerland)*, vol. 15, no. 6, pp. 13159–13183, 2015.

[145] T. V. Duong, H. H. Bui, D. Q. Phung, and S. Venkatesh, "Activity recognition and abnormality detection with the switching hidden semi-Markov model," *Proc. Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. I, pp. 838–845, 2005.

[146] J. Ye, G. Stevenson, and S. Dobson, "KCAR: A knowledge-driven approach for concurrent activity recognition," *Pervasive Mob. Comput.*, vol. 19, pp. 47–70, 2014.

[147] H. Zhou, H. Hu, and S. Member, "Reducing Drifts in the Inertial Measurements of Wrist and Elbow Positions," *IEEE Trans. Instrum. Meas.*, vol. 59, no. 3, pp. 575–585, 2010.

[148] Y. Dong, J. Scisco, M. Wilson, E. Muth, and A. Hoover, "Detecting periods of eating during free-living by tracking wrist motion," *IEEE J. Biomed. Heal. Informatics*, vol. 18, no. 4, pp. 1253–1260, 2014.

[149] D. Trabelsi, S. Mohammed, F. Chamroukhi, L. Oukhellou, and Y. Amirat, "An Unsupervised Approach for Automatic Activity Recognition Based on Hidden Markov Model Regression," *IEEE Trans. Autom. Sci. Eng.*, vol. 10, no. 3, pp. 829–835, 2013.

[150] M. El-Gohary and J. McNames, "Shoulder and elbow joint angle tracking with inertial sensors.," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 9, pp. 2635–41, 2012.

[151] W. Shi, Z. Gao, S. Shah, X. Zhao, and T. Feng, "Continuous fine-grained arm action recognition using motion spectrum mixture models," *Electron. Lett.*, vol. 50, no. 22, pp. 1633–1635, 2014.