Information Fusion 55 (2020) 269–280

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

An overview of data fusion techniques for Internet of Things enabled physical activity recognition and measure

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ARTICLE INFO

Keywords:
Physical activity
Lifelogging
Review
Activity recognition
Activity monitoring
Information fusion

ABSTRACT

Due to importantly beneficial effects on physical and mental health and strong association with many rehabilitation programs, Physical Activity Recognition and Measure (PARM) has been widely recognised as a key paradigm for a variety of smart healthcare applications. Traditional methods for PARM relies on designing and utilising Data fusion or machine learning techniques in processing ambient and wearable sensing data for classifying types of physical activity and removing their uncertainties. Yet they mostly focus on controlled environments with the aim of increasing types of identifiable activity subjects, improved recognition accuracy and measure robustness. The emergence of the Internet of Things (IoT) enabling technology is transferring PARM studies to an open and dynamic uncontrolled ecosystem by connecting heterogeneous cost-effective wearable devices and mobile apps and various groups of users [35]. Little is currently known about whether traditional Data fusion techniques can tackle new challenges of IoT environments and how to effectively harness and improve these technologies. In an effort to understand potential use and opportunities of Data fusion techniques in IoT enabled PARM applications, this paper will give a systematic review, critically examining PARM studies from a perspective of a novel 3D dynamic IoT based physical activity collection and validation model. It summarized traditional state-of-the-art data fusion techniques from three plane domains in the 3D dynamic IoT model: devices, persons and timeline. The paper goes on to identify some new research trends and challenges of data fusion techniques in the IoT enabled PARM studies, and discusses some key enabling techniques for tackling them.

1. Introduction

As one of the most representative indicators to personal health and well-being, effective and efficient Physical Activity Recognition and Measure (PARM) has been posing great significance on a wide range of clinical practice and health applications. Objective assessment of physical activity (PA) will provide a personalised manner for various people with chronic disease in terms of a series of behaviour analysis [1]. A World Health Organization (WHO) survey has identified physical inactivity as the fourth leading risk factor for global mortality causing an estimated 3.2 million deaths [2]. Low levels of PA are detrimental to health and functioning of older people, and may cause many chronic diseases such as diabetes, obesity, cancers, etc.

To date, a large amount of studies of PARM have been carried out in a variety of smart healthcare applications. The primary goal of PARM is to recognize the type, duration, intensity of a wide range of activities and quantify their associated parameters like the energy expenditure. Amongst these studies, multiple sensor data fusion approaches for PARM have been increasingly utilised due to its remarkable accuracy on classification and estimation. Typical workflow of these methods is to first place multiple sensors [3–5] at different locations on the human-body, and extract distinguished features from these sensors, finally investigate machine learning or data fusion algorithms for training these features into specific several activity subjects [6–9]. For example, support vector machines (SVM) have been studied in fall detection [10], gesture classification [11], electroencephalogram artefact removal [12], etc. K-nearest neighbour (KNN) and Bayes technique have been investigated for classifying PA types from either single accelerometer [13] or multiple types of sensors [12]. Artificial neural network (ANN) and decision tree model are also used for PA recognition with fusing data from accelerometers and GPS [14]. While these techniques have demonstrated good classification results in PARM application, their utilisation is

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https://doi.org/10.1016/j.inffus.2019.09.002
Received 18 March 2019; Received in revised form 13 July 2019; Accepted 6 September 2019
Available online 9 September 2019

subject to a number of constraints: (1) a prior knowledge and intuitive modelling of different PA activities are required to build a classification model. (2). Features of many complexed or translational PA are too weak and insensitive to be recognised. (3). They are only suitable to the experimental controlled environments with small variations and little influencing issues, but hardly copy with uncontrolled environment.

Apart from that, recent emergence of the Internet of Things (IoT) enabling technology is transferring PARM studies to an open and dynamic uncontrolled ecosystem by connecting heterogeneous cost-effective wearable devices and mobile apps and various groups of users. This trend even poses more challenges in expanding traditional data fusion technique into IoT ecosystem. Foerster et al. [15] demonstrated 95.6% of accuracy for PARM in a controlled data collection experiment but dropped to 66% in an uncontrolled environment. Another investigations reported in [16,17] also found the same results. The crucial factor is that the free living environment contains numerous uncertainties, capturing one's entire life using digital devices for health and wellness becomes extremely difficult [18]. The uncertain factors include the quantity of wearable sensors, battery and capacity consumptions and personalised physical characteristics.

To our knowledge, data fusion are effective approaches to reduce uncertainties, enhance reliabilities, and improve recognition accuracy and precision. Multi-sensor data fusion techniques have a mature foundation and provide satisfactory performances in many subjects of activities. Some surveys also have well summarized them from the perspective of view of techniques' level in sensing, feature and learning fusion [12]. However, little work has been systematically surveyed on whether existing data fusion techniques can be extended to real living environment for lifelogging PARM applications. For instance, typical IoT enabled PARM applications include: (1) abnormal behaviours or activity identification from life-long high-volume data or activity and physical states changes towards independent living elder citizens. (2) How to offer assisted information for physicians to carry out medical intervention and PA recommendation. In these IoT personalized healthcare environments, PA data are discretely daily basis from globally heterogeneous third party devices. Traditional multi-sensor data fusion methods in PARM hardly deal with these scattered and heterogeneous data. Also, due to diversity and changes of personal lifestyles, lifelogging physical activity (LPA) data in IoT enabled personalized healthcare systems has remarkable uncertainties.

In an effect to understand advanced data fusion technology in IoT enabled PRAM, this paper conducts a survey on recent advanced data fusion technology from the perspective of a novel 3D dynamic IoT based physical activity collection and validation model [19]. As shown in Fig. 1, the review is taking consideration of three aspects of PA data fusion from devices, persons and timeline, respectively. Each plane is made of two fusion dimensions: *Devices × Timeline, Persons × Devices* and *Timeline × Persons*. The first one emphases multi-device fusion applied on different group of people. The second one is to utilise a single device to adopt different group of people for lifelogging PARM and the third one is to fit multi-device fusion to different group of people.

We undertook an extensive literature review by examining relevant articles from major academic databases (IEEE Xplore, ACM digital library and Science-Direct). Key search terms include the key words 'wearable computing', 'data fusion', 'sensor fusion' and 'activity recognition' and a wide range of other technologies. In addition, we reviewed the research projects related to IoT, e-health, smart healthcare, etc., by searching from EU, TSB and EPSRC funded projects. Our review focuses on identifying the breadth and diversity of existing research in advanced data fusion techniques in IoT enabled PRAM, including from three aspects in an IoT platform: devices, persons and timeline. The paper goes on to identify some new research trends and challenges of data fusion techniques in the IoT enabled PARM studies, and discusses some key enabling techniques for tackling them.

The rest of the paper is organized as follows. Section II presents the survey methodology of this paper. Section III, IV and V separately review key enabling technologies from device-timeline, device-person, and person-timeline. Section VI discusses research challenges and future trends. Conclusion is given in Section VII.

2. Methodology

2.1. IoT based PA data acquisition model

Our survey methodology is based on our work related to lifelogging data validation model LPAV-IoT [33], which has concerned the acquisition of physical activity data in an IoT environment from three aspects: devices, person and timeline.

Fig. 2 shows the data of PA collected from an IoT environment, PA data are measured as a 3D cube which are type of devices, number of persons and timeline. In terms of increment in any dimension results in an expansion of the PA data grid, the fusion techniques are categorised into three 2D plane (Persons × TimeLine), which refers to scenarios that single device is used by increasing population over time. PAR with sensing level fusion appears on a 2D plane (Devices × TimeLine) for classifying individual person's activities with historical PA data. And another 2D plane (timeline × persons) demonstrates the flexibility of existing sensors performance on PARM. Categories and their explanation are shown in the Table 1.

As shown in Fig. 2, The model validates the workflow of PA as a dynamic recursive process along the time axis. Validation rules are initiated by entering a set of historical raw PA data in the 3D model, and then is exploited to verify the existing PA. Historical raw PA data would expand with more users or devices over time. Also, the validation rules can be dynamically updated through new PA data. In addition, the 3D model provides a configuration for adding information of people and device dimensions. It adaptively supports requirements from different users or groups.

In the model, the plane of devices and timeline refers to multiple devices attached on different part of an individual's body, especially targeting on a specific type of group such as age or heathy statues. The PA data are scattered along with timeline axis, so as to monitor lifelogging PA. It tends to be, however, impractical and uncomfortable to place multiple devices/sensors on an individual's body for permanent monitoring. Whilst the current requirements of power and consumption of the motion devices may also lead to difficulties in PARM in free living environment. For that purpose, the fusion procedures are normally achieved in sensory level. Typical approaches include Kalman filtering [20,21] and weight average [12]. Also, some commercial devices like Fitbit (a wristband) [22] or Moves (an mobile app) [23] with wrapped and processed datasets (i.e., steps or calories) are exploited in our previous work [19,24,25] for lifelogging PA monitoring under such uncontrolled environment.

The plane of persons and devices is to attaching multiple devices on an individual's body in order to adapt to different group of subjects with different physical characteristics for a short-term PA recognition mostly in the lab or uncontrolled environment. The data collected through precise motion devices (e.g., Shimmer TM) [7,26–28]. Advanced machine learning algorithms are the popular approaches adopted in this circumstance for multiple sensors' fusion. However, due to the diverse physical characteristics, different people may perform PA in different manners, the training model fits one type of group may not be fit another one, thus, two types of PAR adaptability method are proposed which are subject dependant and subject independent [29]. The first one is to use fold cross-validation over each subject's data and averaged the results over all the subjects. The latter one is to train the model with the data of all the subjects but leave one subject out validation method. Owing to the controlled PA settings and less expensive labelling, the grid of

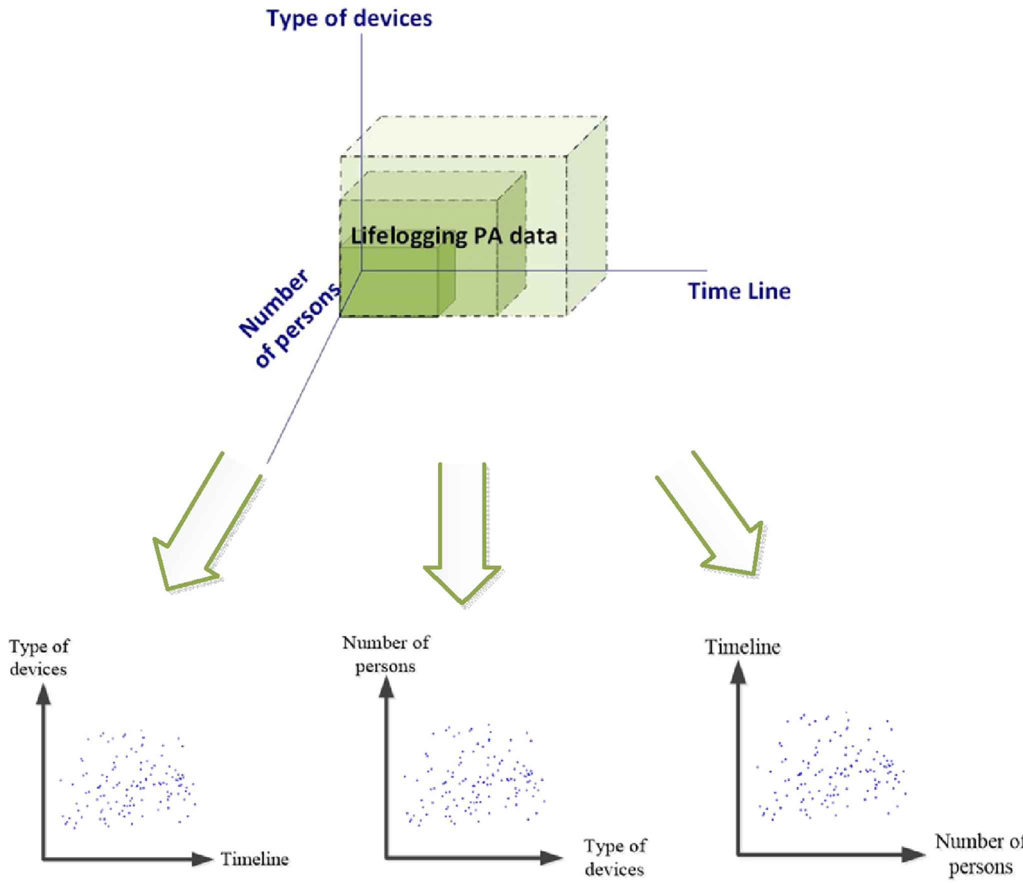

Fig. 1. Concept of an IoT-based data fusion of PARM.

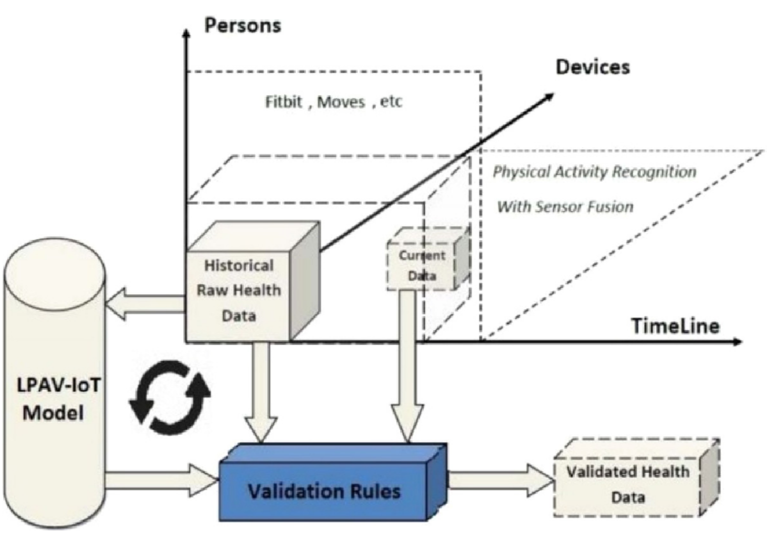

Fig. 2. PA data collection and validation in IoT ecosystem [33].

Table 1
PARM fusion concepts, keywords and their descriptions.

Fusion concept	Fusion keywords	Description
Device × Timeline	Multiple sensors + *a* single group + lifelogging	Use multiple wearable or ambient devices for a group of people with the similar physical characteristics (e.g., height, weight, age) for long-term PA monitoring in uncontrolled environment.
Persons × Devices	Multiple devices + multiple groups	Use multiple wearable or ambient devices to adapt different groups of people with the different physical characteristics (e.g., height, weight, age) for short term PA recognition, mostly in controlled environment.
Timeline × Persons	A single device + multiple groups + lifelogging	Use a single wearable device to adapt on different groups of people with the different physical characteristics (e.g., height, weight, age) for long-term PA monitoring, in uncontrolled environment.

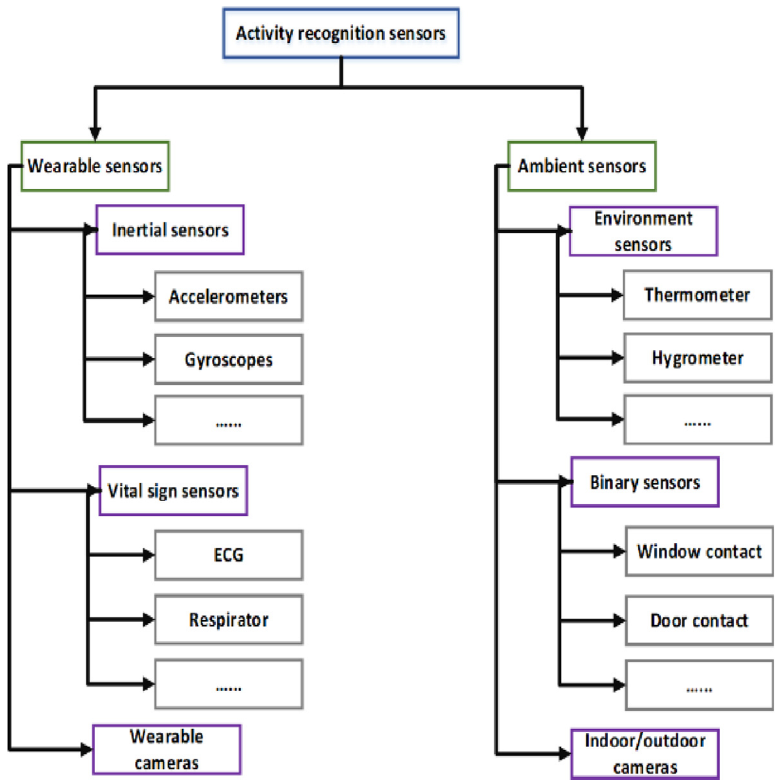

Fig. 3. Typical sensors categories for PARM.

fusion of persons and devices is capable to achieve high recognition rate in variety of PA types across numerous subjects.

The plane of timeline and people represent with only one device continuously long-term monitor PA in a number of PA patterns especially in free living environment, which are optimal state but one of the most challenging issues at the moment. The output of one sensor, on the other hand, may vary at different placement of an individual's body. As such, position-dependant and position-independent theories are proposed to address the issue.

2.2. Sensor categories for PARM

The first one is to mount a single sensor on a certain place of the body such as hip [16,17], back [30], wrist [43], chest [43], waist or thigh [32,36]. Even the same PA from different placement may lead to various results. For example, Purwar et al. [37] found that placement on the chest is better than the wrist in fall detection. Whereas from the perspective of fusion of timeline and persons, fixing at a specific position would limit recognised PA types and impede long-range monitoring in a real daily environment, so the other method is to allow the device/sensor to put on any part of an individual,'s body and thus improve its flexibility. For instance, Khan et al. [38] validate an accelerometer freely carried in any pocket of the body and achieved 94% accuracy in dynamic and static PAR rate.

Sensing techniques are adopted for the identification of objects and gathering information from sensors, tags, etc. Fig. 3 presents some typical wearable sensor categories. The development of low-cost and small-in-size wearable inertial sensors such as accelerometer, gyroscope and physiological sensors such as ECG, skin temperature sensor, also commercial wearable devices such as wrist band or smart phones, with imbedded GPS localization, Bluetooth etc., have facilitated the process of measuring an individual PAs. An individual's interaction with objects need to be assessed for home-based activity recognition like watching TV [41,42]. For these purposes, low-cost, easy-to-install on-object sensors (e.g., environment sensors, binary sensors or RFID) can provide this data in an unobtrusive and private way. Environmental sensors are used for measuring indoor environmental conditions such as humidity, temperature and energy [39,40]. Binary sensors can sense an object's state with a digit of 0 or 1, representing on/off, open/close [53] . Indoor localization sensors include Bluetooth, Radio-Frequency Identification (RFID) [44,45] and outdoor localization such as GPS [46,47].

2.3. Data fusion categories for PARM

In typical multi-sensor data fusion study, the categories of the data fusion methods have already been explored by many researchers [72–74]. The data fusion methods could be categorized as *probabilistic, statistic, knowledge base theory and evidence reasoning* methods. As shown in Table 2, probabilistic methods include Bayesian analysis of sensor values with Bayesian networks, state-space models, maximum likelihood methods, possibility theory, evidential reasoning and, more specifically, evidence theory, KNN and least square-based estimation methods, e.g., Kalman filtering, optimal theory, regularization and uncertainty ellipsoids. Secondly, statistic methods include the cross-covariance, covariance intersection and other robust statistics. Thirdly, knowledge base theory methods include intelligent aggregation methods, such as ANN, genetic algorithms and fuzzy logic. Finally, the evidence reasoning methods include Dempster-Shafer, evidence theory and recursive operators. Depending on the research purpose of the data fusion, these methods have advantages and disadvantages presented. We will use this category to carry out our review in this paper.

3. Data fusion from device and timeline

Data fusion from devices and timeline refers to multi-sensor data fusion technique for individual person based PARM. An amount of studies has been carried out for one or more subjects targeting on different Scenes. Some typical works are shown in Table 3. Results have a high accuracy and there is a low computational load on each sensor. To distinguish more PA types, placing multiple sensors/devices across

Table 2
Category of typical data fusion methods.

Methods	Advantages	Disadvantages
Probabilistic methods	Model estimation, allow unsupervised classification	Require a prior knowledge of information, Classification depends on the starting point
Statistical methods	High accuracy, Robust with unknown cross-covariance	Complexity and larger computational burden
Knowledge based theory methods	Easy to implement, Inclusion of uncertainty and imprecision, Robust to noisy data Learning ability	Require the intervention of human expertise, Lack of transparency of data, Difficulty in determining the size of hidden layer
Evidence reasoning methods	Assign a degree to uncertainty to each source	Assigning a degree of evidence to all concepts

Table 3
Typical works of data fusion from devices and timeline.

Works	Persons and devices		Approaches			Advantages	Disadvantages
	Sensor/Devices	Group of Persons	Analytic or Fusion approaches	Targeted activities	Result		
Multi-Sensor Signal Fusion	2 3D ACC, 1 ventilation sensor	50 persons	SVM [49]	Postures, vacuum, cycle, play balls, work	89.3% accuracy	Measure PA types and associated data e.g., intensity	Experiment carried out in controlled environment
	1 ECG, 1 ACC	Multiple subjects	SVM, GMM [31]	Postures, play games, brisk walk, slow walk, run	79.3%–97.3% accuracy	Multi-modality fusion	Less robust system due to sensitive signals
	5 biaxial ACCs	20 subjects	KNN [14]	ambulation, posture, stretch, laundry, brush teeth, eat, drink, read, vacuum	43%–97% accuracy	One type of sensor applied in context-aware environment	Results and data from controlled environment
	1 3D acc, 1 3D gyro, 1 3D magnetic	8 subjects	Kinematic modelling [50]	circular, reach, hand to mouth, flexion-extension, elevation	95%–98% accuracy	Robust and easy setup on home-based stroke rehabilitation	High cost
	1 3D seismic acc, 3 gyro	15 older patients	Statistics for each axis [51]	lying-to-sit-to-stand-to-walk (LSSW) test	90%–100% accuracy	Fall detection for elderly and patients	Limited test conditions
Multi-Sensor Data fusion	Ambient sensors, mobile phone	One person	Relational transformation [52]	Read newspaper, eat and drink	75.4 ± 7.8 F-measure	Better performance over HMM on ADL	Only two activities evaluated
	Ambient sensors	One person	temporal evidence theory [53]	Toilet, shower. dinner, breakfast, sleep, drink, leave house	0.68 F-measure	No need a large number of training data	Less suitable for mapping of sensors to activities
	Ambient sensors	One person	Dempster–Shafer theory [54]	Get drink, prepare dinner, and prepare breakfast	0.82 Precision 0.32 Recall 0.46 F-measure	Reduce uncertainties of multiple sensors	Results obtained in controlled environment
	Ambient sensors	One person	Ontology [55]	Activities of Daily Living	94.44 accuracy	No need a large number of training data	Rules need to be predefined
Cross Device and Sensor Data fusion	1 3D ACC, 1 wearable camera and microphone	Many people	SVM [56]	Run, go down-stairs/upstairs, take an elevator, walk forward, etc	90%–99% accuracy	Can be used in lifelogging health monitoring	Capacity of large number of images are not mentioned
	1 watch with 1 acc, 1 gyro, 1 iPhone 4	43 subjects	Bayes [57]	Belt on waist, thigh, shank	79%–95% accuracy	Long-term monitoring	inconvenient phone placement on wrist
	6 mobile devices and 2 smartphone apps	44 people	Gold Standard Measures [77]	Five health indicators	N/A	As a PA related function outcome	No fusion method
	7 wearable devices	60 people	DPAS [78]	EE and HR	N/A	As a PA related EE outcome	No fusion method

the participant's body. There are three multimodal data fusion methods shown in the Table 3: fusion of wearable sensors consisted of *consistent datasets* such as signals, fusion of high-level device comprised with *discrete datasets* like the context-aware sensor types, last is the hybrid data fusion from the both sources (Tables 4 and 5).

However, battery consumption of the devices is high when increasing timeline operation. Also, numerous sensors attached on the human's body is obtrusive and uncomfortable in daily lives, reduction of quantity may cause the reduction of accuracy. Whilst the training models may suffer from performances in natural environment due to a majority of uncertain factors.

Fusion of consistent datasets is by placement of multiple inertial sensors (e.g., accelerometers, gyroscope, etc.) across the human body which is capable to facilitate the process of recognition performance through fusion of sensing level and learning level, respectively. From the perspective of timeline longitude, by combing accelerometers with other sensor types such as GPS is a significant setting to improve accuracy. In the sensing level, Kalman filtering [20,21], weight average, and compo-

Table 4
Typical works of data fusion from persons and devices.

Works	Persons and devices		Approaches			Advantages	Disadvantages
	Devices	Group of Persons	Analytic or Fusion approaches	Targeted activities	Result		
Multi-Device Data Fusion	Smart Phone, Smart Watch	one person	Twi-AdaBoost [66]	User Location	0.38 m in X, 0.39 m in Y	Good location results by fusing the co-occurrence correlation, Low cost.	Not direct measure PA associated data.
			GRNN [67]		0.79 m in X, 1.06 m in Y		
			SVM [68]		5.07 m in X, 6.47 m in Y		
			LR [69]		6.74 m in X, 7.72 m in Y		
	Wrist band, Smart Glasses	One Person	Offline Extreme Learning Machine + Probability vector [70]	Fall detection	N/A	can be used for dynamic health monitoring.	Not sure about the accuracy
Multiple Wearable Device Data Analytic	ActiGraph, Fitbit	19 volunteers	Statistical significance [71]	Frequency and Duration of Bout, PA Intensity Level	Fitbit accuracy 62–100% AG accuracy 25–64%	Fitbit has more potential for largescale PA assessment study.	Not consider all possible population.
	Fitbit flex, Polar Loop	Two persons	Mean, STD [75]	Steps count and distance	Fitbit accuracy +4% PL accuracy −11%	Fitbit Flex is more accuracy for Distance measure.	Not consider all possible population
	Fitbit, Nike Fuelband, Nike Sportsband, Moves, Pedometers	One person	Mean, STD, data correlation [75,76]	Steps count and distance	Fitbit accuracy +1% for step recording, Nike Fuel band accuracy −8%	Fitbit Flex is the best one for step recording. Move is the worst one for step recording	Not consider all possible population
	Flex, One, iHealth, Vifit, Withings, Jawbone, Moves	One person	Mean, STD [33]	Steps, Distance, Calories	Fitbit one accuracy STD +1.5%, Moves accuracy STD 25%	Fitbit Flex is the best one for step recording. Move is the worst one for step recording	Not tested all possible population
Cross-device PA assess indicator	No specific devices	Many people	MAPS Score [81]	PA intensity level	N/A	As a PA related function outcome	No fusion method
	7 wearable devices	30 people	DPAS [33]	PA intensity level	N/A	As a PA related function outcome	No fusion method
	6 mobile devices and 2 smartphone apps	44 people	Gold Standard Measures [77]	Five health indicators	N/A	As a PA related function outcome	No fusion method
	7 wearable devices	60 people	DPAS [78]	EE and HR	N/A	As a PA related EE outcome	No fusion method

nent analysis are the typical approaches to process the sensor signals. The match scores from the different models are then fused on the score level to generate a final recognition decision. Score level fusion is the most commonly used in recognition systems [31] as the some feature sets from multiple models may not be compatible and it is therefore easier to access and combine scores created by different subsystems. Other works have more focused point on the learning level fusion through machine learning approaches Classifying PA using features extracted multiple sensors or a network of accelerometers have typically made use of the K-nearest neighbour (KNN) and naïve Bayes (NB) techniques [12], etc. For example, using an SVM algorithm to fuse data collected from various sensors is investigated by Qian et al. [48] in order to more accurately determine the PA. This is done using SVM as it can calculate a decision boundary to separate activities from one another. For multiple activities, they take a "one against one" approach to separate them and produce a model for each. Each model produced will be tested against a data point, which will then receive a vote to decide which activity should be associated to it. The activity with the majority of votes will be identified as the new data point that the activity is associated with. For many applications in machine learning, the use of all relevant data to extract more information from multiple sources can achieve a desired increase in accuracy [58]. Consulting multiple classifiers and combining the outputs always tend to provide a performance increase compared to using an individual classifier [59]. Data fusion of persons and devices can be achieved by employing available information from each model that complements one another. Feature level fusion is proposed by Li et al. [31], which requires feature sets from multiple models to be compatible. Their aim is to fuse two feature sets in order to produce a new feature vector that can more accurately represent a physical activity. Only different axis features from accelerometers were used in the feature level fusion from the cepstral domain. This is due to cepstral features may not be compatible with temporal features and the calculation for temporal features is greater.

Fusion of high-level devices make use of ambient sensors (e.g., RFID) or wearable camera at context-aware and home-care elderly environment for long-term monitoring. With installing of numerous ambient sensors, A knowledge driven approach is the mostly used for continuous activity recognition. Defining profiles for each activity performed based upon gathered knowledge can greatly improve activity recognition [60]. A knowledge-based approach addresses the difficulty in modelling activities of daily living due to their diversity and flexibility by providing a unified model [61]. Knowledge of the environment, events and how a person performs an activity contribute to how results are modelled. The data-centric models proposed by Chen et al. [61] makes extensive use of domain knowledge in the activity recognition life cycle. A knowledge-based approach addresses the challenges of modelling activities due to the diversity in daily living activities and the flexibility when performing them by providing an ontological model. Ontological models can model daily activities as generic activity structures for example: the terminology for daily activity ontologies and specific user activity profiles. Eight daily activities that are typical in the home environment were select for [61] experiment. For each activity, an appropriate sensor was

Table 5
Typical works of data fusion from persons and timeline.

Works	Persons and Timeline		Approaches			Advantages	Disadvantages
	Persons	Timeline	Analytic or Fusion approaches	Targeted activities	Result		
Adherence analysis of PA data	753 users (Fitbit)	77,000 days	Percentage, Mean, SD, CI [83]	Average step count	N/A	Adherence measure is key to analysis incompleteness of PA Data	Not direct measure No fusion method
	50 community participants (Fitbit)	4 weeks	Percentage [82]	PA data incompleteness	94% people wore it for all 28 days, 6% people wore it for 26 days	Adherence can be measured for better data fusion	Not test all population. No fusion method
	188 participants (ActiGraph GT3X+)	2 years (2013 and 2016)	Mean, SD, Frequency and Percentages [90]	PA data	Adherence to 53.5% in the AR group and 63% in the PR group	Adherence to PA is objective and not easily affected.	Not test all population. No fusion method
Interpersonal Difference analysis of PA data	17 participants two groups	18 days	T-test, Sliding Pairs P-value, Baseline pairs P-value [86]	Heart rate, Steps.	N/A	Different groups of participants have significant difference on daily steps	Not test all population. No fusion method
	2 participants	40 nights	Bland-Altman plots [87]	Sleep tracking	N/A	Validity of wearable device is strongly associated to personal lifestyle habit	Not test all population No fusion method
Density Map Fusion	42 Infrared motion sensors	2–3 months	Colour Level Density map + Fuzzy rules [45] [91,92] Colour Level Density Map + Linguistic Protoform Summaries [93]	PA intensity level	N/A	Better accuracy than single month measure	No fusion method
	12 people	8 months	Grey Level Density Map + Dempster-Shafer Theory [88]	PA intensity level	N/A	Better accuracy than single month measure	Need more data to verify the method
Time Series PA change detection	11 people Fitbit	1 week	Unconstrained Least-Squares Importance Fitting [94] Textured dissimilarity [95] Sw-PCAR [96] Virtual classifier [97]	Number of bouts, Bout minutes, Daily Steps	N/A	Contextual features are easily detected	Need continuous PA data

attached to an object. For example, a kettle had a tilt sensor attached to it to detect the pouring of water. The performance of each activity is specified based upon domain knowledge. Three male participants took place in the experiment and repeated each activity three times. An interval of thirty seconds was set between two consecutive actions. Collected data was used for activity model learning and user profile learning. Furthermore, the purpose to use the probabilistic reasoning is to handle ambiguous and noisy information from multiple sensors in smart home. A typical work like [62], 77 low-cost environmental sensors are installed in occupants' homes which are uncontrolled living environments to detect specific activities to medical professionals such as toileting, bathing and grooming. It is to encode large numbers of binary temporal relationships in the naive Bayesian network classifier with a feature window for each activity duration. Similar studies [63,64] propose Dempster–Shafer theory of evidence (DST)-based structure to incorporate the uncertainty derived from the sensor errors in a context-aware environment. Activity "toileting" as a typical case study in [64] makes use of five sensors (toilet light, bathroom hot tap sensor, bathroom cold tap sensor, bathroom cabinet sensor and flush sensor) under the condition of unavoidable and unpredictable sensor errors.

In the hybrid data fusion method, combinations of wearable camera, wearable sensors and ambient sensors are the key tools for lifelogging activity monitoring. The wearable camera is a form of visual lifelogger that can be worn over one's neck. It is explored as an everyday activity data recorder via computer vision techniques. Compared with surveillance cameras, its personal privacy is highly improved. Nam et al. [56] present lifelogging PA monitoring using wearable camera and accelerometer with optical flow for video processing. A series of rules are defined based on Priority Maximum Values to identify PA. The work also compared the results of each sensor and sensor fusion toward nine PAs like taking elevator, walking forward, going upstairs, etc. The fusion approach gives overall recognition accuracy over 92.78%. Similarly, Using an SVM algorithm to fuse data collected from various sensors is investigated by Liu et al. [49] in order to more accurately determine the physical activity. This is done using SVM as it can calculate a decision boundary to separate activities from one another. For multiple activities, they take a "one against one" approach to separate them and produce a model for each. Each model produced will be tested against a data point, which will then receive a vote to decide which activity should be associated to it. The activity with the majority of votes will be identified as the new data point that the activity is associated with. A system based on a network of multiple wireless-interconnected-medical sensors is proposed by the work [34]. This setup allows for the collection of medical data from typical daily activities. They note that the typical solution of a single versatile system is less flexible and takes longer to design and implement. Instead, the multi-sensor solution provides the benefit of the components being ready to use.

4. Data fusion from persons and devices

Differing with multi-sensor data fusion techniques, data fusion from persons and devices is based on a fact that an IoT enabled platform will be connected with heterogeneous devices and be used by a large group of populations. The data fusion techniques in this 2D plan is similar to multi-devices data fusion approaches, but we only concern one type of PA associated data. Meanwhile, due to difference of physical fitness and acceptance of wearable devices, persons wearing different devices will produce PA data with huge uncertainty. The qualitative identification of impacting factors and quantitative measure their impacts to IoT enabled PA data are key to data fusion approaches. There are work [28,65] in studying intrinsic and extrinsic factors through wearable data analytic and comparison in multiple devices. Lastly, some standardized PA measure scores have been built up for specifically validating and benchmarking PA fitness cross devices and persons. Consequently, we category the work in this direction into three subjects: (1) Multi-devices data fusion, (2) Multiple devices data analytic, (3) Cross-device PA assess indicator.

Multi-devices data fusion techniques have been studied for decades, especially fusing in wireless sensor network or indoor localization. For instance, Yuan et al. [66] have proposed an effective Twi-Adaboost algorithm for pursing the location data fusion of smart watch and smart phone, which reduce the localization errors up to 0.387 m on X axis and 0.398 m on Y axis. This data fusion approach offers better localization accuracy than Generalized Regression Neural Network (GRNN) [67], Support Vector Regression (SVM) [68] and Linear Regression [69]. Also, the study [70] developed a mobile phone based open pervasive wearable data fusion platform WearableHuB for real-time personal health management. In this method, they represent a case that fusing wristband and glasses with a probabilistic vector fusion enable accuracy fall detection. But the limitation of these work to PARM is that their targets are not directly associated PA data. But we believe these multi-device data fusion approaches can be used in PARM cases.

Regarding to multiple wearable device data analytic, it focuses on studying a variety of wearable devices in the market regarding their accuracy in data acquisition. Barrett, et al. [71] has compared the accuracy and robustness of two wearable devices (Fitbit and ActiGraph) in bouts and intensity of PA. The results show that Fitbit is more suitable to large-scale PA assessment, with accuracy 62–100% over 16 PA subjects in 19 volunteers.

Similarly, Schneider et al. [75] has compared Fitbit Flex and Polar Loop in measuring steps count and walking distance in a simple experiment. It shows that Fitbit Flex gives rough 5% up to accuracy than Polar loop, which is more suitable to PA measure. The work in [76] has examined the performance of five key wearable devices that record the physical activity of a user throughout a day in terms of accuracy, type of data provided, available APIs, and user experience. The results also show that Fitbit is the best one for step recording, with only 1% accuracy error. From above work, it appears that there are definitely some intrinsic tracking errors with different wearable devices. But to quantitatively identify these errors enable a simple and easy mode of data-fusion process. The only issue is that the impact of these errors might differ with different possible group of populations. It needs to be weighted in future fusing these PA data.

Apart from above work sorely comparing performance of wearable devices on one person, some researchers have begun to consider evaluating cross-device PA assess indicator like energy expenditure (EE), distance, level of PA, etc. amongst a large group of population. Xie et al. [77] has evaluated six devices (Apple Watch 2, Samsung Gear S3, Jawbone Up3, Fitbit Surge, Huawei Talk Band B3, and Xiaomi Mi Band 2) and two smartphone apps (Dongdong and Ledongli) in 44 healthy participants; the authors measured five major health indicators (HR, number of steps, distance, energy expenditure, and sleep duration) under various activity states (resting, walking, running, cycling, and sleeping) against gold standard measurements. The tested wearables had high measurement accuracy with respect to heart rate, number of steps, distance, and sleep duration, but EE measurements made by these wearables were associated with lower measurement accuracy. Also, Shcherbina et al. [78] tested seven wrist worn devices (Apple Watch, Basis Peak, Fitbit Surge, Microsoft Band, Mio Alpha 2, PulseOn, and Samsung Gear S2) in estimating HR and EE against continuous telemetry and indirect calorimetry while 60 volunteers engaged in sitting, walking, running, and cycling. The results indicate that most wrist-worn devices adequately measure HR in laboratory-based activities but poorly estimated EE [78]. Also, in the work [81], the MAPS formula was created to incorporate measures of activity, time, and location to produce a single composite score: Movement and Activity in Physical Space (MAPS) score. We also extended this MAPS score as DAPS score [33] into our early lifelogging PA analysis model. These two indicators encompass both physical activity and environmental interaction. A higher score indicates a higher level of function, which is based on a combination of more activity and greater environment interaction. The results provide a foundation of convergent and known-group difference validity evidence along with reliability evidence for the use of MAPS and DAPS as a unified PA functional outcome measure across a wide range of different wearable devices or mobile apps.

Thus, while there are no specific definition of data fusion methods in these cross-devices PA health-related indicators, they could be used to accurately and precisely define and detect pathophysiological phenomena. While a large portion of clinical care relies on the use of patient-specific health data (e.g., history and physical examination, laboratory and other test results, imaging tests, etc.) and human clinical decision making, much of this care occurs in the traditional brick-and mortar health setting, under a multitude of systemic constraints [79]. Given that changes in health status often occur gradually outside of the hospital and clinic [80], there is a clear role for remote monitoring of various patient populations to collect and process longitudinal health data into diagnostic, prognostic, and treatment-related insights.

5. Data fusion from timeline and persons

Regarding data fusion from timeline and persons, it is more like longitude analysis of a group population personal data over a long period. Thus, typical statistical analysis and fusion approaches in longitude data analysis are widely used and surveyed. However, the incompleteness and validity of PA data are important in this plane of persons and timeline. Recent study has pointed the importance of adherence to incompleteness of wearable data and the interpersonal difference to validity of wearable data in an IoT enabled ecosystem. Lastly, some recent studies have proposed some ideas to build up a monthly density map of PA intensity for fusing a long period of data in order to better predict users' PA level with life pattern. Thus, we category the work in this direction into three subjects: 1) Adhere analysis of PA data, 2) Interpersonal difference analysis of PA data, 3) Density map fusion techniques.

The adherence analysis of wearable PA data has been studied [82,83,89,90] and focused on measure of data completeness, since people do not wear or carry tracking devices every day. Early studies of Wearing Behaviour have explicitly studied wearing behaviour and patterns. It indicates wide differences in wearing behaviour and associated with these diverse levels of data completeness [84]. Meyer et al. [85] also reported wide differences in daily adherence, 20% to 100% of days being valid. At the same time, some work has studied the factors affecting wear-time, including age, gender and environment; day of week; time of day. This small but growing body of work highlights that there are diverse levels and patterns of wearing behaviour and so diverse levels of data completeness.

More recently, in [82], Tang et.al has provided guidelines for defining adherence, analysing their impact and reporting it along with the results of the tracker data analysis over different datasets. Their finding shows that minimum step-measures were similar to most datasets, the through-the-day measures had diverse impacts on PA data. The data fusion method needs to identify the correct threshold parameters for ignore some PA data in the dataset. Similarly, Xu et.al [83] has also utilised Fitbit devices to collect and observe 50 community participants' PA data in a 4-week study. The overall results show that 94% people wore it for all 28 days, and 6% people wore it for 26 days. Overall, participants wore their Fitbits (for at least part of the day) on almost all days (99.57%) of the study, although there were individual differences. In addition, Rudolf et al. [89] has studied the impact of different recruitment strategies on ActiGraph GT3X+ devices by regression analysis, Results show that PA data were objectively collected by individual, and not impacted by external interventions. Importantly, Qi et al. [88] has conducted a review in studying the use of wearable trackers for measuring a series of PA associated data for older adults. His survey includes 12 different wearable devices and 20 studies, where the finding highlighted that methodological designs for PA data collection in IoT environment were heterogeneous, so that there is no standardised method for quantifying data for wearable devices in older adults. In other words, there are also no concluded data fusion approach for integrating these wearable PA data perfectly so far.

The second category in this field is to investigate the impact of interpersonal difference on PA data. In [86], Dahmen etal. studied fine-grained, continuous physical activity and heart rate data collected from Fitbits worn by 8 participants in the health group and 9 participants in the rehabilitation group. They analyse the longitudinal physical activity data collected from both groups to gain insights into the detected changes over time in both an inpatient setting and a free-living setting. And it found that two groups of participants have similar variation on daily heart rates, but significant difference on daily steps. Similarly, Liang and Mattell [87] have investigated interpersonal difference by two participants over 40 nights in validating wearable sleep-tracking technologies including Fitbit and Neuroon. They use Bland-Altman plots of aggregated sleep metrics measured by Fitbit and Neuron. The results show that the validity of wearable device is strongly associated to personal lifestyle habit. Thus, above work proves that each individual has its own lifestyle pattern, which possibly affects wearable sensing PA data. Utilising statistical analysis method could potentially explore the weights of these data and further fusing them accordingly.

Apart from statistical analysis method, 1D time serious based PA analysis approaches have been studied a lot. These approaches have quantified change statistically [94], graphically [95] and algorithmically [96,97]. Liu et al. [94] extracted features derived from actigraphy data collected for at least one year. Each feature was individually correlated with a component of the Resident Assessment Instrument for insights into how longitudinal changes in actigraphy and functioning are associated. Albregtsen et al. [95] introduced another activity-based change detection approach in which passive infrared motion sensors were installed in apartments and utilized to estimate physical activity in the home and time away from home. The data were converted into co-occurrence matrices for computation of image-based texture features. Relative Unconstrained Least-Squares Importance Fitting (RuLSIF) [96] is one such approach used to measure the difference between two samples of data surrounding a candidate change point. Hido et al. [97] formalized this problem as change analysis, a method of examination beyond change detection to explain the nature of discrepancy. Hido's solution to change analysis utilizes supervised machine learning algorithms, specifically virtual binary classifiers (VCs), to identify and describe changes in unsupervised data.

Some recently pilot studies [45,88] have proposed an idea to transfer 1D time series-based PA data into 2D day-hour based monthly density map for analysis and fusion. In [45], Wang et.al present a methodology for analysing PA data captured by home based passive infrared motion sensor. Though building up a PA intensity level-based density map, they measure dissimilarity and detect changes in PA pattern between two monthly maps via texture features. The results show that activity density maps can be used in an ageing in place senior housing community to aid clinicians in early illness detection, particularly track general activity level and daily patterns over time, showing changes in physical, cognitive, and mental health. Also, we [88] have used a similar idea by constructing a PA intensity based grew level density map using Fitbit device by 12 people. After measuring the dissimilarity of each two monthly maps, we have proposed an evidence theory-based Bayes probabilistic model to fuse multiple monthly maps in order to identify a validated human PA intensity pattern. The results indicate that our density map-based data fusion approaches effectively improve the accuracy of predicting PA intensity of individual person.

6. Discussion and future directions

6.1. Quantifying uncertainty of PA data in an IoT ecosystem

As we demonstrated in Section 2, PA data collected in an IoT ecosystem is dynamically increased from three dimensions. Thus, it will be affected by a lot of influencing factors, which has not been properly defined and quantified. In most IoT environments, it will be equipped with a majority of ambient sensors for ADLs detections, and data captured from the heterogeneous sensors may contain a variety of uncertainties including hardware errors, battery exhausted or transmission issues. Some intrinsic uncertainties are unavoidable and uncontrolled.

Moreover, there are also unpredictable errors from using popular PA tracking devices such as mobile phone and smart watch. For example, irregular uncertainties may come from malfunctions or faults, breakdown of a third-party server. And regular uncertainties often occur like battery life, differentiation of personal physical characteristics and changes of environment. As the possibility of each sensor's uncertainty can be obtained from the manufacture's testing statistics, probabilistic fusion approaches are generally able to address the issue. Nevertheless, PA recognition results offered by third party devices are widely divergent so that making its information turn to be scattered, erroneous and limited for healthcare uses.

Thus, one important direction of future data fusion technique in IoT enabled PARM study is to identify the potential factors leading to uncertainties of PA data, and potentially quantitatively measure their impacts. For instance, as we reviewed in previse sections, adherence to wearable devices and acceptance to technologies are both causes leading to potential uncertainties in PA data. How to handle with uncertainties and more effectively harnessing these PA data would be greatly importance.

6.2. Human-in-the-loop

Another key issue we surveyed before is that human factors play important role in collecting and analysing PA data in an IoT environment. Traditional data fusion approaches usually do not consider the human factors too much, where is more suitable to a human-out-the-loop system. In the IoT environment, human life patterns greatly affect the uncertainty of observed PA data. Thus, we need to consider future data fusion methods as a human-in-the-loop mode.

More specifically, Human-in-the-Loop refers to that the fusing rules are supposed to be adaptively altered regarding the properties of its human factor, like age, gender, group or interaction, etc. For instance, in our work [33], it gives a performance comparison of individual and group population (14 persons with similar professions and backgrounds) on removing IUs. We estimate the change of daily steps Ts and DAPS with different periods (from 1 month to 12 months) with a confidence interval of 95%. The results indicate that the rules of LPAV-IoT model will be altered in terms of different setting of human factors. However, this experiment only deals with a nature increment of life-logging PA on timeline and population dimensions. It is not a strict performance evaluation of human-in-the-loop in the proposed model by considering a human interaction with model. The involvement of collecting user feedbacks as a step of the validation algorithm is not hard to be implemented in the model but requires a long period of time on redesigning experimental strategies and collecting relevant life-logging data.

Thus, it will be put as one of key future works in developing data fusion approaches, which is to continue a formal human-in-the-loop validation of the model by involving users' feedbacks for updating fusing rules.

6.3. Advanced learning approaches for IoT enabled PA data fusion

There have been always advanced and new learning approaches on the board of data mining, such as multi-task learning and deep learning techniques in processing large-scale IoT data.

Due to great utilisation in multi-modality data fusion applications, multi-task learning techniques have recently been drawn a great attention. The multi-task model is constructed based on the traditional linear regression algorithm. This idea is developed from the theory of Frequentist in statistics and belongs to the category of statistical machine learning. The core strategy of this idea is to optimize by constructing a loss function. For many multi-modality data fusion applications, multi-task can be customized to explore contacts based on research scenarios. For example, in the face of fusing a large number of features from heterogeneous data resources, the concept of introducing "groups" can apply all group feature factors in batches or choose to discard. In order to make the model also have the ability to fuse multiple sources of data, the multitasking model can be further developed to consider multimodal data in the learning process.

On the other hand, deep learning techniques are also quite popular. Deep learning could abstract the features of a multi-layer network structure to expect deep network nodes that can directly predict disease progression. For instance, in the prediction of AD disease progression, the most commonly used deep learning model is the recurrent Neural Networks (RNN), and its greatest advantage is the prediction of time series problems. Using longitudinal data for disease model building is a challenging task. RNN can help to resolve the relationship dependence between different time points by using its characteristics that can memorize historical information. In addition, longitudinal data is valuable due to its difficulty in obtaining and excessive cost, and RNN can supplement incomplete data to further improve forecast performance.

Above two key techniques have already been widely used in multi-modality healthcare related applications, such as disease prediction. The appliance of PARM is strongly associated to healthcare, thus we believe these two techniques have huge potential in further exploration for IoT enabled PARM study.

6.4. Practical value

Practical value of data fusion approach is importance but rarely verified in IoT enabled systems in literature. The primary issue is that most of valuable data is kept by companies and not open to public. In this paper, we have provided a pioneered investigation perspective for considering data fusion techniques from 3 dimension in an IoT environment. While data fusion techniques have been seen as a hot topic in research in the last twenties years, it recently becomes more accessible and practically significant with the recent prevalence of mobile devices connecting in IoT systems. In the healthcare field, due to significant population ageing in the coming decades, data fusion technology requires considering its mode from conventional hub-based system to personalised healthcare system. The successful design and utilization of data fusion into practical will enable more accurate measure and monitoring of daily physical activity with low cost devices, further lead to faster and safer preventive care for chronic diseases. Therefore, we believe the transferring and verification existing data fusion methods into valuable practice will be an important future direction.

7. Conclusion

PARM has significant benefits for improving the quality of life of a person who suffers with chronic diseases and maintain fitness for active healthy people. Data fusion is an effective approach to achieve better performance of the PA model. From numerous literatures, we can safely conclude that the PAR using a small number of wearable devices in the uncontrolled environment within different categories of subjects are not fully and successfully resolved. In an effort to understand potential use and opportunities of Data fusion techniques in IoT enabled PARM applications, this paper gave a systematic review, critically examining PARM studies from a perspective of a novel 3D dynamic IoT based physical activity collection and validation model. It summarized traditional state-of-the-art data fusion techniques from three plane domains in the 3D dynamic IoT model: devices, persons and timeline. The paper goes on to identify some new research trends and challenges of data fusion techniques in the IoT enabled PARM studies, and discusses some key enabling techniques for tackling them.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.inffus.2019.09.002.

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