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Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges

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ABSTRACT

Body Sensor Networks (BSNs) have emerged as a revolutionary technology in many application domains in health-care, fitness, smart cities, and many other compelling Internet of Things (IoT) applications. Most commercially available systems assume that a single device monitors a plethora of user information. In reality, BSN technology is transitioning to multi-device synchronous measurement environments; fusion of the data from multiple, potentially heterogeneous, sensor sources is therefore becoming a fundamental yet non-trivial task that directly impacts application performance. Nevertheless, only recently researchers have started developing technical solutions for effective fusion of BSN data. To the best of our knowledge, the community is currently lacking a comprehensive review of the state-of-the-art techniques on multi-sensor fusion in the area of BSN. This survey discusses clear motivations and advantages of multi-sensor data fusion and particularly focuses on physical activity recognition, aiming at providing a systematic categorization and common comparison framework of the literature, by identifying distinctive properties and parameters affecting data fusion design choices at different levels (data, feature, and decision). The survey also covers data fusion in the domains of emotion recognition and general-health and introduce relevant directions and challenges of future research on multi-sensor fusion in the BSN domain.

1. Introduction

About a decade ago, the research area on wireless sensor network (WSN) technologies and applications led to the introduction of Body Sensor Networks (BSNs): a particular type of WSN applied to human body monitoring. Since their definition, BSNs promised disruptive changes in several aspects of our daily life. At technological level, a wearable BSN comprises wireless wearable physiological sensors applied to the human body (by means of skin electrodes, elastic straps, or even using smart fabrics) to enable, at low cost, continuous and real-time non-invasive monitoring. Very diversified BSN applications were proposed during the years, including prevention, early detection, and monitoring of cardiovascular, neuro-degenerative and other chronic diseases, elderly assistance at home (fall detection, pills reminder), fitness and wellness, motor rehabilitation assistance, physical activity and gestures detection, emotion recognition, and so on.

Key benefit of this technology is the possibility to continuously monitor vital and physiological signs without obstructing user/patient comfort in performing his/her daily activities. Indeed, in the last few years, its diffusion increased enormously with the introduction, at mass industrial level, of smart wearable devices (particularly smart watches and bracelets) that are able to capture several parameters such as body accelerations, electrocardiogram (ECG), pulse rate, and bio-impedance.

However, since many BSN applications require sophisticated signal processing techniques and algorithms[1–4], their design and implementation remain a challenging task still today. Sensed data streams are collected, processed, and transmitted remotely by means of wearable devices with limited resources in terms of energy availability, computational power, and storage capacity. In addition, BSN systems are often characterized by error-prone sensor data that significantly affect signal processing, pattern recognition, and machine learning performances. In this challenging scenario, the use of redundant or complementary data coupled with multi-sensor sensor data fusion methods represents an effective solution to infer high quality information from heavily corrupted or noisy signals, random and systematic error-affected sensor samples, data loss or inconsistency, and so on.

Most commercially available wearables assume that a single device monitors a plethora of user information. In reality, BSN technology is transitioning to multi-device synchronous measurement environments. With the wearable network becoming more

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complex, fusion of the data from multiple, potentially heterogeneous, sensor sources becomes a non-trivial tasks that directly impact performance of the activity monitoring application. In particular, we note that the complex processing chain used in BSN design introduces various levels of data fusion with different levels of complexity and effectiveness. Only in recent years researchers have started developing technical solutions for effective fusion of BSN data. To the best of our knowledge, while interesting surveys on sensor fusion in WSN have been published already [5,6], the community is currently lacking a comprehensive review of the state-of-the-art techniques on multi-sensor fusion in the area of BSN.

The reminder of the paper is, hence, organized as follows. Section 2 discusses the background context of the survey and provides useful insights on the main motivations for multi-sensor data fusion on BSNs. In Section 3 a systematic categorization of multi-sensor fusion in BSN domain is provided; distinctive properties and parameters are identified with the goal of providing a common comparison framework of the analyzed literature. Section 4 covers a comprehensive analysis and comparison of data-fusion state-of-the-art in the domain of human activity recognition and monitoring. To provide a broader view to the readers, Section 5 covers data-fusion strategies and design choices for emotion recognition and general-health applications. Section 6 provides insights on emerging research directions and challenges of future multi-sensor fusion generation. Finally, Section 7 concludes the paper.

2. Background

2.1. Body sensor networks

Body Sensor Networks (BSNs) have emerged as a revolutionary technology in many application domains in health-care [7–21] fitness [22–26], smart cities [27–29], and many other compelling Internet of Things (IoT) applications [30–33]. In particular, BSNs have demonstrated great potential in health-care. These systems hold the promise to improve patient care/safety and result in significant cost savings [34–37]. According to the United Nations, if current health trends are not reversed, five common diseases, cancer, diabetes, heart disease, lung disease and mental health problems will cost, by 2030, the world $47 trillion each year [38,39].

One of the most important interventions in managing these diseases is physical activity [40–52]. Consequently, the last decade has witnessed tremendous efforts in utilizing smart technologies such as BSNs for health monitoring and diagnosis through physical activity monitoring/assessment. Recent years have seen considerable research demonstrating the potential of BSNs in a variety of physical activity monitoring applications such as activity recognition [9–11,15–17], activity level estimation [18], caloric expenditure calculation [19,20], joint angle estimation [21], activity-based prompting [53–58], medication adherence assessment [59,60], crowd sensing [61–66], social networking [67–70], and sports training [22–26].

A wearable BSN is comprised of a number of wearable sensor nodes wirelessly capturing and collaboratively processing physiological signals on humans. BSNs, which gather data from body-worn sensors, utilize computational algorithms including signal processing and machine learning techniques to extract useful information from the sensor data. Physiological sensors include accelerometers, gyroscopes, pressure sensors for body movements and applied forces, skin/chest electrodes (for electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), and electrical impedance plethysmography (EIP)), (PPG) sensors, microphones (for voice, ambient, and heart sounds), scalp-placed electrodes for electroencephalogram (EEG). Generated raw and processed data are wireless transmitted; communication protocols depend on the radio chip of the hardware platform; the most popular standards are IEEE 802.15.4 [71], Bluetooth Low Energy [72], and ANT+ [73]. BSN nodes can be realized with different hardware architectures [74]; TelosB [75] was very common in early BSN research prototypes, while more recently Shimmer [76] has gained more popularity. It is also worth noting that in many studies, custom hardware is designed and prototyped. BSN nodes are programmable units that usually run lightweight operating systems atop which application software is implemented; among them, probably the most supported are TinyOS [77] and Contiki [78]. Some developers prefer to program the application code directly atop the basic development environment (operating system and/or software libraries) provided by the adopted node platform; however, the use of domain-specific programming middleware is recommended [2]. CodeBlue [79] represents the first embryonic middleware specifically tailored for BSN systems, while Titan [80] is a more general-purpose framework which has been successfully applied to the BSN domain. SPINE [1] is the first domain-specific programming framework for BSNs and its effectiveness has been widely proved [4]. More recently, with the advent of Cloud paradigm, BSN middlewares has evolved to support long-term monitoring, data storage and analysis, community management, and application services interaction (e.g. BodyCloud [81,82] and Cloud BAN e-Health [83]).

Although BSNs originated as a research branch of WSNs, and given their intrinsic similarities, there are several differences between these networks [84]. WSNs have typically larger scale both in terms of number of nodes and obviously geographical range; however, WSNs can use redundant nodes so individual robustness is often not a priority, whereas, due to the critical concern of wearability and user's comfort, BSNs must use the least number of nodes, each ensuring high accuracy and robustness. For the same reason, BSN nodes pose much higher requirements in terms of physical dimensions, weight, bio-compatibility and ergonomics. In contrast, in terms of energy supply, since batteries of BSN nodes can usually be recharged or replaced more easily, the trade-off among requirements goes toward accuracy, while WSNs have hard low-power constraints. Moreover, BSN applications typically require higher sensors sampling, data transmission rate, and continuous monitoring. Finally, the vast majority of BSNs adopt star network topologies, while WSNs are intrinsically multi-hop.

Typically, BSN applications perform a distributed computation that analyzes and synthesizes responses, and forwards data to a local hub (e.g. a smartphone) for possibly further processing. The local hub may transmit final results to a back-end server for clinical decision making and interventions. Each sensor node in a BSN performs a series of computing tasks on the collected physiological signals in order to extract partial information about the user [85]. The overall status of the user is determined through distributed and collaborative processing of this data.

Major processing tasks performed on the BSN sensor data may include data sampling, filtering segmentation, feature extraction, and classification. Examples of data sampling techniques are fixed rate, variable rate, adaptive sampling, compressed sensing, and sensor bit-resolution tuning [86,87]. The level of complexity of the filtering algorithm depends on the application of interest and the type and quality of sensor readings [88–90]. Segmentation algorithms divide continuous data streams into discrete time intervals of the type expected by the information processing step [15,91,92]. Each segment has a multidimensional (feature) vector extracted from it, which will be used for classification [11,93]. The most widely used classification and event detection algorithms include k-NN (k-Nearest-Neighbor), Support Vector Machines (SVM), Hidden Markov Models (HMM), Neural Network (NN), Decision Tree Classifiers, Logistic Regression, and the Naive Bayesian approach [94–99].

2.2. Motivations for multi-sensor data fusion on BSNs

As in any measurement system, BSNs relying on a single sensor, or on multiple sensors individually considered, suffers several limitations and issues, such as [100]:

- *Sensor Deprivation*: a sensor failure causes loss of perception on the desired physical parameter.
- *Limited spatial coverage*: an individual wearable sensor often covers a restricted body location. For example, an accelerometer placed on the left arm cannot measure movements of the opposite one.
- *Imprecision*: measurements from individual sensors are limited to the precision of those specific units.
- *Uncertainty*: it arises when features are missing, when a single sensor cannot measure all relevant attributes of the phenomenon/event, or when the observation is ambiguous [101]. Due to the limited spatial coverage issue, single sensor systems cannot effectively reduce uncertainty.

An effective solution to the aforementioned issues is represented by multi-sensor fusion. Indeed, the use of multiple (heterogeneous or homogeneous) sensors combined with data fusion techniques introduces several advantages, such as the following [102,103]:

- *Improved signal to noise ratio*: fusion of multiple sensor data streams reduces the noise effects.
- *Reduced ambiguity and uncertainty*: using data from multiple sources decreases output uncertainty.
- *Increased confidence*: individual sensors are often not sufficient to provide reliable data; multi-sensor data fusion comes again into help.
- *Enhanced robustness and reliability*: the use of multiple homogeneous sensors provides redundancy, which enhance fault-tolerance of the system even in the event of sensor failure.
- *Robustness against interference*: increasing the dimensionality of the measurement space (e.g. measuring the heart rate using both electrocardiogram (ECG) and photoplethysmogram (PPG) sensors) significantly enhances robustness against environmental interferences.
- *Improved resolution, precision and hypothesis discrimination*: when multiple independent measurements of the same feature/attribute are fused, the resolution of the resulting value is higher than what can be achieved using a single sensor.
- *Integration of independent features and prior knowledge*: to better catch specific aspects of the target application domain and improve robustness against interferences of data sources.

A further motivation for sensor fusion is the reduction of application logic complexity. In conventional systems, raw or traditionally pre-processed sensor measurements reach the application directly, which has to deal with imprecise, ambiguous and incomplete data streams. In contrast, sensor fusion preprocessing allows to standardize the application input, so simplifying application development, maintenance, and extensibility [104]. Indeed, moving (part of) pre-processing logic to a lower level than the application (typically, in or on the surface of the middleware level, as shown in Fig. 1) is both cost-effective (e.g. in terms of development time/efforts savings, since the application developer does not need to implement pre-processing logic but rather would deal with it by means of APIs) and, often, more efficient (because the fusion pre-processing logic could be optimized better than what could be done by a typical application developer). This “separation of concerns”, in addition, is an approach that favors software modularity and, therefore, maintainability.

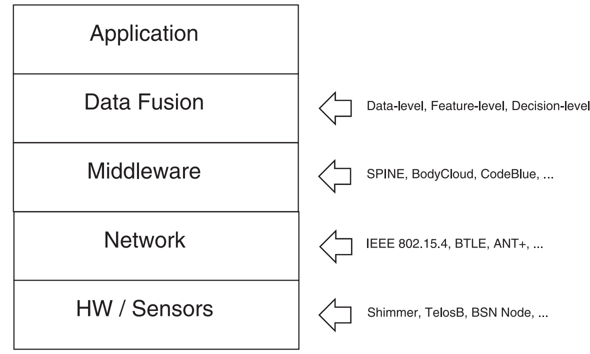

Fig. 1. Typical layering of a BSN system.

3. Sensor fusion strategies in BSNs

As we discussed in the previous sections, BSN systems need to cope with multiple sources of information at different levels. According to the specific problem and the corresponding solution, different sensor fusion approaches are adopted. The purpose of this section is to draw a categorization of the different types of sensor fusion and to discuss their characteristics and use in practical applications.

Independently from the abstraction level, sensor fusion can be grouped in *competitive, complementary*, and *cooperative* [105]. Competitive fusion implies the use of multiple equivalent source of information and is used to obtain redundancy and self-calibration. In BSN systems, however, it is in practice very uncommon as even when multiple equivalent sensors are used, they are typically placed in different location on the human body and hence each can actually provide complementary information. In complementary fusion indeed each sensor captures different aspects of the monitored phenomena and it is used to improve system accuracy and reliability. High-level information is obtained by the joint analysis of the complementary signals. Finally, cooperative fusion comes into play when multiple sensor signals are needed to obtain information that could not be achieved by looking at any of these signals independently. As we will show in the following subsections, in the BSN domain, cooperative fusion is the most common form of sensor fusion.

In terms of data processing level of abstraction, multi-sensor fusion is typically divided in three main categories: *data-level* fusion, *feature-level* fusion, and *decision-level* fusion [106], [107]. In [108], they expanded the three level (data-feature-decision) hierarchy of fusion, into five fusion process I/O dependent modes. Under one set of conventions, the fusion model has been characterized by the nature of the input components, that is, fusion of specific category of entities, while under another, the fusion model is characterized by the nature of the output. In this paper, we will focus on the well-known triplet approach (data-, feature- and decision-level) based on the processing level.

Tables 1 and 2 depict some relevant characteristics and techniques, respectively. In the following, we discuss each category in separate subsections.

Depending on the processing level, *centralized, distributed* and *hybrid* data fusion approaches are possible. The centralized approach relies on a fusion center in which the processing is performed, while in the distributed approach each sensor executes independent processing on its own data and transmits the results to a fusion node where global analysis is eventually performed. Hybrid data fusion has been proposed too; in this case, data-collection and pre-processing are usually performed with a distributed approach while a central node is still responsible for

Table 1
Fusion characteristics at different levels.

Fusion Level	Model	Communication load	Processing complexity	Information loss	Performance loss
data-level	competitive	high	high	no	no
feature-level	competitive complementary cooperative	medium	medium	yes	yes
decision-level	competitive complementary cooperative	low	low to high	yes	yes

Table 2
Applications and techniques at the different fusion levels.

Fusion Level	Use	Technique
data-level	Spectral Datamining Data Adaptation Estimation of Parameters Robustness and Calibration Source recovery	Digital Signal Processing Coordinate Transforms Kalman Filtering Weighted Averaging Independent Component Analysis
feature-level	Classification	Pattern Recognition, Clustering, Neural Networks
decision-level	Decisional Action	Expert Systems, Artificial Intelligence

fusing data gathered from distributed sources and for performing decision-level computation.

3.1. Fusion levels

If the system involves multiple homogeneous sensors measuring the same physical phenomena, then sensor data can be directly fused. On the contrary, data generated from heterogeneous sources cannot be combined directly and feature or decision-level fusion techniques must be adopted.

3.1.1. Data-level fusion

At the lowest level of abstraction, it is usually assumed that communication, storage, and processing systems are reliable and therefore focus is on fusion algorithms that combine multiple homogeneous sources of raw sensory data with the aim of achieving more accurate, informative, and synthetic fused data than the original sources [107,109].

The key technologies in data-level fusion studies are mostly the design and implementation of de-noising, feature extraction, data classification, and data compression [110].

Data-level fusion requires a centralized processing approaches and is used in combination with sensor arrays, typically for redundancy and therefore improved robustness. In the BSN domain, however, it is more frequently adopted for source separation of mixed signals, e.g. in the case of brain and cardiac activity monitoring applications where the measurements cannot be taken directly at the source and hence the gathered data are actually a combination of homogeneous physiological signals (e.g. with the EEG and ECG signals). A number of parameters are affected by specific application requirements and design choices of sensor fusion methods and techniques at data-level. Table 3 summarizes the most significant data-level fusion parameters that have been identified analyzing the state-of-the-art.

3.1.2. Feature-level fusion

The feature sets extracted from multiple data sources (generated from different sensor nodes or by a single node equipped with multiple physical sensors) can be fused to create a new high-dimension feature vector that represents the input for the classification/pattern recognition step [111].

In addition, in this level of fusion, machine learning and pattern recognition, depending on the type of application, will be applied to the multi-dimensional feature vectors that can then be fused to form joint feature vectors from which the classification is made [107].

Since it is not convenient (nor efficient) to simply concatenate the feature sets, it is typically useful to apply feature selection algorithms to obtain the so called *most significant* feature vector. Hence, one of the major advantages of feature-level fusion is the detection of correlated features generated by different sensor signals so to identify a feature subset that improves recognition accuracy. However, the main drawback is that to find the most significant feature subset, large training sets are typically required.

Table 4 summarizes the most significant feature-level fusion parameters that have been identified analyzing the state-of-the-art.

3.1.3. Decision-level fusion

Decision-level fusion falls is the process of selecting (or generating) one hypothesis from the set of hypotheses generated by individual (local, and often weaker) decisions of multiple sensors [112,113]. Decision-level fusion output is a unique decision obtained from local decisions of multiple (homogeneous or heterogeneous) sensors; therefore it utilizes the information that has been already abstracted to a certain level through preliminary sensor data-or feature-level processing such that high-level decision can be made.

Main decision-level fusion advantages include communication bandwidth savings and improved decision accuracy. Another important aspect of decision fusion is that is allows the combination of the heterogeneous sensors whose measurement domains have been processed with different algorithms [111].

Table 5 summarizes the most significant decision-level fusion properties that represent important design choices to achieve accurate recognition results.

3.2. Processing approach

Centralized data fusion methods involve a fusion center in which the measurements or feature vectors from each of the sensors are processed to form a global decision.

In distributed fusion, each sensor makes an independent decision based on its own observations and passes these decisions to

Table 3
Data-level fusion parameters.

Parameter	Description
Number of sources	Multiple homogeneous data sources are collected and fused at data-level. Specifically, data signals can come from (i) different channels of the same sensor (e.g. in the case of a three-axis accelerometer), (ii) different nodes with the same sensor type, or (iii) by a combination of the previous options.
Sampling rate	The sampling rate of the sensors is a relevant parameter as it can affect the possibility to perform online data fusion. In addition, if the sensors are sampled at different rates, then synchronization techniques (when required) become more complex.
Sensing synchronization	Data-level fusion techniques often require fine synchronization among sensor sources, although in some cases it is the fusion task itself that introduces the synchronization property.
Sensing periodicity	Data from multiple sources can be collected at fixed, regular time (periodic sensing) or enabled according to low-level events (trigger-based sensing).
Data buffering	Data-level fusion can be performed on a sample-by-sample basis (typically when the signals are synchronized) or on data buffers.
Aggregation strategy	The aggregation strategy is also an important parameter of data-level fusion as it determines the way in which data reach the fusion node. Most commonly it follows a star-based collection approach (the fusion node is at the center of the star and one-to-one communication channels are established with each sensor); however, data can be collected using buses (typically in case of big sensor arrays) or token ring approaches.
Sensor node platform	Although direct data-level fusion requires homogeneous sensor signals, the same node platform as well as heterogeneous platforms (yet equipped with the same sensor type) could, in principle, be used.

Table 4
Feature-level fusion parameters.

Parameter	Description
Feature domain	According to specific application requirements, features can be extracted in the time domain feature, in the frequency domain, or in a combination of both.
Feature extraction method	Features are normally extracted periodically over fixed or adaptable data windows, but in some case their extraction from raw data is trigger-based.
Feature normalization	When individual feature values may variate both in range and distribution, feature normalization task must be performed to normalize their baseline and amplitude to ensure that the contribution of each feature is comparable.
Feature selection method	As aforementioned, feature-level fusion is heavily influenced by the quality of the feature selection result. There exists a wide range of feature selection methods whose objective is to identify an optimal (or suboptimal) feature subset.
Source diversity	Data signals can derive from homogeneous sensors (e.g. in the case of multiple accelerometers placed on different body segments) or from heterogeneous sources (e.g. when the ECG signal is fused with acceleration data to filter out motion artifacts).
Data window size	The size (or *length*) of the data window is an important parameter as it influences on one hand the time frame the feature value is referred to (together with the sensor sampling rate) and on the other hand the processing requirements (intuitively, the larger the window is, the longer the execution time to extract features; particularly in the case of online feature extraction this is a relevant concern). It is often set a priori, but in some cases is dynamically adapted according to the variance of previous feature values.
Window overlapping	Features are typically extracted on moving (sliding) windows over the sensor data streams. Designers may choose to introduce overlap (also known as *shift*) between adjacent windows.
Processing model	Feature-level multi-sensor fusion can be performed centrally at a single fusion node or distributed among the sensor nodes (that in this case are in charge of sensing and extracting features). In the former case, the fusion node receives raw data from the sensors, extracts the features and performs the fusion. In the latter case, there still exists a fusion node, but it receives feature sets from each sensor and hence it only has to perform the fusion task.

Table 5
Decision-level fusion properties.

Parameter	Description
Decision fusion method	Common decision-level sensor fusion methods include Bayesian inference, fuzzy logic, heuristic-based (voting), and classical inference.
Source diversity	Decisions can derive from homogeneous or heterogeneous sensor sources.
Classification periodicity	Single source classification results are normally generated periodically, but in some case the classification step can be triggered by simple IF THEN ELSE evaluations over the inputs (feature sets). In both cases, particular attention is required to make sure the individual local classification results received by the fusion node are referring to the same time frame.
Processing model	Decision-level sensor fusion is typically a task distributed among the sensor nodes (that perform classification locally and send the result to the fusion node). However, it can be performed also centrally at the fusion node (typically a local coordinator such as a personal mobile device or even a Cloud server).

the fusion node where a global decision is made. Since the distributed fusion technique transmits less information to the fusion node, its performance may be degraded relative to the centralized approach. This approach provides a more practical solution to near real-time systems, and it offers maximum benefit when there is simultaneous sensing by the various sensors.

An alternate approach that utilizes the advantages from both the centralized and distributed techniques is known as hybrid fusion. First, each sensor makes an independent report based on its own observations or features. Thus, a list of candidate targets is independently generated from each sensor. This preliminary detection hypothesis is a soft decision. The combined hypothesis space is focused only on candidate targets that appear in each individual domain. This results in a significant reduction in the number of hypotheses for subsequent processes. This approach is applicable only if the probability of detection is high in each sensor domain, otherwise the probability of detection will be driven by the lowest performing sensor.

4. Sensor fusion in activity recognition

Physical activity monitoring provide health-promotive awareness of personal habits to individuals. Therefore, it is crucial to be able to accurately keep track of the physical activities people conduct during daily life [114]. Inertial sensors such as accelerometers, gyroscopes and magnetometers are the most common wearables utilized in human activity recognition [115]. Human activity Recognition (HAR) can be done using a single wearable sensor [116], however, researchers started to fuse data from multiple sensors to increase the accuracy of activity recognition systems. The state-of-the-art of multi-sensor fusion in HAR has been investigated in many research studies [107]. Sensor fusion models in HAR can be categorized in terms of (i) information levels; (ii) the objectives of the fusion process; (iii) the application domain; (iv) the types of sensors employed; (v) the sensor suite configuration; (vi) fusion process; (vii) I/O characteristics, and so on [108].

4.1. Data-level fusion in activity recognition

In data-level multi-sensor fusion, the raw data coming from the wearable sensors are combined directly [107].

However, this level of fusion has not been thoroughly explored by the community of the researchers in activity recognition. The reason for this is that current activity recognition systems only consider a limited set of different activities (4 to 16, in the studies literature) to distinguish. Therefore, the more practical way to process data is to first extract features from sensor nodes and then transmit the features for activity recognition. This will reduce the communication burden and consequently the power consumption of the activity recognition system [117–119]. However one limitation to this approach is that transmitting the high-level abstract features would not meet the requirements for fine-grained activity recognition.

One of the few studies that has explored direct data fusion in activity recognition is in [120] which proposes a human daily activity recognition method by fusing the data from two wearable inertial sensors attached on one foot and the waist of the subject, respectively based on SVMs. Their method correctly recognized the activities 88.1% of the time, which was 12.3% higher than using a hip accelerometer alone.

4.2. Feature-level fusion in activity recognition

In the activity recognition domain, the feature extracted from multiple sensors data with different modalities such as accelerometers, gyroscopes [121], magnetometers [122,123], pressure sensors, microphones [124], temperature sensor, light sensor [125], could be time domain features such as mean, standard deviation [122], variance [125], energy, entropy, correlation between axes, signal magnitude [124] and root mean square [123], percentiles [126], or frequency domain features such as FFT and discrete cosine transform [124], spectral energy, entropy [126]. The time domain features are usually extracted from fixed sized windows which can have overlap with each other or not [121,122]. Next step is to select the optimal set of features using feature selection methods such as windowing technique, kernel discriminant analysis [122], minimal redundancy maximal relevance heuristic [126], Correlation based Feature Selection [121,125]. Afterwards, the selected features are fed into supervised classifiers including Naive Bayes [122], SVM [124,126], Decision Trees [121], Neural Networks [15], k-Nearest Neighbor [125] or un-supervised clustering methods such as LDA, MFA [127] depending on the availability of the labels for each class of activity to detect the activities including static physical activities like sitting, standing, lying, watching TV [15,122], and dynamic like walking and up stairs [122], down stairs, running [125], ramp up and down [121].

Table 6 summarizes our analysis of the literature on feature-level sensor fusion in activity recognition systems; for the sake of clarity, we reported only the most representative (in terms of citations and novelty) analyzed works.

4.3. Decision-level fusion in activity recognition

The main goal in decision fusion is to use a meta-level classifier where first the sensor data is preprocessed by extracting features from them [128]. In activity recognition, these features again can be time domain features [123] including, mean value, standard deviation [129], median, percentiles [130,131], number of peaks, mean amplitude of the peaks [93] or frequency domain features such as correlation between the axes [129] and sensors, energy and entropy [130] or combination of both [130,131]. Afterwards, the features extracted from each sensor are given to the classifiers (base classifier) like k-NN [132], HMM [93,112,133], SVM, Decision Tree [134], Naive Bayes [135], Neural Networks [112,134], to detect their class labels individually. In activity recognition, these class labels are the type of the activities such as walking and running, jumping, jacking, punching [123] and non-exercise activities like climbing up stairs, climbing down stairs, cit-ups, vacuuming, brushing teeth [129], sitting and standing [136,137], clapping, throwing, bending [123], computer work, moving box [130,131], writing on notepad, closing and opening the door [112], lying down, turning left and right [132], falling down [138]. Finally, these class labels are combined using different fusing techniques including classical inference (summation, majority voting [112,134], borda count, highest rank, logistic regression [93]), voting and ensemble [130,139], boosting [140], Bayesian inference [112], and Dempster-Shafar's method [123].

The two most common approaches to this level of fusion are majority voting and naive Bayes. In majority voting, all the sensors are weighted equally without using any previous statistics [112,134]. The final label is simply the class label that occurs the most among all the base classifiers. The naive Bayesian approach combines the Bayes probabilistic model with a decision rule. A common rule is to classify an input instance as belonging to the class that maximize the *a posteriori* probability [112,141].

Table 7 summarizes the attributes of the most representative (in terms of citations and novelty) analyzed works.

5. Sensor fusion beyond activity recognition

The main focus of our paper is the application of the body sensor fusion in activity recognition, however, it is worth to investigate the sensor fusion usage in other areas of interest. Therefore, in this section, we will give a brief description on the applications of sensor fusion in emotion recognition and then the general health.

5.1. Emotion recognition

Although early research in emotion recognition stressed the importance of single modality analysis (here the term stands for mode of recognition), this approach often fails in providing reliable information for emotion recognition. Indeed, except from specific target emotions (e.g. for stress or fear detection) where an individual sensor source can be used to obtain sufficiently robust results [142–144], current multi-emotion recognition systems involve multimodal information extraction to improve reliability and accuracy of the recognition process [145]. Typically, emotions are in fact recognized by analyzing video signals (for facial expressions), audio (for voice/speech imprints), inertial signals (for hand gestures and body postures).

Table 6
Feature-level fusion parameters in the activity-recognition domain.

Attribute	[122]	[124]	[126]	[125]	[15]
Feature domain	Time	Time, and frequency	Time, and frequency	Time	Time
Features	Mean, standard deviation	Mean, variance or standard deviation, energy, entropy, correlation between axes, signal magnitude area, tilt angle, autoregressive (AR) coefficients, FFT, discrete cosine transform (DCT) coefficients, altitude differences	Mean , standard deviation, percentiles correlation, spectral energy and entropy	Mean value, standard deviation, (median), 75th, 90th percentiles, and correlation between the vector magnitudes, dominant frequency of the respiratory signal that is the breathing frequency, spectral Energy, entropy	Empirical Mean, Root Mean Square, Standard Deviation, Variance, Mean Absolute Deviation, Cumulative Histogram, Interquartile Range, Zero Crossing Rate, Mean Crossing Rate, nth Percentile
Feature selection method	Windowing technique, kernel discriminant analysis	Windowing technique	Minimal-redundancy maximal- relevance	Correlation based Feature Selection (CFS)	n.a.
Source diversity	Accelerometers	accelerometer sensor, the pressure, and the microphone	Accelerometers, Respiratory sensor	a dual axes accelerometer, light, temperature sensor and microphone	n.a.
Data window size	0.5 second	3.5 seconds		seconds	10 seconds
Window overlapping	No	Yes	No	No	No
Processing model	Naive Bayes	Support Vector Machine	Support Vector Machine	Decision Trees, k-Nearest Neighbor, Naive-Bayes and the Bayes Net classifier	Decision Trees, Neural Networks
Activities	sitting, standing, lying down, walking, ascending the stairs	walking, walking on treadmill, running, running on treadmill, ascending and descending the stairs, riding elevator up, riding elevator down, hopping, riding a bike, idle (sitting/standing), watching TV, vacuuming, driving a car, riding a bus	not specified	walking, standing, sitting, running, ascending and descending the stairs	walking, jogging, ascending and descending the stairs, sitting, standing, lying down

Table 7
Decision-level fusion parameters in the activity-recognition domain.

Attribute	[123]	[129]	[130]	[93]	[134]
Decision fusion method	Dempster-Shafer theory	Boosting, bagging, plurality voting, stacking with ordinary-decision trees and stacking with meta-decision trees	multi-sensor ensemble classifier, voting and ensemble	highest rank, Borda count, and logistic regression	Reputation-based voting and majority voting
Base classification method	Sparse representation classifier, collaborative representation classifier	Support Vector Machine	Decision trees, K-nearest neighbors, Support vector machine , Naive Bayes	linear discriminant analysis, Hidden Markov Model	Feed Forward Neural Network, Nave Bayes, Decision Tree
Activities	jumping, jacking, bending, punching, waving, clapping, throwing, sitting, standing	standing, walking, running, ascending and descending the stairs, sitting, vacuuming, brushing teeth	walking, running, ascending and descending the stairs, sitting, vacuuming, brushing teeth	workshop assembly tasks	walking, sitting, standing
Processing model	Centralized	Centralized	Distributed	Centralized	Distributed

Table 8 summarizes some of the features of the most representative studies on emotion recognition with use of the sensor fusion. Most of the studies utilized Support Vector Machine (SVM) as their base classification model, while other models such as Neural Networks (NN) K-nearest Neighbor (KNN), Local Binary Pattern (LBP) have been used to classify the features from various sensor data including physiological data, facial expression and voice to detect emotions like sadness, happiness, anger, and etc.

Multi-sensor fusion in emotion recognition is useful for complementary information management [153] (e.g. some emotions are better recognized by speech (sadness and fear) while others by facial expression (anger and happiness) [154], and to achieve better performance and increased robustness [155].

In emotion recognition, multimodal information are fused at feature-level and decision-level (see Section 3). Feature-level (early) fusion classifies emotions from their individual modalities in the first step and then attempts to fuse the results of unimodal classification with an aim to reduce uncertainty in classification. In this case one simple method consists in majority vote classification. On the contrary, decision-level (late) fusion feeds all measurements obtained from sensors employed for different modalities to a pre-trained classifier, which in turn determines the class label of the unknown measurement.

In [146], emotional states of car-racing drivers have been investigated applying feature-level fusion using facial electromyograms, electrocardiogram, respiration, and electrodermal activity and a centralized classification approach based on SVMs and adaptive neuro-fuzzy inference. Feature-level fusion of voice, video, and thermal images have been also studied in [147].

Decision-level fusion of speech data has been proposed in [148]. Specifically, authors proposed a two level hierarchical ensemble of classifiers. At the first level, Mel Frequency Cepstral Coefficients of input speech are classified independently by trained SVM and Gaussian Mixer Model (GMM) classifiers. Then, posterior probabili-

Table 8
Application of BSN fusion in emotion recognition.

Reference	Fusion Level	Sensor Data	Feature Selection Method	Base Classification Model
[146]	*feature-level*	ECG, respiration, EDA, EMG	Manual	SVM, adaptive fuzzy
[147]	*decision-level*	microphone, camera	Manual	HMM, NN
[148]	*decision-level*	Berlin emotion corpus sound complementary	Manual	SVM, Gaussian Mixer Mode
[149]	*feature-level decision-level*	cameras, microphone	sequential backward	SVM, KNN
[150]	*decision-level*	Interactive Emotional Dyadic Motion Capture	Manual	SVM
[151]	*feature-level decision-level*	cameras, microphone	Adaboost.M2	HMM, LBPs
[152]	*decision-level feature-level*	ECG, EEG, GSR, Video respiration, skin temperature	one-way ANOVA	SVM

ties of GMM and discriminate function values of SVM are extracted and given as input to a second level SVM emotion classifier.

On the basis of the fact that certain emotional characteristics are best observed at different temporal lengths [149], a novel decision-level multimodal fusion method [150] proposes multimodal multi-temporal information fusion of individual classifiers outputs.

Wagner et al. [156] addressed the significant issue of missing data in one or more modalities in online emotion recognition systems. The authors proposed an enriched ensemble-based decision-level approach with strategies to handle temporarily unavailable modalities data.

In [151], the authors applied both feature-level and decision-level fusion on face and speech using HMM-based and Adaboost algorithms and concluded that the fusion at the semantic level provides better performance for the multimodal emotion analysis. Also in [152] feature-level and decision-level fusion techniques of EEG and eye gaze data are studied. Results obtained by authors showed that, contrary to feature-level fusion, decision-level fusion outperformed the best single modality for arousal classification and did not under-performed for valence classification.

Conversely, in [149], the authors observed that the results of the feature-level bimodal (face and speech) classifier and decision-level bimodal classifier are similar. However, the analysis of the confusion matrix showed that the recognition rate for each emotion type was totally different, so authors claimed that “the best approach to fuse the modalities will depend on the application”.

An interesting research effort [157], proposed a multimodal emotion recognition framework, called Smart Sensor Integration (SSI) that support offline and online tools for data segmentation, feature extraction, and pattern recognition. The framework allows to handle input from various input modalities and provides tools for multimodal fusion.

5.2. General-health

Recent advances in design of wearable sensors enabled deployment of body sensors networks that are capable of continuously and autonomously monitoring the human vital signs [158]. These systems namely remote health monitors, are usually constructed of multiple physiological and inertial sensors strategically placed on the body, and are able to provide feedback to the users and clinicians on the health status of the individuals [159].

One of the major advancements in the design of the body sensor networks is sensor fusion techniques to improve the accuracy and reduce the wide bandwidth of huge data coming from multiple sensors on the body [160]. Sensor fusion techniques in remote health monitoring systems, combine the data captured from the sensors at two feature and decision levels. Sensors for the purpose of health-care are accelerometers, gyroscopes, magnetometers, and pressure sensors to capture movement and glucose monitors, ECG monitors, pulse oximeters, and blood pressure monitors [161] to exploit physiological measurements [162,163].

In [164], authors fused the signals from an ECG sensor and tri-axial accelerometer at both feature- and decision-level to implement an analysis method to remote health monitoring of the older adults and patients. Their system was capable of continuously recording and analyzing the ECG and accelerometer received from the human body.

A study in [165] proposed a scalable system for remote user physiological data and movement detection using wearable sensor feature and decision-level data fusion. Their system integrates and analyze the data from body temperature, current geographical location, electrocardiography, body posture and fall detection in real-time to determine user health status like instant heart beat rate, body orientation and possible fall recognition.

In another work in [166], they presented a low-cost non-obstructive monitoring and rehabilitation system to detect long-term problems by identifying the discerning body posture and movement of the user, and accident by identifying the normal falls. Their system uses the feature-level fusion of sensory data provided by a network of wireless sensors placed on the periphery of the user.

In [167], a multisensory decision fusion system has been presented with biometric and medical monitoring applications. Their system consists of an ECG sensor, a temperature sensor, an accelerometer. and provides distinctive haptic feedback patterns to the userâÇÖs health state. They utilized the collected biometric information from the sensors to monitor the health state of the person involved in real-time or to get sensitive data to be subsequently analyzed for medical diagnosis.

Table 9 summarizes some of the features of the most representative studies on the application of sensor fusion in general health. Most of these studies fuse the features or decision extracted from motion sensors and physiological sensors such as EEG, ECG, heart rate, blood pressure, oxygen saturation, body temperature and etc., to remote monitor the health status of the individuals.

6. Future research challenges

Current research on sensor fusion is being interested by emerging research directions and challenges, particularly in the context of Autonomic BSNs, Context-aware BSNs, Collaborative BSNs, and Cloud-Assisted BANs. In the following, we provide some insights of each of the aforementioned directions.

Table 9
Application of BSN fusion in general health.

Reference	Fusion Level	Process	Sensors
[164]	*feature-level* *decision-level*	complementary cooperative	ECG, accelerometer
[165]	*decision-level*	complementary cooperative	accelerometer, temperature, ECG
[166]	*data-level* *feature-level*	complementary cooperative	accelerometer, gyroscope, magnetometer
[168]	*decision-level*	complementary cooperative	heart rate, blood pressure, oxygen saturation, temperature, EEG, ECG blood sugar, accelerometer

6.1. Autonomic BSNs

Autonomic BSNs are BSN systems based on self-healing, self-optimization, self-configuration, and self-protection properties. Each properties need to be carefully addressed by novel multi-sensor fusion methods. For instance, self-healing will be based on real-time sensor calibration and data filtering [169,170], self-optimization will support dynamic model evolution (such as on-line re-trained classifiers), and self-configuration will deal with wearable sensors displacement or replacement.

6.2. Context-aware BSNs

When context changes, multi-sensor fusion methods need to deal with such changes as they can greatly affect the properties of the methods such as accuracy. Knowledge transfer frameworks based on transfer learning could be exploited to allow BSNs to adapt to different contexts by extracting and transferring knowledge from one context to another. As an example, activity classification can be transferred from one context to another [171]. To do so, if the dataset generated by body sensors is annotated, a function to evaluate the divergence between features in the source- and target-domain datasets are to be defined. If the dataset is not annotated (or data labels are unavailable), a method to encode the background knowledge, like the sensor profiles, is required. Such design can facilitate each sensor in the source-domain dataset to match its counterpart in the target domain. In this case, the position of a body sensor attached to may be an important property in the sensor profile.

6.3. Collaborative BSNs

Collaborative BSNs (CBSNs) [172] are BSNs able to collaborate with each other to fulfill a common goal. Multi-sensor data fusion among CBSNs is fundamental to enable joint data analysis such as filtering, time-dependent and synchronized data integration and classification. CBSNs can be programmed by exploiting C-SPINE [173], which is an extension of the SPINE framework [2,174–176]. By using C-SPINE, the e-Shake CBSN system was developed [177]. e-Shake is based on a multi-sensor data fusion schema to perform automatic detection of handshakes between two individuals and capture of possible heart-rate-based emotion reactions due to the individuals meeting.

6.4. Cloud-assisted body area networks

Cloud-Assisted Body Area Networks (CABANs) are overlay infrastructures integrating BANs atop cloud systems to provide body sensor stream efficient collection, effective body sensor stream management, scalable body sensor stream processing framework, persistent body sensor data storage, workflow-oriented body analysis and decision making, advanced visualization services, and multi-layer security [178]. A notable example of CABAN is BodyCloud [179]. Although CABANs will allow to create new community-oriented BSN systems, they will raise new interesting issues such as definition of novel fusion methods for community oriented BSNs (involving even millions of BSNs), inputting high-volume of streamed data into fusion algorithms that have to provide real-time output, and efficient management of ”Big” multi-sensor data.

7. Conclusion

Multi-sensor data fusion is a well established research area and even in the BSN domain there is wide literature addressing sensor fusion at different levels and using diversified approaches. However, to the best of our knowledge, the community was lacking a comprehensive and systematic review of the state-of-the-art techniques on multi-sensor fusion in the BSN research area. This survey therefore has aimed at providing a systematic categorization and common comparison framework of the literature. Starting from the traditional classification (data-level, feature-level, and decision-level) of fusion techniques, we have identified distinctive properties and parameters affecting fusion design choices at each level. We have discussed clear motivations and advantages of multi-sensor data fusion in BSNs and particularly we have focused on physical activity recognition, comparing the reviewed works according to the proposed categorization framework. The survey has also covered data fusion in the domains of emotion recognition and general-health. We have finally introduced relevant directions and future challenges raised by the emergence of autonomic, context-aware, collaborative, and cloud-assisted BSNs that require new research to adapt current state-of-the-art approaches and techniques of multi-sensor fusion.

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