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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].