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Application of data fusion techniques and technologies for wearable health monitoring

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ABSTRACT

Technological advances in sensors and communications have enabled discrete integration into everyday objects, both in the home and about the person. Information gathered by monitoring physiological, behavioural, and social aspects of our lives, can be used to achieve a positive impact on quality of life, health, and well-being. Wearable sensors are at the cusp of becoming truly pervasive, and could be woven into the clothes and accessories that we wear such that they become ubiquitous and transparent. To interpret the complex multidimensional information provided by these sensors, data fusion techniques are employed to provide a meaningful representation of the sensor outputs. This paper is intended to provide a short overview of data fusion techniques and algorithms that can be used to interpret wearable sensor data in the context of health monitoring applications. The application of these techniques are then described in the context of healthcare including activity and ambulatory monitoring, gait analysis, fall detection, and biometric monitoring. A snap-shot of current commercially available sensors is also provided, focusing on their sensing capability, and a commentary on the gaps that need to be bridged to bring research to market.

1. Introduction

Many countries, including the United Kingdom, have an ageing population, with an increase in the average age and proportion of older people [1]. In 2010, there were approximately 10 million people over the age of 65 in the United Kingdom, with this number projected to rise by over 50% by 2020 [2]. One consequence of the ageing population is an increase in life expectancy implying greater healthcare needs. However, the relationship between age and dependency is complicated and not determined by age alone. Indeed, the risk factor profile of those born more recently is worse than previous generations [3]. This can be attributed, in part, to the link between economic development and increased risky behaviours [4]. Risk factors such as tobacco and alcohol use, inactivity, and poor diet choices are associated with chronic diseases including obesity, cardiovascular disease, and diabetes [4].

Recent advances in wearable technology including microelectromechanical (MEM) devices, physiological sensors, low-power wireless communications, and energy harvesting, have set the stage for a significant change in health monitoring. Technology can be discreetly worn and used as a means to monitor health and potentially enable older adults to live safely and independently at home. Early detection of key health risk factors enables more effective interventions to reduce the impact of, or even avoid, serious or chronic illness. Inertial measurement devices, such as accelerometers, represent a range of sensors that can be used for healthcare monitoring and are being extensively investigated for the monitoring of human movement [5] and daily activity [6]. Another application for wearable systems is rehabilitation [7]. There are also currently many systems commercially available for the monitoring of sports and some aspects of health.

The richness of data available using wearable sensors presents challenges in the way that it is processed to provide accurate and relevant outputs. To fully exploit this data for the purposes of healthcare monitoring, data fusion techniques can be employed to make inferences and improve the accuracy of the output. Hall and Llinas [8] provide a detailed introduction and discussion to multi-sensor data fusion. A review of data fusion techniques is also pro-

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vided by Castanedo [9] including the different categories of data fusion techniques. With a focus on body sensor networks, Fortino et al. [10] discuss wearable multisensor fusion with an emphasis on collaborative computing.

This paper introduces wearable sensors for human monitoring in the context of health and well-being, including a snap shot of current commercial wearable sensor systems. An overview of data fusion techniques and algorithms is offered, including data fusion architecture, feature selection, and inference algorithms. These are put into the context of wearable technology for healthcare applications including activity recognition, falls detection, gait and ambulation, biomechanical modelling, and physiological sensing. Related challenges of data fusion for healthcare are presented and discussed.

2. Wearable sensors

Wearable sensors can be considered in three categories: motion, biometric, and environmental sensors. Sensors used to capture human motions include inertial sensors such as accelerometers, gyroscopes, and magnetometers. By combining a tri-axial accelerometer, gyroscope, and magnetometer, inertial measurement units can be made for 9 degree of freedom tracking and are used for biomechanical modelling. Common biometric sensors are used to measure heart rate, muscle activation, respiration, oximetry, blood pressure, galvanic skin response, heat flux, perspiration, and hydration level. Electrocardiogram (ECG) and electromyography (EMG) detect the electrical activity produced by the heart and muscles respectively and are interpreted into heart rate and muscle activation.

For a wearable monitoring system to be practical it needs to meet several key criteria: to be non-invasive, intuitive to use, reliable, and provide relevant feedback to the wearer. The number of devices, location, and attachment method would be considered during design, and are usually application specific. Wearable sensor systems also have to take the target users' needs, such as dexterity or cognitive ability, into account. Devices can be either attached directly to the skin using some form of adhesive, mechanically using a clip, strap or belt, or incorporated directly into clothing or shoes. Advanced fabrication techniques can now create 'flexible/stretchable electronics' for integrated circuits, electronics and sensors [11]. Such systems can be applied directly to the skin enabling discrete sensing possibilities e.g. devices developed by MC10 Inc. [12].

It is essential the system is reliable and measures with acceptable accuracy, providing the user with relevant feedback. In the research literature this is often presented as the accuracy of identifying specific events or health aspects, or in terms of selectivity and specificity, the proportion of the data that is positively identified correctly and the proportion of the data that is negatively identified correctly, respectively.

The past decade has seen major advances in sensing technologies, including MEMs and physiological sensors. Wireless low power communications, such as BLE, enable sensing technology to be integrated into wearable devices, clothing, and in the future embedded about the person without the restrictions of wires or the need to download data. Low power sensing and communications also enable wearable energy harvesting to be a viable option for powering and recharging these systems.

Commercially, wearable sensor systems are available for human monitoring and some of their output features are tabulated in Table 2. Much of the software developed for commercial devices is proprietary; however, some systems are able to provide raw data, or have been explicitly designed for the purposes of research. Table 3 describes wearable devices that are commercially available for activity, physiological, and biomechanical monitoring, including both consumer and research devices. The table presented gives a snapshot overview of commercial wearable devices as this is a wide and rapidly changing landscape, with the features monitored and the sensors used for daily monitoring, including a few examples for specific applications. Devices that only provide step count have not been included. A large proportion of these sensors target the health and fitness industry, and track the amount and intensity of activity performed including measures such as an estimate of energy expenditure and calories burned. For purposes of research however, a much broader range of outputs are being investigated and will be described in greater detail, including the techniques used to achieve them, in Section 5.

Table 1
Table of abbreviations.

Abbreviation	Definition	Terminology
ADL	Activities of daily living	Medical
ANN	Artificial neural networks	Technical
BLE	Bluetooth low energy	Technical
COPD	Chronic obstructive Pulmonary disease	Medical
DT	Decision tree	Technical
ECG	Electrocardiogram	Medical
EEG	Electroencephalogram	Medical
EMG	Electromyography	Medical
GMM	Gaussian mixture models	Technical
HR	Heart rate	Medical
HRV	Heart rate variability	Medical
KF	Kalman filter	Technical
k-NN	*k*-nearest neighbour	Technical
MEM	Microelectromechanical	Technical
PF	Particle filter	Technical
QoL	Quality of life	Medical
SpO2	Capillary oxygen saturation	Medical
SVM	Support vector machines	Technical

2.1. Sensor placement

The placement of wearable sensors for health monitoring is motivated by three main driving forces: (1) what data is required or provided by the sensors; (2) where it is considered acceptable to wear the sensors; and (3) the number of sensors the user is willing to wear. For commercial systems the most common place to wear a sensor is on the wrist or arm although many systems can be worn at multiple locations, such as on the chest using a clip or as a pendent, and the thigh and ankle (Table 3). The waist and wrist are intuitive and unobtrusive places to wear sensors as many people are already accustomed to wearing watches or belts. In a study conducted by van Hess et al. [13] to investigate the estimation of daily energy expenditure using a wrist-worn accelerometer, the acceptability of wearing the device on the hip or wrist was also examined. It was found that both sensor placements were rated as highly acceptable, however, men on average preferred wearing the sensor on the wrist.

Systems with more niche applications need to be worn at more specific locations relevant to the information being acquired, e.g. the Reebok Checklight with MC10 helmet [14] that determines the number and severity of impacts to the head while participating in sports.

Sensor placement for activity recognition has been investigated in several studies. Atallah et al. [15] investigated the most relevant features and sensor locations for discriminating activity levels, demonstrating the dependence of sensor location on the activities being monitored. Liu et al. [16] investigated different combinations of sensors and locations for physical activity assessment. The "best" results, i.e. the ones giving the highest activity recognition accuracy, were obtained using all the sensors, followed by a combination of the wrist and waist worn sensors. Patel et al. [17] also investigated the different combinations of sensors for monitoring