Sensors for Wearable Systems

Introduction

When designing wearable systems to be used for physiological and biomechanical parameters monitoring, it is important to integrate sensors easy to use, comfortable to wear, and minimally obtrusive. Wearable systems include sensors for detecting physiological signs placed on-body without discomfort, and possibly with capability of real-time and continuous recording. The system should also be equipped with wireless communication to transmit signals, although sometimes it is opportune to extract locally relevant variables, which are transmitted when needed. Most sensors embedded into wearable systems need to be placed at specific body locations, e.g. motion sensors used to track the movements of body segments, often in direct contact with the skin, e.g. physiological sensors such as pulse meters or oximeters. However, it is reasonable to embed sensors within pieces of clothing to make the wearable system as less obtrusive as possible. In general, such systems should also contain some elementary processing capabilities to perform signal pre-processing and reduce the amount of data to be transmitted. A key technology for wearable systems is the possibility of implementing robust, cheap microsystems enabling the combination of all the above functionalities in a single device. This technology combines so-called micro-electro-mechanical systems (MEMS) with advanced electronic packaging technologies. The former allows complex electronic systems and mechanical structures (including sensors and even simple motors) to be jointly manufactured in a single semiconductor chip. A generic wearable system can be structured as a stack of different layers. The lowest layer is represented by the body, where the skin is the first interface with the sensor layer. This latter is comprised of three sub-layers: garment and sensors, conditioning and filtering of the signals and local processing. The processing layer collects the different sensor signals, extracts specific features and classifies the signals to provide high-level outcomes for the application layer. The application layer can provide the feedback to the user and/or to the professional, according to the specific applications and to the user needs. Recent developments embed signal processing in their systems, e.g. extraction of heart rate, respiration rate and activity level. Activity classification and more advanced processing on e.g. heart signals can be achievable exploiting miniaturization and low-power consumption of the systems. Examples of data classification are[1, 2, 3]: classification of movement patterns such as sitting, walking or resting by using accelerometer data [4] or ECG parameters such as ST distance extracted from raw ECG data [5, 3]; another example is the estimation of the energy consumption of the body [6, 7]; in [8] the combined use of a triaxial accelerometer and a wearable heart rate sensor was exploited to accurately classify human physical activity; estimation of upper limb posture by means of textile embedded flexible piezo resistive sensors [9]. Examples of integrated systems for health monitoring are in [10, 11]. In the following paragraphs, two classes of sensors which can be easily integrated into wearable systems are reported and described. More specifically, inertial sensors to monitor biomechanical parameters of human body and sensors to capture physiological signs are addressed, describing the operating principles and indicating the possible fields of application.

Sensors for Wearable Systems

Biomechanical Sensors

Biomechanical sensors are thought to be used to record kinematic parameters of body segments. Knowledge of body movement and gesture can be a means to detect movement disturbances related to a specific pathology or helpful to contextualize physiological information within specific physical activities. An increasing of heart rate, for example, could be either due to an altered cardiac behavior or simply because the subject is running.

Inertial Movement Sensors

Monitoring of parameters related to human movement has a wide range of applications. In the medical field, motion analysis tools are widely used both in rehabilitation and in diagnostics. In the multimedia field, motion tracking is used for the implementation of life like videogame interfaces and for computer animation. Standard techniques enabling motion analysis are based on stereo-photogrammetric, magnetic and electromechanical systems. These devices are very accurate but they operate in a restricted area and/or they require the application of obtrusive parts on the subject body. On the other hand, the recent advances in technology have led to the design and development of new tools in the field of motion detection which are comfortable for the user, portable and easily usable in non-structured environments. Current prototypes realized by these emergent technologies utilize micro-transducers applied to the subject body (as described in the current paragraph) or textile-based strain sensors. The first category, instead, includes devices based on inertial sensors (mainly accelerometers and gyroscopes) that are directly applied on the body segment to be monitored. These sensors can be realized on a single chip (MEMS technology) with low cost and outstanding miniaturization. Accelerometers are widely used for the automatic discrimination of physical activity and the estimation of body segment inclination with respect to the absolute vertical. Accelerometers alone are not indicated for the estimation of the full orientation of body segments. The body segment orientation can be estimated by using the combination of different sensors through data fusion techniques (Inertial Measurement Units, IMU). Usually, tri-axial accelerometers (inclination), tri-axial gyroscopes (angular velocity), magnetometers (heading angle) and temperature sensors (thermal drift compensation) are used together. Main advantages of using accelerometers in motion analysis are the very low encumbrance and the low cost. Disadvantages are related to the possibility of obtaining only the inclination information in quasi-static situations (the effect of the system acceleration is a noise and the double integration of acceleration to estimate the segment absolute position is unreliable). Accelerometers are widely used in the field of wearable monitoring systems, generally used in the monitoring of daily life activities (ADL). Physical activity detection can be exploited for several fields of application, e.g. energy expenditure estimation, tremor or functional use of a body segment, assessment of motor control, load estimation using inverse dynamics techniques [26, 27] or artificial sensory feedback for control of electrical neuromuscular stimulation [28, 29, 30]. Usually, three-axial accelerometers are used. They can be assembled by mounting three single-axis accelerometers in a box with their sensitive axes in orthogonal directions or using a sensor based on one mass [31]. An accelerometer measures the acceleration and the local gravity that it experiences. Considering a calibrated tri-axial accelerometer (the accelerometer signal (y) contains two factors: one is due to the gravity vector (g) and the other depends on the system inertial acceleration (a), both of them expressed in the accelerometer reference frame :The inclination vector (z) is defined as the vertical unit vector, expressed in the accelerometer coordinate frame [4]. In static conditions, only the factor due to gravity is present and the inclination of the accelerometer with respect to the vertical is known. In dynamic conditions, the raw accelerometer signal does not provide a reliable estimation of the inclination, since the inertial acceleration is added to the gravity factor. This estimation error grows as the subject movements become faster (e.g. running, jumping). Many algorithms have been developed and tested to perform a reliable estimation of the subject body inclination: most of them use low pass filters with very low cut-off frequency in order to extract z[4] (i.e. introducing a considerable time delay), others implement more complex techniques which use a model-based approach mainly based on Kalman filter techniques. An example of integration of these sensors in a garment was developed in the frame of the Proetex project (FP6-2004-IST-4-026987), which aimed at using textile and fibre based integrated smart wearables for emergency disaster intervention personnel. The ProeTEX motion sensing platform is used to detect long periods of user immobility and user falls to the ground and it is realized by means of two tri-axial accelerometer modules. One accelerometer is placed in the higher part of the trunk (collar level) in order to detect inactivity and falls to the ground. The second sensor is placed in the wrist region and its aim is to achieve more accuracy in inactivity detection, since an operator can move his arms while his trunk is not moving. The core of the motion sensor is the processing algorithm described in, which allows to perform a reliable estimation of the body inclination even in the case of intense physical activity such as running or jumping. This algorithm allows a good estimation of subject activities and generated fall alarms with very high sensitivity and extremely low level of false positives.

Respiration Activity sensor

The most challenging vital sign to accurately record during continuous monitoring is the respiratory activity due to the fact that the signals are affected by movement artifacts and filtering or feature recognition algorithms are not very effective. Monitoring of respiratory activity involves the collection of data on the amount and the rate at which air passes into and out of the lungs over a given period of time. In literature, there are several methods to do this, both directly, by measuring the amount of air exchanged during the respiration activity, and indirectly, by measuring parameters physically correlated to breathing, such as changes in thorax circumference and/or cross section, or trans-thoracic impedance.

Direct methods are based on a spyrometer that measures directly the airflow in the lung exchanged during inspiration and expiration, but of course it cannot be integrated into a wearable system because it employs a mouthpiece, which could interfere with the freedom of movements, disrupting the normal breathing pattern during measurement, thus causing discomfort for the user. Indirect methods exploit displacements of the lung that are transmitted to the thorax wall and vice versa, and therefore measurements of chest-abdominal surface movements can be used to estimate lung volume variation. In literature, a number of devices have been used to measure rib cage and abdominal motion including mercury in rubber strain gauges, linear differential transducers, magnetometers, and optical techniques, but almost all cannot be comfortably integrated into a wearable system. For reference only, it is worthwhile citing a more sophisticated technique, called stereo photogrammetry, which makes it possible to estimate the three-dimensional coordinates of points of the thorax, estimating therefore volume variations. Nevertheless, this system presents a considerable drawback in that it is cumbersome, extremely expensive, and can only be used in research environments or in laboratory applications. Indirect techniques that can be implemented in wearable systems are respiratory inductive plethysmography, impedance plethysmography, piezo resistive and/or piezoelectric pneumography. These systems are minimally invasive and do not interfere with physical activity.