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Wearable Computing and Sensor Systems for Healthcare

Franca Delmastro and Marco Conti
Institute of Informatics and Telematics (IIT) at the National Research Council of Italy (CNR), Pisa, Italy.

8.1 Introduction

In recent years wearable computing and sensors technology has gone hand in hand with medical healthcare representing an innovative and leading solution designed to improve the quality of life of patients and prevent critical situations both inside and outside medical facilities. However, more work is needed in this research field to respond appropriately to both medical and technological challenges in deploying efficient and reliable e-health systems. First of all, we have to identify the main issues in current healthcare systems in order to design and adapt the technology in this direction. Following the international reports on healthcare [1], national health systems need essentially a reduction of costs for maintaining high quality of treatment and guaranteeing high quality of life for patients. They should also provide easy access to care for as many people as possible, anywhere and anytime, addressing in particular the increase in the aging population and the care of chronic diseases, which represent one of the major causes of death worldwide. With this aim in mind, healthcare professionals are trying to improve the efficiency of the patient care, focusing on the *'continuum of care'* [2]. This requires continuous medical assistance to the patient, from the beginning of his/her hospitalization to discharge and consequent rehabilitation at home, increasing the demand for portable and versatile medical devices that can support both the patient and the doctor in continuous monitoring, thus becoming the medium of communication between these two entities. The American Institute of Medicine [2] summarized six aims for healthcare improvement identified by: safety, effectiveness, patient-centered, timeliness, fairness and efficiency across the different nations. To address all of these features the experts claimed that it is necessary to define a mobile information infrastructure tailored to the individual's requirements that can take advantage of the advances in telemedicine systems and information processing techniques. Following these guidelines, wearable and ubiquitous sensors, together with personal mobile devices, represent the new frontier moving towards a novel definition of e-health systems that we can define as *pervasive healthcare systems*. With this definition we can aggregate both patient-centered and hospital-centered systems. The former are mainly dedicated to remote and continuous monitoring of patients outside the medical facility and during daily activities, while the latter are designed to improve the medical workflow inside the facility. The former, defined also as *Personal Health Systems*, represent the most challenging solutions in terms of pervasive technologies and communications, with reference especially to wearable computing. These systems will provide the collection, processing, storage and transmission of medical information, maintaining the fundamental requirements of user acceptability and comfort. In fact, the main functionality of wearable sensors for healthcare (i.e. vital signal monitoring, storage, communication with external devices, low power consumption) must be defined in accordance

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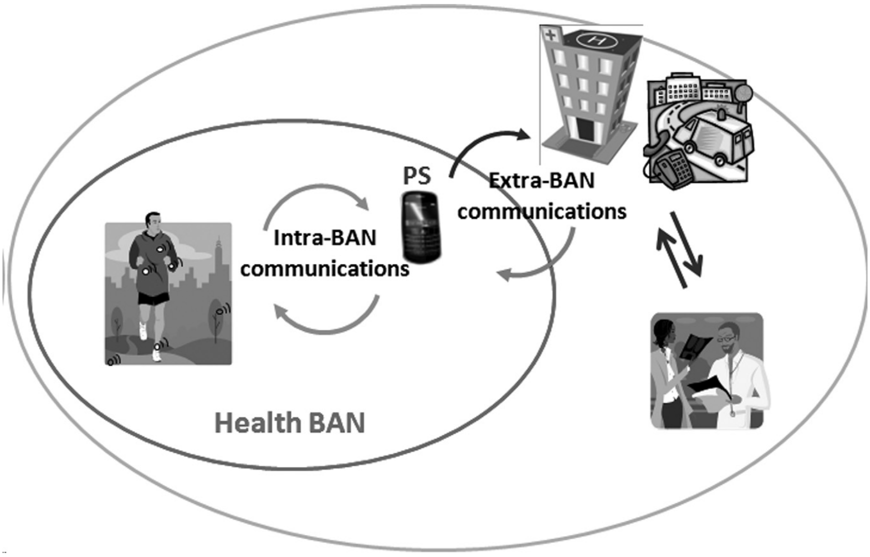

Figure 8.1 Personal Health System architecture.

with the patient's basic needs (e.g. wearability, unobtrusiveness, no skin irritation, easily maintainability) in order to guarantee the correct and constant usage of the system. In this chapter we survey the technological aspects of the design and development of wearable sensor networks for healthcare, analysing and comparing the different solutions proposed in the literature and trying to envisage some future trends in this research area. Specifically, we introduce the concept of the Health Body Area Network (Health BAN) in Section 8.2, providing a general overview of the system architecture of Personal Healthcare Systems, as illustrated in Figure 8.1. Then, focusing on wearable technologies, we describe the medical and technological requirements of health sensors in Section 8.3, analyzing the correspondence between most common diseases and the physiological and non-physiological parameters that are useful in monitoring applications. Further to this, we refer to three main categories of wearable sensors designed for three different purposes: vital signals monitoring (Section 8.4), activity recognition (Section 8.5) and emotion recognition (Section 8.6). In these sections, existing wearable computing solutions are presented, highlighting the main advantages, drawbacks and possible enhancements for the design and development of the next generation. In addition, the analysis and correlation of the parameters derived from these different categories allows the system to have a complete clinical profile of the patient; however, some technological issues have to be addressed in order to guarantee an efficient and reliable system. Specifically, wireless communications in Health BAN represents one of the main aspects to be investigated with particular attention given to power consumption, reliability, data rate and delays. In Section 8.7 we describe the consolidated wireless standards for sensor networks (i.e. Bluetooth and ZigBee) and their performance evaluations in healthcare environments, followed by a description of the novel specification of Bluetooth aimed at low energy consumption as the most promising technology for Health BANs. We conclude the chapter with a brief discussion on users' acceptance of wearable technology as further inputs for new design and development.

8.2 The Health Body Area Network

Initially, sensor networks were designed for collecting sensing information from stationary nodes, spread in the environment, transmitting data at a relatively low data rate to achieve best effort data collection at a central base station. Medical monitoring and related applications, essentially working with critical information, have more stringent requirements (e.g. reliable communications, high data rate, small dimensions and the possibility of sending data to multiple receivers), thus introducing the concept of *Health BAN* [3]. It consists mainly of a network of communicating devices (sensors, actuators and other mobile devices) generally worn on or implanted in the body providing mobile health services to the user. To guarantee efficient and reliable services, the Health BAN needs to communicate with a remote medical information system where care professionals can monitor the patient's status constantly and provide the correct care plan or related actions. To realize this aim, an additional component of the Health BAN is selected to collect and transmit sensed data to the medical server. Generally, this role is undertaken by a mobile device with a discrete storage and processing capacity, able to support multiple wireless protocols and inter-device communications. It has been defined in the literature in several ways: Mobile Base Unit (MBU) [3], Personal Mobile Hub (PS) [4], Personal Server [5] and others, depending on its technical features, from the basic collection of sensed data [3, 4] to the more sophisticated elaboration and correlation of several values to provide at least a preliminary feedback to the patient [5]. In this chapter we generally refer to it as Personal Server (PS) since this definition includes the most complete set of functionalities associated with its role. Therefore, these three elements (i.e., Health BAN, PS and medical server) represent the three tiers of the architecture of a pervasive Personal Healthcare System (see Figure 8.1), dedicated mainly to patient monitoring.

Another important factor in the system is represented by communication protocols between the components. Specifically, we refer to the communication protocols among health sensors and the PS as Intra-BAN communications, and those between the PS and the medical server as Extra-BAN communications. Since the main target of this work is to describe the main impacts of wearable and ubiquitous technology on e-Health, we focus on the description and evaluation of health sensors, specifying their medical, technological and communication requirements (especially in terms of Intra-BAN communications), with detailed examples of developed technologies for specific application scenarios.

8.3 Medical and Technological Requirements of Health Sensors

With regard to the general technological features of a sensor node, we can describe its architecture as a set of components: the sensing element that collects an analog signal, an analog-digital converter, a processor, a wireless transceiver, a flash memory, an antenna and the battery. Indeed, depending on the way they are empowered (local or shared power supply), they are divided into two main categories: *self-supporting* and *front-end supported* sensors. Self-supporting sensors have their own power supply and represent independent building blocks of the BAN, guaranteeing a high configurability but, at the same time, characterized generally by independent internal clocks and sample frequency, thus requiring synchronization mechanisms. By contrast, front-end supported sensors share a common power supply and generally also share data acquisition procedures, operating on the same front-end clock and providing multiplexed samples as a single data block; thus they do not require synchronization procedures. Health sensors contain both of these categories, and different systems exploit them depending on their requirements and final objectives. In general, the main features of a sensor node and its performance depend strictly on the specific application scenarios it is designed for. In case of healthcare systems, there are so many differences among the physiological signals to be monitored and the possible system configurations that there does not exist a single scenario involving all possible diseases and medical characteristics; thus every system defines a set of customized features for the sensors involved. However, before analyzing the existing solutions and their detailed characteristics, we identify a set of medical and technological requirements that are shared among most health sensors:

- *Wearable*: in order to guarantee user acceptability and the correct use of this technology in healthcare applications, sensors must be characterized by very small dimensions, light weight and possibly be integrated in the textile fabric.
- *Reliable wireless communications*: initial solutions for pervasive healthcare systems proposed wearable sensors connected through wires integrated into the textile fabric, but they displayed some drawbacks related to interference created by wires that act as antennae in the woven, fixed positions of the sensors, and possible structural damage caused during patient activity [6, 7]. Thus, to solve these problems and improve ability to wear the sensors, wireless communications are needed. However, at the same time, they should guarantee reliable transmission of data, avoiding persistent packet loss (due to network congestion or node mobility) and consequent loss of important vital signals.
- *Efficient power consumption*: pervasive healthcare systems need power saving policies designed for increasing the life time of the Health BAN reducing the dimensions of battery packs. This is also a general feature for sensor networks, but its implementation depends strictly on the data delivery model and communication standards used for the specific application scenario, since it has been proven that most of the energy is consumed during transmissions [8].
- *Multiple receivers*: patient data can be sent to a central server through the PS as a central aggregation point and then forwarded to the interested care givers or, in some (emergency) cases, it could be necessary to transmit critical

data directly to the interested users such doctors, nurses and family care-givers. Thus, multicast transmission should be also considered as a general feature of Health BANs.

- *Mobility*: data communication should address the mobility issue both for the patient and the care-givers, establishing ad hoc communications or exploiting the network infrastructure, if it exists.
- *Security/Privacy*: patient information is highly sensitive both in terms of security and privacy, since malicious use could even cause the death of a patient (e.g. in the case of data manipulation in the re-programming phase of implantable devices) and violate the professional confidentiality of the doctor. Therefore a general framework including authentication, authorization and appropriate security schemes must be defined for Health BANs.
- *Adaptability*: health sensors should allow custom calibration and tuning of the sensing procedure depending on the patient's status at a specific period of time or during a particular activity.
- *Interoperability*: sensors should be easily integrated and able to interoperate among them and with the PS. The definition of standard interfacing protocols for the configuration of the sensing platform and their possible interactions would favour vendor competition resulting in more affordable systems for pervasive healthcare.

These requirements address the main technical and medical issues in designing Health BANs and related systems. However, the existing solutions do not address all of these aspects, especially adaptability and interoperability.

In the following we present a set of health sensors developed within the framework of projects and experimental activities in the e-health research field in order to give an overview of the state-of-the-art and discuss possible enhancements, related mainly to the integration of several sensors in different healthcare solutions in order to improve the accuracy and reliability of measurements. To better understand the objectives and implementations of current Health BANs, it is important to have a view of the relationship between the diseases that can benefit from continuous monitoring of the patient's status, and the specific signals that should be measured. In this way, we can have an overview of the sensors that can be used for specific medical conditions. Specifically, in Table 8.1 we identify the physiological and non-physiological parameters that are generally associated with the most common diseases.

Most physiological parameters listed can be measured directly by wearable sensors (e.g. ECG, blood pressure) or can be derived from the analysis and correlation of different signals (e.g. heart rate derives from ECG). However, in specific cases, the evaluation of particular biochemical parameters is necessary in order to obtain a complete diagnosis and monitoring of the disease. For example, cardiac and tumour markers, for ischemic heart disease and cancer respectively, can be measured through the use of implantable biosensors. Biosensors are used to transform biological actions or reactions into signals that can be processed to improve the accuracy of specific physiological measurements. For example, an implanted 'excitable-tissue' biosensor can be used as a real-time, integrated bioprocessor to analyze the complex inputs regulating a dynamic physiological variable such as the heart rate [9]. The study and development of biosensors are addressed by bioengineering researchers working in harness with medical specialists owing to the intrusive features of these devices. However, the analysis and correlation of biosensor output, together with physiological and additional parameters that characterize the history and clinical profile of a

Table 8.1 Relationships among diseases and signals to be monitored

Disease	Physiological parameters
Hypertension	Blood pressure
Ischemic Heart disease	Heart rate, Electrocardiogram (ECG), cardiac markers, cardiac stress testing, coronary angiogram
Heart failure, cardiac arrhythmias	Heart rate, blood pressure, ECG, fluid balance, body weight
Cardiovascular diseases	Heart rate, blood pressure, life style, ECG
Post-operative monitoring	Heart rate, blood pressure, ECG, oxygen saturation, body temp.
Cancer (breast, prostate, Lung, Colon)	Weight loss, tumor markers, blood detection (urine, feces. . .)
Asthma/ Chronic Obstructive Pulmonary Disease (COPD)	Respiration rate, oxygen saturation
Diabetes and obesity	Dietary and activity parameters, blood glucose value
Neurological diseases	Emotional parameters, ECG, EEG, heart rate, Blood Volume Pulse (BVP), skin temperature, Galvanic Skin Response, Pupil Diameter

patient, represent the focal point of pervasive healthcare systems, and they can lead to improving the accuracy of single measurements and the diagnosis of related diseases.

Looking at Table 8.1 we may notice that there are two main categories of diseases: chronic diseases [10] (e.g. cardiovascular diseases, heart failure, hypertension, cancer, diabetes) that mainly need the monitoring of vital signals such as heart rate, ECG and blood pressure, in addition to life style information, and neurological (e.g. Parkinson, Alzheimer) and neuro-psychological (e.g. obesity and dietary) diseases, which are related mainly to physical activity, motion-analysis and emotion recognition.

This distinction is reflected in the solutions proposed in the literature. In fact, some propose general platforms that can be used to monitor patients affected by different cardiovascular diseases. They focus mainly on sensing the most common physiological signals that are also identified as 'vital signals' (i.e. heart rate, ECG, blood pressure). Instead, specific solutions are proposed to address neurological and neuro-psychological diseases, analysing activity and/or emotional signals to prevent critical episodes and make the patient able to react accordingly. The details of these solutions and related wearable sensors are described in the following sections.

8.4 Wearable Sensors for Vital Signals Monitoring

Vital signals monitoring represents the basic feature of all pervasive healthcare systems, and the evolution of wearable technology has improved its accuracy and reliability significantly. In Table 8.4 (at the end of the chapter) we summarize the most important solutions of Health BANs designed mainly for physiological monitoring, analyzing the main differences in sensors development and communication strategies. The Georgia Tech Wearable Motherboard (GTWM) [7], also known as 'Smart Shirt' (see Figure 8.2), represents one of the first applications of wearable sensors for healthcare. Designed originally to improve medical assistance in military scenarios (such as detecting the penetration of a projectile and monitoring the vital signals of soldiers on the battlefield), it introduced the concept of sensors array integrated in the garment. It exploits commercial off-the-shelf sensors such as ECG and pulse oximeter[1] for vital signals monitoring, a microphone for voice recording, and it integrates plastic optical fibres in the fabric and a low power laser for penetration sensing [7]. In this case, sensors are connected to the Smart Shirt Controller that acts as PS to collect and transmit data to the central medical server exploiting Bluetooth or 802.11b wireless communications. This solution presents some problems related mainly to the integration of sensors in the textile fabric. First of all, the ECG sensor was developed using conventional electrodes that can suffer from noise during movement, causing the corruption of the signal. In addition, the physical structure of the shirt requires fixed positions for the sensors and the wires used to connect them can generate interference. The idea of sensors integrated in the textile (also known as textile sensors) was then evolved in other projects: Smart Vest [11], MagIC [12], WEALTHY [13] and MyHeart [14]. The first follows the Wearable Motherboard model, increasing the number of integrated sensors. It is able to monitor ECG, PPG (photoplethysmogram), heart rate, blood pressure, body temperature and Galvanic Skin Response (GSR) continuously, all integrated in specific locations on a shirt [11]. The measurement and analysis of PPG waveform, correlated with the ECG signal, allows the system to implement a non-invasive method of monitoring blood pressure, without using the conventional cuff method [15]. For this purpose, the PPG sensor is realized mainly through a pulse oximeter placed on the patient's finger/ear lobe which is connected to the shirt. The authors also developed a customized ECG sensor in the form of two belts of silicon rubber with pure silver fillings designed to improve the accuracy of measurement during the patient's movements with respect to traditional electrodes. Finally, the GSR is measured by passing a small current through a pair of electrodes placed on the skin and measuring the conductivity level. The shirt has a wired connection to the 'Wearable Data Acquisition Hardware' (the correspondent PS) that transmits sensed data wirelessly to the central server, and all sensors are powered by a rechargeable battery. The MagIC system integrates only sensors for ECG and respiration monitoring in the vest, and provides a portable electronic board designed for data collection and motion detection. More specifically, the ECG sensor consists of two woven electrodes made by conductive fibers; the elastic properties of the garment guarantee direct contact with the patient's body (thorax) without requiring gel or other medium. The respiratory frequency is then measured through a textile transducer analyzing the assessment of the changes in the thorax's volume. Finally, the electronic board, in charge of collecting sensed data, is also equipped with a two-axis accelerometer to detect the subject's movements. In fact, to evaluate

[1] Pulse oximetry is generally used to assess heart rate and blood oxygen saturation (SpO2) reliably. It consists of monitoring the pattern of light absorption by hemoglobin. The level of SpO2 is measured detecting the amount of absorbed light at two different wavelengths, while the heart rate is determined observing the pattern over time since blood vessels contract and expand with the pulse [11].

Figure 8.2 Georgia Tech Wearable Motherboard^{TM}. Reproduced by permission of © Georgia Institute of Technology.

the physiological parameters correctly, especially in the case of patients affected by cardiac diseases, it is important to correlate the information with the activity and movements of the patient. The board has a fixed position on the shirt and is connected to the sensors through the conductive fibers of the garment. It communicates with the medical server through a wireless connection. Experimental evaluations demonstrated a close similarity of the ECG signal measured by the MagIC system and a traditional ECG recorder, also during physical exercise, with an accuracy of about 95% [16]. Following the same model, the WEALTHY and MyHeart projects developed a shirt equipped with textile sensors. The former proposes an innovative method for sensor development based on the standard textile industrial processes, while the latter focuses on the enhancement of signal quality and management of a huge quantity of sensed data, which is one of the main challenges for smart clothing. To resolve this issue the MyHeart project proposes two embedded signal processing techniques designed to extract relevant data from physiological sensed data before being transmitted outside the Health BAN (see [14] for detail).

In all of these examples we may note that, even though sensors are developed to be as integrated as possible in a vest that is comfortable for the patient, there are drawbacks that represent a limitation for both user acceptance and continuous and long-term monitoring of physiological signals (especially in daily life). They are related mainly to wires integrated into the fabric, the fixed position of sensors, the presence of a centralized processing unit to elaborate, digitize and transmit all data and the specific structure of the vest [6]. Recent advances in integration and miniaturization of sensors (see Micro-ElectroMechanical Systems (MEMS) and Nanotechnology) allow for the definition of a new generation of wireless sensor networks suitable for several application scenarios, especially in healthcare. Following this line, several alternative solutions to textile sensors for health monitoring have been proposed in the literature. For example, the CodeBlue project [17] proposes a set of wearable health sensors based on the Mote technology. They developed a pulse oximeter integrating an available OEM module for heart rate and SpO2 calculations (BCI Medical Board [18]) whose board is able to relay data on a serial line that can interface with the mote platform. They also developed Mica2/MicaZ and Telos mote platforms providing continuous ECG monitoring by measuring the differential across a single pair of electrodes (Mote-EKG). Finally, they developed a motion-analysis sensor board containing a 3-axis accelerometer, single-axis gyroscope and an EMG (electromyographer[2]). The triaxal accelerometer is used to measure the orientation and movement of a body segment; a gyroscope measures the angular velocity and, combined with an accelerometer, is used to improve

[2] Electromyography (EMG) detects the electromechanical properties of muscle fibres. It requires correct positioning and excellent contact with the skin, in addition to complex signal processing that make the devices bulky and expensive.

accuracy in limb position measurement. The EMG sensor consists of two surface electrodes designed to capture the electrical field generated by depolarized zones in muscle fibres during contraction. Since the root mean square of EMG data is nearly proportional to the force exerted by the monitored muscle, EMG analysis is especially useful in activity recognition. Code Blue motion board was designed originally for monitoring stroke patients' rehabilitation and the efficacy of the care plane for patients affected by Parkinson's disease, but it can be applied in several other scenarios. Finally, it also proposes a RF-based location system (MoteTrack [17]) to locate patients using only the low-power radios already incorporated in the previous sensors (performance analysis shows an 80th percentile location error).

In order to coordinate and support these different sensor platforms, CodeBlue also proposes a middleware framework implemented in TinyOS [19]. It implements a publish/subscribe routing framework to allow multiple sensors to relay data to all interested receivers, a discovery protocol to make the Personal Server able to discover available sensors and a query interface to select sensed data to be downloaded on the mobile device through the use of filters, or specifying the source sensor through a physical address. Thus, CodeBlue represents one of the most complete pervasive healthcare solutions, from the design and development of customized wearable sensors to the definition of a general software architecture involving all the components of the Health BAN. However, some issues arise from an initial evaluation of the system: lack of reliable communications due mainly to patients' mobility, the need for efficient techniques for sharing bandwidth among sensors (e.g. prioritize critical message with respect to standard physiological values) and the lack of security (this is a critical aspect that affects all pervasive healthcare systems).

An extension of CodeBlue software and hardware has been proposed in AID-N (Advanced Health and Disaster Aid Network) [5] as an electronic triage system for medical support in case of disaster. In this case, the three-tier architecture differs mainly from the classical pervasive healthcare system in the second tier, where the concept of PS for data gathering and transmission is designed for the medical personnel and not for the patient. AID-N exploits CodeBlue sensor technology to develop an ETag sensor board able to embed mote-based pulse oximeter and mote-EKG creating low-power and low-data rate ETag devices. In fact, the sensor board communicates with the mobile personal server of care-givers through the IEEE 802.15.4 standard with a maximum data rate of 250 kbps (referring to MicaZ and TmoteSky motes), while the personal server communicates with the remote medical server using the IEEE 802.11 standard. CodeBlue software then allows the care-givers to control multiple ETags simultaneously, creating a mesh network between patients and care-givers in mass casualty events, able to support hundreds of patients. The miTag device in [20] further enhances the electronic triage system of AID-N, introducing additional tags with temperature sensor and GPS to track patients at every stage of disaster recovery (i.e. disaster scene, ambulance, hospital). Regarding the organization of the Health BAN, the system elects one of the miTags on the patient's body to operate as the hub for data aggregation before transmission to the personal server of the care-giver. In addition, miTag introduces the concept of the dynamic health monitoring platform, making the sensor hardware and software able to adjust their configuration dynamically to suit the current scenario. For example, miTag can increase the sensing frequency when the patient's status deteriorates, select the appropriate sensors for the current patient conditions, and enter the sleep-mode appropriately so as to save energy.

Another example of a remote patient monitoring platform has been proposed in the MobiHealth project [3] and the subsequent Awareness project [21]. The former proposes a general monitoring platform based on the classical Health BAN architecture, i.e. self-supporting and front-end supported sensors, SpO2 and ECG respectively, communicating to the PS that transmits data to the central server. Here, intra-BAN communications exploits Bluetooth technology, while extra-BAN communications use UMTS/GPRS standards. Awareness evolves MobiHealth BAN introducing EMG, respiration and temperature sensors in addition to various motion sensors (step counter and triaxal accelerometer), since it is designed essentially for neurological diseases (e.g. epilepsy, spasticity and chronic pains). Here, the main objective is to predict a critical condition, and alert the patient, just before it happens to make him/her able to react accordingly. For this reason the system also provides vibration and auditory signals as biofeedback to the patient.

In contrast with the previous solutions, based on the use of separate wearable sensors for the different physiological signals to be monitored, other health monitoring systems tried to reduce the number of separate devices, integrating all of the necessary sensors in a single wearable device. The Scalable Medical Alert and Response Technology (SMART) system [22] proposes a Waist pack containing SpO2 and ECG sensors, a sensor box with two AA batteries to power the sensors, and a PDA (equipped with a location tag) to collect sensed data. Depending on the chosen SpO2 sensor (located on the finger), its communication with the sensor box and the PDA can be wired through a serial line, or Bluetooth, even though this last solution results in unreliable communications and high power consumption. Regarding the ECG sensor, the sensor box contains a Cricket Mote processor to analyze data and transmit them to the PDA used as PS. SMART is designed for monitoring patients in the waiting areas of emergency rooms, to provide a constant monitoring of unattended patients, at least regarding the most significant vital signals. This is an important application scenario, considering that patients spend several hours in emergency rooms before being visited, based on a preliminary diagnosis. Thus, the monitoring platform can help care professionals prevent critical situations inside the facility.

As a further evolution of integrated wearable sensors for healthcare, the AMON system [23] proposes a health monitoring system integrating basic physiological and activity sensors, communication and processing modules in a single wrist-worn device. AMON monitors SpO2, skin temperature, blood pressure, ECG and the level of physical activity through an accelerator (it mainly detects walking or running pace). The device is also equipped with a cellular engine connected to the GSM network to transmit data to the central server. Experimental evaluation of this wearable device highlights the difficulties in signal acquisition (especially for ECG) with respect to previous distributed systems that place sensors in specific and favourite positions on the body. However, the study demonstrates the feasibility of the integration of multiple health sensors in a single device, improving user acceptance and comfort, especially in case of daily monitoring.

In the next section we present specific examples of wearable sensors and systems for activity and emotion recognition. Regarding environmental sensors useful in health monitoring, their features depend mainly on the specific application scenarios and their possible correlations with the related diseases, thus involving many possible combinations and correlations that we cannot address in this chapter due to lack of space. However, we can say that the use of basic environmental sensors (like temperature, light and humidity) is made easier by their integration in commercial sensor boards, such as the Telos platform used in ActiS sensor nodes [25, 26], or by their deployment in the home environment of the patient (as presented in ALARM-NET system for assisted living and residential monitoring [27]).

8.5 Wearable Sensors for Activity Recognition

As explained previously, the correct diagnosis and monitoring of many diseases can depend strictly on the relationship and correlation of physiological signals and specific user's movements or activities (see Table 8.1). In addition, for specific neurological diseases, emotional parameters can further enhance the description of the patient's health status. Wearable technology can support both activity and emotion recognition establishing accurate relationships among different physiological signals, or developing novel dedicated sensors.

Several of the systems presented in the previous section take into account activity recognition, with particular attention paid to neurological scenarios such as stroke rehabilitation, Parkinson's and epilepsy. However, these solutions exploit inertial sensors (e.g. accelerators, gyroscopes) to evaluate the level of activity of the patient (i.e. walking, running, sitting), but they are not able to detect the exact movement or the specific activity. Where this feature is available we can talk about activity recognition and motion characterization systems [28]. Detailed information about user motion can improve the accuracy of activity recognition providing additional indicators (e.g. user fatigue). Some of the work in this direction has been proposed in the literature, designing and developing innovative wearable sensors. However, the main innovation is represented by the correlation of data derived from motion analysis with the patient's health profile.

As with vital signals monitoring, sensors and systems for activity and motion recognition depend on the application scenario they are designed for. For example, [28] explores the possibility of using wearable force sensors placed on the muscle surface to obtain information about locomotion problems and user fatigue (this could be especially useful in the rehabilitation of patients affected by disorder of the central nervous system, e.g. stroke). Wearable force sensors can be realized as ultra thin foils, or even in textiles, using capacitance change between two conductive layers. Sensed data can be used both as additional source of information, to improve the accuracy of measurements derived from standard techniques (generally EMG and MMG[3]), and as a novel type of information, providing behavioral and physiological indicators. Specifically, the work in [28] demonstrates that locomotion modes can be derived from the relationship between signals from front-leg and back-leg muscles, and that long-term muscle inflation can be used as a muscle fatigue indicator. Thus, it shows that the information derived from this kind of sensor goes beyond that derived from inertial motion sensors, enriching the context derived from classical activity recognition procedures. As a more specific application, [29] proposes the use of force sensors

[3] Mechanomyography (MMG) detects the mechanical oscillation over a contracting muscle by attaching electrodes on the skin overlying the selected muscle.

and fabric stretch sensors (attached to the lower arm) to capture muscle contractions during specific hand and arm movements. Most of the work on wearable sensing for activity recognition is based only on arm motion analysis, since movement of the lower arm can be measured easily and unobtrusively through inertial sensors, while hand action recognition is generally implemented using gloves or other obtrusive instruments. In [29] the main idea is to exploit the analysis of lower arm muscle contraction and circumference variations to detect hand motion. The proposed sensors provide an alternative method to implement motion and activity recognition with respect to the more obtrusive EMG technique that requires several electrodes and complex signal processing schemes. It could be especially useful in cases of rehabilitation to support patients in executing physical exercise correctly, or monitoring their daily activities. However, this work represents only a first step towards specific wearable sensors for muscle and motion analysis and it must be validated in larger studies, considering also that muscle properties depend greatly on usage, age and sex, thus providing different results for different subjects.

As a more general solution for activity recognition in terms of daily activities and life style [30] proposes a wrist-worn device that is able to monitor and log the patient activities continuously using a model based on the 'user's rhythms'. The system exploits environmental sensors such as light and temperature in addition to inertial sensors (accelerometer and tilt switch, used alternatively to save energy) able to detect the level of activity and posture information. The correlation of sensed data improves the accuracy of activity recognition corresponding to specific circadian frequencies (heart rate). The basic rhythm model corresponds to a single day sampled in a 5-minute time slot. In order to initialize the model and support subsequent sensed data, the user is requested to register the high-level information of planned and usual activities following the same time scale, to make the system able to correlate the user's information and sensed data. Specifically, the system stores the start, stop and duration of an activity providing three probability distributions for each activity in relation to heart rate and circadian rhythm. Activities include eating (breakfast, lunch, dinner), driving, sleeping, taking shower, sauna and so on. The rhythm model is trained and evaluated for long periods (by weeks to months) and past activities are used to improve accuracy in recognition of current activities. Preliminary results show that accuracy in specific activity recognition depends mainly on the type of activity and its duration within the one-day period of time (e.g. sleeping is easily recognized since it has a long duration). However, the rhythm model improves the recognition of specific activities with respect to the exclusive use of sensors' data in the case of usual and recurrent activities, while it has no effect on recognizing activities that do not belong to the user's habits. This solution is not designed specifically for the healthcare environment, but it can be integrated in pervasive healthcare systems, especially in the case of remote monitoring applications, enriching the system with information about the life style of the patient. This could improve the monitoring system, adding coaching and counselling features to classical medical feedback, such as alert and updates of the care plan, especially in the case of chronic diseases where a correct life style can improve both the quality and duration of the patient's life.

Nowadays, one of the main diseases highly influenced by life style is obesity. Estimations presented in [31] account for over one billion overweight and 400 million obese patients worldwide, and this trend is increasing. This is mainly due to wrong dietary habits that can involve other important diseases such as diabetes mellitus, cardiovascular diseases and several types of cancer. Thus, dietary monitoring can be seen as another possible application for activity recognition in pervasive healthcare. Original solutions designed for this purpose are based on food intake questionnaires, specifying an estimation of the calories as a manual acquisition method, shopping receipts scanning [32] as well as products' bar codes or patient's voice log [33]. These methods require a constant interaction with the patient and they are generally prone to errors due to imprecision and missing detail. To overcome these limitations [31] proposes an innovative solution based on the use of wearable sensors. More specifically, it focuses on three main activities:

- arm and trunk movements associated with food intake actions. This information is obtained by inertial sensors (accelerator, gyroscopes);
- chewing of foods, recording the sound of food breakdown with an ear microphone[4];
- swallowing activity obtained by EMG electrodes and stethoscope microphone integrated in a sensor-collar.

Using the sensed data the system is able to derive pattern models for dietary activities and improve the event recognition procedures. The approach to detect and classify the activities is divided into three steps: signals segmentation to define search bounds, event detection based on a feature similarity search algorithm and event

[4] The ear canal has been proven to provide the best SNR between chewing and user speaking considered as a noise [28].

Table 8.2 Performance evaluation of dietary activity recognition [32]

	Movement recognition	Chewing recognition	Swallowing recognition
Recall	80%	93%	68%
Precision	64%	52%	20%
Recognition rate	75–82%	85–87%	64%

fusion. Event fusion procedures can combine events of different types (*competitive fusion*) or different modalities of the same type of activity (*supportive fusion*). It is important to note that by using multiple detectors for each event, a competitive fusion method is used to select the final event, while supportive fusion is used to combine the detection of different modalities related to the same activity, to reinforce the final selection. To evaluate the performance of the activity recognition procedure based on these methods, the authors define two indexes: *Recall* as the ratio between the number of recognized events (i.e. events returned and recognized correctly by the system) and the number of relevant events (i.e. events annotated manually as they actually occurred) and *Precision* as the ratio between the number of recognized events and the number of retrieved events (i.e. events returned by the event recognition procedure). For each activity a set of event categories have been defined; regarding movement recognition, four categories were defined for each intake session (i.e. eating meat with fork and knife, fetching a glass and drinking from it, eating a soup with a spoon and eating slices of bread with one hand); regarding chewing recognition, food is divided by consistence (i.e., dry, wet, soft); swallowing recognition does not require specific categories even though its frequency depends on food category. Experimental evaluations show that good results can be obtained in specific dietary activity recognition exploiting different event fusion methods, but further studies are necessary in this field both to identify the categories inside each activity and to correlate the information derived from each activity recognition in order to improve the overall accuracy (in addition to basic information such as meal schedule, intake timing and food quality). Table 8.2 shows a summary of the performance results presented in [32]. Note that we present only the best results among those obtained with the different event fusion methods.

8.6 Sensors and Signals for Emotion Recognition

Emotion recognition has a great importance in healthcare systems dedicated to neurological and neuro-psychological diseases. Since the relationship among physiological parameters, activities and the emotional status of a person is completely subjective and dependent on the health conditions of the patient, it is especially hard to define a set of objective parameters to be monitored and their relationship with specific emotional concepts. In addition, based on medical experience, these patients generally reject the use of pervasive technology, thus few solutions in this field have been proposed so far, maintaining classical solutions based on questionnaires related to patients' activities and feelings. The starting point is to identify possible relationships among physiological signals and emotional status. A summary derived from most of the work presented in the literature is shown in Table 8.3. A more invasive solution is proposed in [37], based mainly on EEG (electroencephalogram) signal analysis, since it has been demonstrated that it generally contains emotional markers. The system is based on a commercially available EEG wearable sensor consisting of an EEG cap, an amplifier and an analog-digital converter, and it is able to distinguish among five different classes of emotions on both valence and arousal dimensions exploiting the IAPS method.

The combination of these parameters is generally used to determine a set of features and inputs for specific learning classifiers able to learn and derive the 'best' result in terms of emotion recognition (in this specific application scenario). Neural networks, Support Vector Machine (SVM), Naïve Bayes and Decision Tree [34] are some examples of learning classifiers used in the systems presented in the following. The classification of the emotional status of a patient is generally defined in terms of *arousal* and *valence* values, whose reference values are obtained through some classical methods. One of the most famous methods is known as the IAPS photo set [35]. It consists of a set of 800 photos classified by a large number of users evaluating how strong the content is (*arousal*) and how positive or negative the content is considered to be (*valence*). In [36] this method is used to initialize the system recording physiological values of the patients looking at pictures with different levels of valence and arousal, to train a neural network classifier, and then test the system on other patients. This work focuses mainly on monitoring EMG, skin temperature and conductivity, Blood Volume Pulse (BVP), ECG and respiration rate. Results presented in [36] show that the estimation of valence values from physiological signals is

Table 8.3 Possible relationships among physiological signals and emotional status

Physiological signals and sensors	Emotional status
EMG as muscle tension measure	High muscle tension generally occurs under stress, but the reference value for this parameter depends greatly on the muscle where it is measured.
Skin Conductivity (GSR)	It increases if the skin is sweaty. It can help differentiating between conflict/no-conflict situations and anger/fear. It is influenced by external parameters (e.g. environmental temperature).
Skin temperature	It decreases when the muscles are tense under strain. It depends also on external parameters.
PPG and ECG to measure heart rate, blood pressure and Blood Volume Pulse (BVP)	Low heart rate variability can indicate a state of relaxation, while high variability can indicate a stress situation.
Respiration rate	Fast and deep breathing → excitement (anger, fear, joy) Rapid shallow breathing → tense anticipation (panic, fear, concentration) Slow and deep breathing → states of withdrawal (depression, calm happiness)
Pupil diameter	Pupil size variation is related to cognitive information processing that, in turn, relates to emotional states (e.g. frustration, stress). It can also be used as indication of affective processing.
EEG	Recognizing emotional markers in EEG signal.

much more difficult than arousal (89.7% with respect to 63.8% considering an error range of 10%), even though the distance between the two parameters decreases greatly considering a light increase in the error range (96.6% with respect to 89.9% with 20% error range).

A more invasive solution is proposed in [37], based mainly on EEG (electroencephalogram) signal analysis, since it has been demonstrated that it generally contains emotional markers. The system is based on a commercially available EEG wearable sensor consisting of an EEG cap, an amplifier and an analog-digital converter, and it is able to distinguish among five different classes of emotions on both valence and arousal dimensions exploiting the IAPS method.

Evaluating the percentage of samples in which the emotion is recognized correctly as classification rate, the system shows a 90% classification rate for both valence and arousal in a case where the same data is used for both training and testing the system, while it falls down to 30% using different data, either using different classifiers or grouping some classes of emotions in a single super-class, simply identifying notions of positive, negative and neutral emotions. Therefore, further work is needed in evaluating the relationship between EEG signals and emotion to improve the accuracy of recognition, but this study has also to take into account user acceptance in wearing this obtrusive equipment or find a more comfortable and unobtrusive solution.

Emotion recognition is an important feature also addressed by the Human Computer Interaction research field, in order to adapt dynamically the user interface and the system's reaction to the affective state of the user. The results obtained in this field exploit wearable sensor technology to define relationships between physiological values and emotional status, and they can be also applied directly in pervasive healthcare systems. For example, [38] proposes a system architecture for the definition of multi-modal affective user interfaces based on emotion recognition. It collects physiological signals – skin temperature, galvanic skin response (GSR), heart rate – in addition to facial expression, vocal intonation and language, to define a database of emotion concepts that maintains a mapping between these parameters and related emotional status. A SenseWear armband is used to collect physiological values while users observe short segments of movies, following the model presented in [39] and selecting a specific set of emotions (e.g., sadness, amusement, fear, anger, surprise). Three different pattern recognition algorithms have been used to evaluate the performance of the system in terms of accuracy of recognition, which has been measured in the range [71%, 83%], comparing system results with emotions reported by users. However, it has been observed that not all people are able to identify accurately single emotions with respect to general feelings (i.e. positive and negative), thus influencing the objectivity of the system evaluation.

Another physiological signal that can be used in emotion recognition is Pupil Diameter (PD). Medical studies showed that pupil size variation is related to cognitive information processing that greatly influences emotional status [40]. In addition, in the Human Computer Interaction field it has been shown that it can be seen as an indicator of affective processing [41]. On this basis, [34] proposes an automatic stress detection system that exploits PD observation in addition to more common physiological parameters (GSR, BVP, skin temperature). To measure PD, an infra-red eye tracking sensor is used to collect eye movements and point of gaze information (see [42] as an example of an eye-tracking commercial device). Considering the combination of all the parameters, the accuracy achieved by the system is in the range [78.65%, 90.1%] using three different learning classifiers. The recognition rate drops dramatically to [53.65%, 58.85%] excluding PD measurement, while it increases to [82.81%, 90.1%] excluding skin temperature.

These results demonstrate the importance of PD as a physiological parameter to be considered in stress and emotion recognition, and considering the new unobtrusive sensor developed for this purpose, additional investigation in this direction could be especially useful for emotion recognition systems. All of the previous systems are based on data acquired from a single subject, thus obtaining a user-dependent system, and requiring from the user a long training procedure before the system is able to recognize his/her emotions. As an alternative solution [43] proposes a user-independent system for emotion recognition based on physiological signal databases obtained by tens to hundreds of subjects following a multi-modal approach (audio, visual and cognitive stimuli) instead of the classical IAPS method. The system exploits skin temperature variation, GSR, ECG and facial EMG as physiological parameters. Applying detection, feature extraction and pattern classification algorithms to those data, the system should be able to improve the classification rate. However, the results show comparable rates with systems based on a single subject. Since it is not feasible to obtain a rigorous definition of emotional status and their relationship with physiological parameters, the possibility of having a general database containing emotions classifications, derived from different subjects and with different shades in terms of valence and arousal, is an important objective for emotion recognition systems, and further investigation in this direction could be especially useful.

Emotion recognition is thus an important part of the multi-parametric monitoring necessary for pervasive healthcare systems, especially in the case of patients affected by neurological and neuro-psychological diseases. These patients are generally characterized by repeated phases of mania or depression, and the best therapy is the ability to recognize the transition phases between normal, manic and depressed conditions in order to make the patient able to react accordingly, even from the psychological point of view. To allow this, a continuous monitoring system is necessary to support patients in their daily life, and several parameters must be involved. Preliminary work focused on the early diagnosis of bipolar disorder is presented in [44], studying the feasibility of a system involving parameters related to insomnia and sleep disorders (heart and respiration rates monitoring in addition to capacitive pressure sensors to monitor sleep motion), activity and emotion recognition, and environmental parameters (to enrich the description of the surrounding context). A first tentative step to evaluate and recognize emotional state in this scenario is based on the analysis of the verbal activities and social contacts or conversations of the patient through automatic speech character identification. In [45], the authors present preliminary results focusing on a set of basic emotional states, but the correlation of this data with sleep analysis and environmental conditions is still the subject of ongoing work. Currently the definition of pervasive solutions for monitoring both mental and stress-related disorders stirs up the research community. This is demonstrated also by the funding of new European projects such as MONARCA [46], focused on bipolar disorder, and INTERStress [47] based on the use of pervasive technologies and virtual reality to support patients affected by stress in their daily activities. Other projects (e.g. Chronius [48] and METABO [49]), dedicated chiefly to chronic diseases, are currently studying the involvement of environmental conditions in health monitoring as further input to multiparametric monitoring. However, this fundamental feature of pervasive healthcare systems requires not only signal analysis and processing, but also reliable communication platforms and interoperability of wireless sensors. Thus, to give a complete overview of wearable computing for healthcare, in the next section we analyse the characteristics of current communication protocols for short-range wireless sensor networks and their main issues for health monitoring.

8.7 Intra-BAN Communications in Pervasive Healthcare Systems: Standards and Protocols

Wireless communications in pervasive healthcare systems represent the conjunction between the generation of sensitive and personal data and its elaboration in order to provide a feedback both to patients and doctors. However, the wireless standards currently available for sensor and personal area networks have several limitations when used in healthcare environments due mainly to the strict application requirements. Specifically, one of the main requirements of Health BANs is low power consumption and radio communications have the greatest impact on it. Thus, low-power communication protocols are necessary to design an efficient and reliable Health BAN. Original solutions aimed at reducing power consumption by exploiting low data rates. In fact, most of them are based on Bluetooth and ZigBee (IEEE 802.15.4) standards to define Intra-BAN communication protocols, while the Extra-BAN communications, involving the rest of the system (i.e. the Personal Server and the medical server), are based mainly on infrastructured networks since those devices have no strict requirements for power consumption. However, in recent years other standards have emerged that are promising for of Intra-BAN communications, such as Bluetooth Low Energy, an evolution of classical Bluetooth standard that greatly reduces power consumption. In this section we provide an overview of all of these standards highlighting their features and their use in e-health systems.

8.7.1 IEEE 802.15.4 and ZigBee

IEEE 802.15.4 represents one of the reference standards for sensor networks communications. In fact, it was designed originally to define physical and MAC layers for very low-power and low-duty network connections in order to allow the deployment of long-lived systems with low data rate requirements. These features fit well the requirements of the Health BAN but the technical detail must be analyzed so as to better understand its impact in this field.

IEEE 802.15.4 can operate in three different frequency ranges: 868 MHz, 902–928 MHz and 2.4–2.4835 GHz. The first band has a single communication channel with a data rate of 20 Kbps, the second has 10 channels with a 40 Kbps data rate each, and the third is divided in 16 channels, each with a 250 Kbps data rate. A device can assume two types of role: Full Function Device (FFD) and Reduced Function Device (RFD). The former can talk to all the others and can operate both as the network coordinator and a simple device. The latter can only talk to an FDD to send small amount of data. Thus, the network must contain at least one FFD device. It is expected that RFD devices will spend most of their operational life in a sleep state to save their batteries, and only wake up periodically to listen the channel in order to determine whether a message is pending.

These roles create two possible network topologies: star topology and peer-to-peer. On the one hand, star topology is the best choice for low-latency communications between a more powerful device and its peripherals. On the other hand, in peer-to-peer topology the network is organized as a multi-hop ad hoc network in which each device communicates directly with the others within its transmission range. Generally, the latter is used to cover large areas in which a single device has not enough power to communicate with all the others. Instead, in the case of a Health BAN, the star topology has the best advantages in terms of higher data rate and the presence of an external coordinator of the network (generally the personal server) that could also be used to access an external power supply.

In this configuration, there are two communication modes: *beacon* and *non-beacon*. In the former, the network coordinator controls the communication directly by transmitting regular beacons for synchronization and control messages such as the start and end of a *superframe*.[5] In this way, the coordinator can communicate with the nodes whenever it is necessary, but the nodes must wake up to receive beacons at regular time intervals. Instead, in non-beacon mode, a node can send data directly to the coordinator using the CSMA/CA technique if required (to avoid power-consuming collisions in case of simultaneous transmissions), but it must wake up and poll the coordinator to receive data from it. In this case the receiver node does not have to wake up periodically to receive the beacons, but the coordinator cannot decide autonomously when to communicate with the nodes. Therefore, the choice between the two communication modes is generally given to upper-layer protocols, depending also on the final application features and requirements.

In fact, on top of 802.15.4 physical and MAC layers, the ZigBee Alliance has defined additional layers dedicated mainly to routing, security and application features. In this chapter we focus mainly on the performance results of this technology in Health BANs, both with simulative and experimental analysis. Specifically, [50] and [51] present the performance results of ZigBee and Bluetooth technologies in order to highlight the advantages and drawbacks of the initial competitors for Health BAN communications (the results related to Bluetooth will be analyzed in the next section).

[5] A superframe is defined as the interval of time between two beacons sending in which nodes are able to transmit (see [63] for details).

The work in [50] focused mainly on battery lifetime evaluation in the case of implanted sensors communicating with an external device as network coordinator (star topology) using ZigBee. In this case, battery lifetime is expected to be on the order of tens of years, to avoid multiple and intrusive operations on the patient. However, analytical model and simulation results showed that, by maximizing the beacon period in order to reduce the number of times the receivers must wake up, the battery is able to reach 15 years' lifetime only under very tight data rate restrictions (on the order of 10 bps for 2.4 GHz band[6]). Therefore, further optimizations of the MAC protocol based on the beaconing approach have been proposed in the literature (S-MAC, T-MAC and B-MAC are some examples summarized in [52] but they mainly present low network throughput and non-negligible delays). Instead, the non-beacon mode results in more efficient performance exploiting larger packets and achieving higher upload and download rates (approximately 20 bps). However, these results are far from the requirements of medical applications that involve a huge quantity of data to be transmitted in almost a continuous way. Even the simulation results presented in [51] revealed the scalability problems of this technology due mainly to bandwidth limitations. In this case, considering an ECG application on a sensor network configured in a star topology, in which the wearable device generates 4 Kbps of data and requires that the additional latency introduced by packing samples and transmission is less than 500 ms, the efficiency of the network drops when more than three sensors are used. To overcome these limitations it is necessary to operate the network protocols in correlation with the requirements of medical applications in terms of data rate and delay. Therefore, it could be useful to move signal processing and preliminary elaboration of sensed data directly to the sensor board. For example, a preliminary analysis could be related to the classification of sensed data based on the frequency of their transmission, e.g. periodic and sporadic, required by the specific application or the amount of data that really needs to be transmitted. For example, [53] proposed an Adaptive Dynamic Channel Allocation (ADCA) algorithm on ZigBee based on the transmission frequency differentiation applied to data derived from an ECG monitoring application. In this physiological signals are classified using two threshold values indicating three health status levels for the patient: good, fair and critical. If a number of consecutive values of a vital signal exceed a specific threshold, the patient status is upgraded/downgraded, indicating also a possible alert to the medical server. Thus, periodical transmissions can be used to monitor the status of the patient and, in case there is a variation in the referenced health status, the application can require an immediate transmission to the central server, impacting thus on the bandwidth requirement of the application. The proposed algorithm tries to reserve bandwidth on the wireless medium in case of emergency transmissions, requesting bandwidth dynamically from neighboring nodes and migrating the transmission on the available bandwidth. In this case nodes share channels and are responsible for their dynamic allocation, guaranteeing a low blocking probability for emergency data transmissions, maintaining low power consumption and reducing critical delays. Naturally, complex processing analysis is required to correlate different physiological signals, that also have external parameters that can influence the health status of a patient. Thus, we have to evaluate carefully the correct trade-off between communications and processing in the development of a Health BAN.

8.7.2 Bluetooth

Bluetooth technology was designed originally for cable replacement and short-range ad hoc connectivity. It operates in the 2.4 GHz ISM frequency band exploiting 79 RF channels of 1 MHz width each, thus defining a maximum transmission rate of 1 Mbps. The building block of a Bluetooth Personal Area Network is represented by the Piconet, i.e. a set of up to eight devices sharing the same physical channel. One of these devices assumes the role of Master (in charge of establishing and managing the communication), and all the others play the role of Slave. These devices are synchronized on the same clock and adopt the same frequency hopping scheme based on a Time Division Multiplexing technique that divides the channel in 625 μsec slots. Transmissions occur in packets that occupy an odd number of slots (up to five) and are transmitted on different hop frequencies with a maximum hop frequency rate of 1600 hops/sec. The communication protocol is divided mainly to in two phases: the discovery phase in which the master device discovers up to seven active slaves in its transmission range and exchanges data necessary for synchronization, and the data exchange. Therefore, data can be transferred between the master and one slave; then the master switches from one slave to another in a round-robin fashion. Two types of communication link are defined: Asynchronous Connection-Less (ACL), an asymmetric point-to-point

[6] These results are obtained by considering a crystal tolerance of better than 25 ppm defined as the initial deviation of the crystal or oscillator frequency as compared to the absolute at 25C.

link between the master and the active slaves using retransmissions to guarantee data integrity; Synchronous Connection-Oriented (SCO), a symmetric point-to-point connection between the master and a specific slave at a regular time interval. The latter is designed mainly for supporting real-time traffic (e.g. voice), while the former is dedicated to data communications as necessary for healthcare applications. Evaluating end-to-end delays, packet loss at the receiving node, and efficiency in terms of the ratio between the successful received data packets and the number of data packets generated by the application layer for that receiver, the simulation results in [51] show that Bluetooth technology presents mainly scalability issues related to the limited number of sensors for the collecting device (max seven slaves for each Piconet) and packet loss problems in case of multiple piconets for the same receiver (master) due to interferences. Even though power consumption during transmission is quite low, the need for Bluetooth devices to be active continuously for device discovery or join new piconets implies higher power requirements. Nevertheless, Bluetooth is one of the most frequently used technologies in Health BAN, probably because it is integrated natively in a high number of mobile devices, while it is not easy to find a smartphone equipped with a ZigBee wireless card.[7] In the last few years, Bluetooth SIG has worked on a new standard aimed at reducing the power consumption of Bluetooth devices, as well as meeting medical application requirements. This standard is called Bluetooth Low Energy and it mainly redesigns the communication protocol while maintaining its basic features.

8.7.3 Bluetooth Low Energy

Bluetooth Low Energy (LE) wireless technology represents the main feature of the latest Bluetooth Core specification (v.4.0) released in December 2009 [54]. It extends the applicability of Bluetooth into low power and low cost applications introducing important features that heated up the competition with ZigBee in the development of efficient and reliable Health BANs. It inherits from the standard Bluetooth specification the operating spectrum (2.4 GHz) and the basic structure of the communication protocol, but it implements a completely new lightweight Link Layer that provides ultra-low power idle mode operation, simple and fast device discovery and reliable and secure point-to-multipoint data transfers. One of the main disadvantages of classical Bluetooth is the time required by devices to discover and synchronize themselves on the same channel, due to the frequency hopping procedure and, consequently, the energy consumed during its execution. In Bluetooth-LE the same procedure is maintained but the number of channels is reduced from 32 to only three. These channels are used for advertising the presence of slaves available to communicate with the master, so that the master node only has to scan three channels to open a connection and start to exchange messages. This procedure takes few msec (less than 3 msec), thus allowing the devices to further save power by staying asleep most of the time and waking up quickly in case of events. The reduction of channels in frequency hopping is also due to a larger modulation index implemented in Bluetooth-LE, increasing the frequency spectrum, and the definition of low-energy consumption filters that require the separation of channels of 2 MHz instead of 1 MHz. In addition, the hopping sequence is simplified in a wrap around sequence instead of pseudo-random, and a functionality similar to the Adaptive Frequency Hopping is maintained in order to detect channels used by other devices and technologies (e.g. WiFi).

Regarding data transfer, Bluetooth-LE inherits 1 Mbps data rate from classical Bluetooth and, in order to provide an ultra-low power transmission, it utilizes short data packets with a dynamic length (8 octects minimum up to 27 octects maximum). This feature, in addition to the fast establishment of a connection, makes this technology especially effective in situations of burst data transfers. In fact, the specification declares that a device can wake up, connect, send some application data and then disconnect again within 3 msec. In this way, the lowest amount of energy is used, maintaining the fastest transmission of event-based data.

Regarding the hardware characteristics of these devices, there exist two types of implementation: single-mode and dual-mode. Single-mode is pure low-energy implementation providing a dedicated controller in highly integrated and compact devices. By contrast, in dual-mode implementation, the LE functionality is integrated into an existing classic Bluetooth controller, allowing the coexistence of these two technologies in the same device, even using the same radio and antenna, resulting in a substantial enhancement of current chips by the new low energy stack with a minimal cost increase. The dual-mode is designed to enable fast adoption of LE functionality in classic Bluetooth applications, such as mobile phones and PDA, through a low cost modification, removing the need to add another radio. Several major mobile phone vendors have indicated that they will adopt dual mode devices in

[7] Mini- and Micro-SD ZigBee cards have recently been launched on the market by a Taiwanese company [64], but the firmware and the related software support is still limited to only a few operating systems.

their upcoming phones [55]. Owing to the double nature of Bluetooth-LE devices, they can generate two types of network topology: star and star-bus. The star topology is considered to be mainly that among single-mode devices only, in which one device assumes the role of Hub and the others the role of Nodes (comparable to the Bluetooth piconet concept, although here there is no a theoretical limit on the number of active slaves). By contrast, the star-bus topology can include both single- and dual-mode devices and even classical Bluetooth devices. Generally, dual-mode devices act as Hubs and the single-mode as Nodes, establishing Bluetooth-LE connections between a Hub and a Node, while the backbone connection between different Hubs is a classic Bluetooth connection. For this reason, in this topology the role of Hub can also be assumed by a classical Bluetooth device connected to dual-mode devices. An example of this topology can be represented by a mobile phone equipped with a dual-mode device that maintains LE connections to single-mode wearable sensors and, at the same time, a classic Bluetooth connection to other standard devices.

This technology fits well with the features and functionalities of pervasive healthcare systems in the case of low data rate requirements. However, where it is necessary to obtain higher data rates we have to take into consideration other technologies such as Ultra Wide Band and 60 GHz millimeter-wave [56], but they are generally used for hospital-centered systems and not for Health BAN communications.

8.7.4 Integrated and Additional Solutions for Health BAN Communications

As shown in Table 8.4, current e-health solutions exploit mainly ZigBee and Bluetooth technologies, but a further enhancement of these systems can be achieved by developing integrated solutions where multiple wireless interfaces on a single mobile device are exploited to communicate with different networks at the same time. For this purpose, the Simple Sensor Interface (SSI) protocol has been proposed within the framework of the MIMOSA FP6 European project [57] as an application protocol that allows a mobile device to communicate and read data from wireless sensors independently of their type, location or network protocol. However, the approach to multiple wireless connections in a Health BAN still has many open issues, related mainly to interference caused by the coexistence of different technologies such as WLAN (mainly for communication with a remote medical server) and ZigBee (as observed in [58]), or ZigBee and Bluetooth [51], in addition to attenuations caused by the human body. Moving around this problem, other work has investigated some alternative communication solutions, such as the body-coupled wireless communication protocol proposed in [59] to improve the trade-off between network performances and power consumption by exploiting the human body as a communication channel. In this case, a method based on the electromagnetic signalling between the polarized contacts of a transmitter and a receiver located on the body is used, allowing a high data rate independent of external influences. Preliminary results show that this method can achieve the same throughput as ZigBee with a high reduction in transmission power. However, the obtrusiveness of this method can impact greatly on its practical applicability in Health BANs, due to its negative influence on user acceptance.

However, in addition to the interference caused by different wireless technologies, a further limitation of the current solutions is represented by the lack of interoperability among different devices. This is due mainly to the proprietary nature of communication protocols and data formatting used by different vendors, so that devices developed by different vendors cannot interact through the same application, even though they support the same wireless technology. To overcome this limitation the IEEE 11073 Personal Health Device group [60] is currently working to develop guidelines and requirements for wireless technologies and applications in healthcare environments, and several industrial partners participating in the Continua Health Alliance [61] are working to develop a unique profile for pervasive healthcare devices.

8.8 Conclusions

Wearable sensors in the healthcare environment obviously improve the quality of measured data allowing patients to move and behave in a manner close to their normal routines while being monitored constantly. Several advances in this technology have been achieved in recent years, making health monitoring one of the hottest research topics in pervasive and ubiquitous computing. However, it is very important to understand the impact of the technology on its final users, evaluating their experience both in *'wearing the technology'* and *'wearing it during their daily life'*. In fact, a patient's acceptance greatly influences the correct and continuous use of the technology, playing a major role in the effectiveness and success of the system. Thus, patients' experiences with current technologies must be taken into account for the design and development of new wearable technologies, in order to make

Table 8.4 Health sensors and platforms for vital signals monitoring

Project	Application scenario	Physiological signals	Wearable Sensors	Networking communications
Georgia Tech Wearable Motherboard (GTWM) [7]	General vital signals monitoring platform with textile sensors.	Heart rate, respiration rate, body temperature, SpO2, voice	EKG, pulse oximeter, voice recorder (commercial off-the-shelf sensors integrated in the garment).	Intra-BAN: wired connections of sensors to the Smart Shirt controller (PS) integrated in the garment (Intra-BAN) Extra-BAN: Bluetooth or 802.11b wireless communication from the controller to the central server (Extra-BAN).
Smart vest [11]	General vital signals monitoring platform with textile sensors.	ECG, PPG, heart rate, blood pressure, body temperature, Galvanic Skin Response.	Development of customized textile sensors (ECG, pulse oximeter, electrodes for GSR measurement) in a shirt.	Intra-BAN: wired connections of sensors to the Wearable Data Acquisition Hardware (PS). Extra-BAN: wireless communication from the PS to the central server.
MagIC [12]	Textile sensors dedicated to patients affected by cardio-respiratory diseases.	ECG and respiration rate. Motion sensors integrated in the electronic board.	textile ECG sensor and a textile transducer for respiration acitivity monitoring. A portable electronic board is equipped with 2-axis accelerometer for motion detection. signal preprocessing module and wireless data transmission to a remote monitoring station.	Intra-BAN: wired connections of sensors to the electronic board (PS). Extra-BAN: wireless communication from the PS to the central server.
WEALTHY [13]	General vital signals monitoring platform with textile sensors.	ECG, EMG, motion detection and temperature.	Strain fabric sensors based on piezoresistive yarns, and fabric electrodes realized with metal based yarns.	Intra-BAN: wired connections of sensors with the WEALTHY box realized with the same conductive yarn used for electrodes. Extra-BAN: wireless communication from the WEALTHY box to the central server.
MyHeart [14]	General vital signals monitoring platform with textile sensors.	ECG and motion detection.	Textile sensors. The main innovation of this system consists in two embedded signal processing techniques to reduce the quantity of data to be transmitted to the medical server.	Intra-BAN: Bluetooth communication between the sensors and a mobile phone. Extra-BAN: GSM communication between the mobile phone and the central server.

(*Continued*)

Table 8.4 (*Continued*)

Project	Application scenario	Physiological signals	Wearable Sensors	Networking communications
Codeblue [17]	General physiological monitoring and motion-analysis dedicated to stroke rehabilitation and Parkinson's disease.	Heart rate, blood oxygen saturation (SpO2), motion analysis	Mote-based pulse oximeter, mote-EKG, motion-analysis sensor board (3-axis accelerometer, single-axis gyroscope, EMG), RF-based localization system (Mote-Track).	Intra-BAN: wireless communication based on ZigBee standard between sensors and PS Extra-BAN: wireless communications between the PS and the central server.
AID-N [5]	Physiological monitoring for medical support in case of disaster or mass-casualty events.	Heart rate, blood oxygen saturation (SpO2).	Use CodeBlue mote-based pulse oximeter and mote-EKG to develop ETag devices.	Intra-BAN: ZigBee standard between ETags and the care-giver personal server Extra-BAN: 802.11 between the personal server and the central medical server.
miTag (medical information Tag) [20]	Patient tracking and monitoring in disaster recovery steps (disaster – ambulance – hospital)	GPS, pulse, blood pressure and SpO2, temperature, ECG.	miTag devices as extension of ETags with GPS and temperature sensor. Dynamic configuration and adaptation of the sensors to the specific scenario.	One of miTag devices on the patient's body is elected as data aggregation hub before transmitting to the personal server.
MobiHealth [3]	General physiological monitoring.	Heart rate, blood oxygen saturation (SpO2).	Pulse oximeter and ECG.	Intra-BAN: Bluetooth communications. Extra-BAN: UMTS/GPRS.
Awareness [21]	Epilepsy and neurological applications.	Extension of MobiHealth adding respiration rate, temperature, and motion-analysis.	Pulse oximeter, ECG, EMG, temperature, motion sensors (step counter, 3D accelerometer).	Intra-BAN: Bluetooth communications. Extra-BAN: UMTS/GPRS. Auditory and Vibration biofeedback to the patient.
SMART [22]	Monitoring in waiting areas of emergency rooms.	SpO2, ECG, location.	Waist pack containing the sensor box (Finger sensor for SpO2 connected to the box, ECG) and a PDA	Intra-BAN: wired or Bluetooth communications. Extra-BAN: wireless communications.
AMON [23]	High-risk cardiac/ respiratory patients	Heart rate, blood pressure, SpO2, skin temp; Activity recognition	ECG, pulse oximeter, temperature, 2-axis accelerator, all integrated in a wrist-worn single wearable device.	GSM communications from the device to the telemedicine center (TMC).
ALARM-NET [27]	Assisted-living home monitoring.	Pulse, SpO2, ECG, accelerometer, environmental parameters.	ECG, pulse oximeter, accelerometer. Environmental sensors: temperature, dust and light.	Intra- and Extra-BAN wireless communications.

them able to reduce their impact on daily life, further improving the quality of sensed data in terms of accuracy and reliability. There is little work that addresses this issue in the literature, and in particular [62] proposes a model of user acceptance based on a pilot study that compares patients' responses to long-term ambulatory Holter arrhythmia procedures with those derived from the use of a wireless ECG sensor for the same purpose. The acceptance model is based on two questionnaires focused on five 'dimensions': hygienic aspects, physical activity, skin reactions, anxiety and equipment. These parameters, collected by asking questions, are then correlated with patient characteristics, like gender and age, and information related to their physical and mental status, in addition to an index called *Pretrial Expectation* in order to evaluate the user's perceptions before wearing the sensors. All of these components form the *Sensor Acceptance Index (SAI)* [62]. The results refer to patient experiences using ECG wireless sensor continuously for three days compared with other remote-care systems. Some important aspects arise from this study. First of all, some patients wish to hide the wireless sensor from the eyes of other people, revealing embarrassment about wearing it in public. Until patients overcome this condition, they will not be able to accept using the technology in their daily activities. Patients also show a need for constant feedback from the system or care professionals; thus the system must be able to provide constant support to patients, both in terms of alerts and suggestions (even as a psychological support). In addition, the strict interaction between the healthcare system and the medical server must be clearly visible to the patients so as to improve their trust in wearing the system. Finally, patients display overall a good degree of confidence in the wearable sensor owing to ease of use and improvement in aspects of hygiene and comfort, with respect to the classical Holter device. Another important aspect in designing novel wearable sensors is the possibility for patients to carry out daily activities such as participating in physical sports, sauna etc, without damaging the system.

All of these aspects influence both the hardware and software design of wearable sensors for healthcare, from wearable characteristics to the ability to correlate physiological, neuro-psychological and environmental parameters that greatly influence the health status of the patients. Low-power, reliable and secure wireless communications, both inside and outside the Health BAN, are also necessary to achieve these objectives. Current technologies and communication protocols focus mainly on optimizing power consumption, moving away from the requirements of medical applications that usually involve a huge quantity of data to be transmitted in almost a continuous way. To better support these requirements we can focus on different research areas. Regarding communication protocols, both novel technologies (e.g. Bluetooth-LE) and the possibility of using multiple wireless interfaces should be investigated further to obtain higher data rates while maintaining low consumption, and to improve the interoperability of wearable sensors with the rest of the system. Signal processing and elaboration of sensed data represent other important research fields in wearable computing. These techniques can be implemented with different features on the sensor board, on the PS, and finally on the central server depending on the hardware and software characteristics of the devices involved. These techniques also enable the correlation of different physiological and non-physiological signals exploiting complex processing analysis, data fusion algorithms and expert systems to make the system able to react correctly to situations that are critical for patient health. In addition, they can be defined so as to improve the adaptability of the system allowing, for example, custom calibration and tuning of the sensing procedure depending on the patient's status within a specific period of time or during a particular activity, or to adapt the power saving policies to the current context (related to both the patient and the surrounding environment).

Therefore, further work on wearable computing is necessary to design and develop a complete and effective Pervasive Healthcare system, and the current results represent a good starting point from which to address the emerging issues.

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