Wellness Sensors Networks: A Proposal and Implementation for Smart Home to Assisted Living

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Wearable Sensors for Human Activity Monitoring: A Review

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***Abstract*— An increase in world population along with a significant aging portion is forcing rapid rises in healthcare costs. The healthcare system is going through a transformation in which continuous monitoring of inhabitants is possible even without hospitalization. The advancement of sensing technologies, embedded systems, wireless communication technologies, nano technologies, and miniaturization makes it possible to develop smart systems to monitor activities of human beings continuously. Wearable sensors detect abnormal and/or unforeseen situations by monitoring physiological parameters along with other symptoms. Therefore, necessary help can be provided in times of dire need. This paper reviews the latest reported systems on activity monitoring of humans based on wearable sensors and issues to be addressed to tackle the challenges.**

***Index Terms*— Wearable sensors, smart sensors, sensor networks, wireless sensor networks, body sensor networks, body area networks, activity monitoring, assisted living, smart home, physiological parameters monitoring.**

I. Introduction

WEARABLE sensors have become very popular in many applications such as medical, entertainment, security, and commercial fields. They can be extremely useful in providing accurate and reliable information on people's activities and behaviors, thereby ensuring a safe and sound living environment. It may be that the smart wearable sensors technology will revolutionize our life, social interaction and activities very much in the same way that personal computers have done a few decades back.

Wearable sensors in the form of panic buttons for emergency help have been in use for a long time and are a huge commercial success [1], [2]. Of course for proper utilization the person needing help should be alert and fit enough to press the button. Most importantly, the panic button should be light in weight so that it is comfortable to wear 24/7.

In recent times there has been a surge of usages of wearable sensors, especially in the medical sciences, where there are a lot of different applications in monitoring physiological activities. In the medical field, it is possible to monitor patients' body temperature, heart rate, brain activity, muscle motion and other critical data [3], [4]. It is important to have very light sensors that could be worn on the body to perform standard medical monitoring. It is possible to measure the blood pressure using wearable sensors through a modified volume-oscillometric technique which eliminates the need for an inflatable pressure cuff [5] and using earphone and mobile device [6].

In the area of sport and training there is an increasing trend of using various wearable sensors. Something, for example, measurement of sweat rate which was possible only in the laboratory based system a few years back is now possible using wearable sensors [7]–[9].

The use of wearable sensors has made it possible to have the necessary treatment at home for patients after an attack of diseases such as heart-attacks, sleep apnea, Parkinson disease and so on [10]–[12]. Patients after an operation usually go through the recovery/rehabilitation process where they follow a strict routine. All the physiological signals as well as physical activities of the patient are possible to be monitored with the help of wearable sensors. During the rehabilitation stage the wearable sensors may provide audio feedback, virtual reality images and other rehabilitative services. The system can be tuned to the requirement of individual patient. The whole activity can be monitored remotely by doctors, nurses or caregivers [13].

A significant amount of research is currently undergoing in the development of a smart sensing system to detect falls of elderly within the home [14]–[16]. Falls are the single largest cause of injury in New Zealand [1] and it may be true for any other country. In New Zealand one in every three people over the age of sixty five years has a fall every year and it increases to one in two for the age of over eighty years [1]. Falls may lead to several major health problems for the elderly and immediate help needs to be provided to reduce the risk of complications. In the absence of quick help, the elderly may suffer pain, go through emotional distress and even develop other medical complications such as dehydration, hypothermia and so on. The wearable smart panic button can also provide a mental peace to the elderly [1], [3].

It is now an everyday news [17] that the wearable electronics devices and technologies, such as heart rate monitors, smart watches, tracking devices (including PillCam) and smart glasses (google glass), etc. are experiencing a period of rapid growth. Fitness devices are by far the most mature market, making up 97% of the projected value in 2013, though this will fall dramatically as smart watch and smart glasses categories develop and products with embedded sensors that track and analyse physical or other movements and activity. Future wearable technology reports that the wearable technologies will impact future medical technology, affecting

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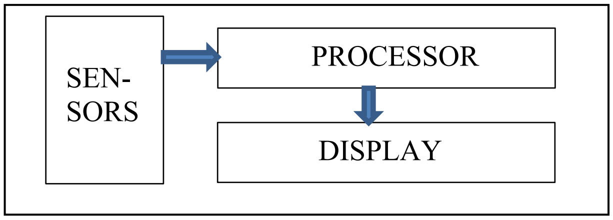

Fig. 1. The block diagram representation of a simple wearable sensing device.

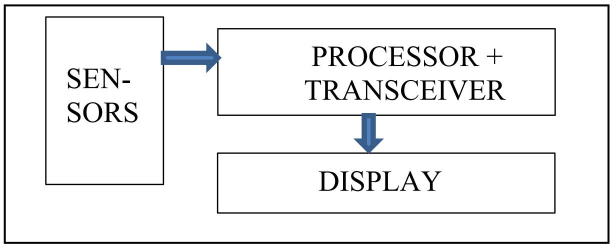

Fig. 2. The block diagram representation of a simple wearable wireless sensing device.

our health and fitness decisions, redefining the doctor-patient relationship and reducing healthcare cost. Looking at the bigger picture, Futuresource research [17] points out that the wearable electronics technologies will undoubtedly continue to expand in consumer sectors, and also acceptance will continue in other sectors, in particular healthcare sectors, and the market growth at a value of over $20 billion by 2017.

The activity monitoring of humans is a very active area of research and a lot of activities are going on. There are many parts which are to be considered in a global way: (1) types of sensors to be used; (2) type of wireless protocols to be employed; (3) monitoring of activities to be considered; (4) methodology to determine activities or extraction of important features; (5) design and development of small, light-weight, powerful and low-cost smart sensor nodes; (6) harvesting of energy for normal operation and communication; (7) ability to be used with the present day mobile devices; (8) flexible to configure the system for a new user without much difficulty.

II. Architecture of the Human Activity Monitoring System

The basic architecture of the human activity monitoring system can be represented with the help of a block diagram; the simplest one is shown in Figure 1. Depending on the task of monitoring, different types of sensors are used. The raw data from sensors are collected by a processor. The data are processed and then displayed on a display. These types of simple wearable devices are used by normal people while jogging, running and other applications where the users look at the display to notice the measured values of the sensors. If the device has the feature of wireless data transmitting capability, the data can be sent to a central station through a transceiver. The block diagram representation of a simple wearable wireless device is shown in Figure 2. The data may or may not be completely processed at the sensing end but most of the data are stored, processed in the computer and extensive display is possible either in a graphical format and/or as a numerical value. Depending on the complexity, the results may be available through an access of a website from a remote place. The block diagram representation of a developed physiological monitoring system is shown in figure 3. The monitoring system may consists of many sensors to measure physiological parameters such as body temperature, heart-rate etc. The picture of the actual developed wearable physiological monitoring system is shown in figure 4 [4], [18]. The system consists of temperature sensor to measure the skin temperature, heart-rate sensor as well as accelerometers to detect any fall that may occur. All the measured physiological data are collected by a microcontroller to process and analyze. Based on the processed data the central controller may either generate a warning message to the caregiver based on the current physiological situation of the person being monitored and/or may help to detect early disease and any possible health threat [19].

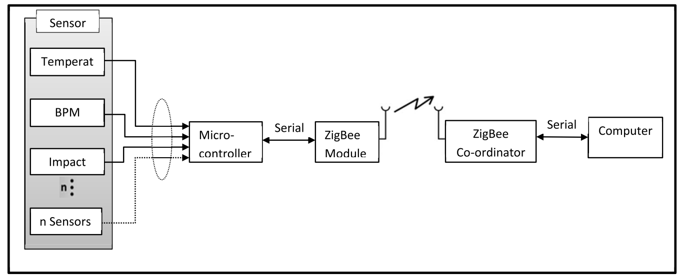

Fig. 3. The block diagram representation of the Human Activity Monitoring (HAM) system [18].

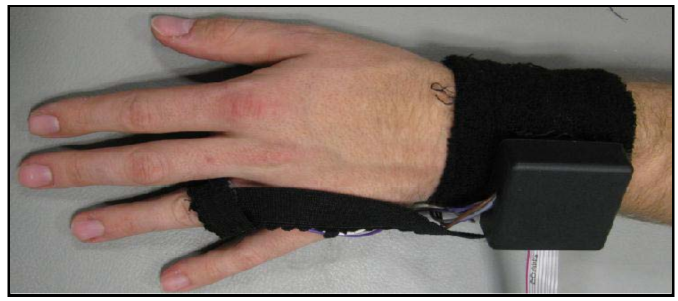

Fig. 4. Picture of the developed wearable physiological parameters monitoring system [4], [18].

III. Sensors for Human Activity Monitoring

In this section we will review a few sensors which are commonly used for monitoring different human activities. Sensors are fundamental elements of the whole monitoring system and should measure the physiological parameters of interest accurately and reliably over a long duration. The rapid development of microelectronics, micromechanics, integrated optics and other related technologies has enabled the development of various kinds of smart sensors to sense and measure data more efficiently and faster, with lower energy consumption and less processing resources.

Body temperature is one of the common physiological parameters measured by wearable sensors for human activity monitoring. The variation in temperature measured on the skin can give an indication of what is happening with the person's body temperature and can be used to detect the symptoms of medical stress that might lead to various health conditions, including stroke, heart attacks and shock. The measurement of body temperature is extremely useful for determining the physiological condition as well as for other things such as activity classification [20], [21], or even harvesting energy from body heat [22].

The next most common physiological parameter is the heart rate of the person under monitoring. Heart rate is a precisely regulated variable, which plays a critical role in health and disease of human. There are many methods available to measure heart rate of a person; Photoplethysmography (PPG) based technology [23], [24], sound based [25], based on changes on brightness of person's face [26], and so on.

Accelerometers are very commonly used in monitoring of human activity and basically are used to measure acceleration along a sensitive axis and over a particular range of frequencies. They can be used for many purposes such as detection of fall [27]–[29] movement and analysis of body motion [28], [29] or a subject's postural orientation [30], [31]. There are several types of accelerometers available based on piezoelectric, piezoresistive, or variable capacitance methods of transduction. Usually all of them employ the same principle of operation of a mass that responds to acceleration by causing a spring or an equivalent component to stretch or compress proportionally to the measured acceleration [27], [30]. In [32] the heart rate has been combined with body movement intensity, calculated on the average acceleration of multiple accelerometers attached to different parts of the body to estimate energy expenditure during physical activity.

Wearable ElectroCardiogram (ECG) sensors are also used for short-time assessment of cardiovascular diseases, especially for people with chronic heart problems. The ECG signal provides very useful information about the rate and regularity of the heart beats, which are used in diagnosis of cardiac diseases. A low power high resolution Thoracic Impedance Variance and ECG monitoring has been developed and incorporated in a compact plaster sensor form for wearable low cost cardiac healthcare [33]. An asynchronous analog-to-information conversion system has been introduced for measuring the RR intervals of the ECG signals [34]. The system contains a modified level-crossing analog-to-digital converter and a novel algorithm for detecting the R-peaks from the level-crossing sampled data in a compressed volume of data [34].

The above sensors are the most commonly used sensors for activity monitoring of humans. There may be many other sensors employed depending on special requirement or critical needs. A flexible, textile capacitive sensor fabricated from conductive textile patches to measure capacitance of the human body has been reported [35] which could reveal information of human activities such as including heart rate and breathing rate monitoring, hand gesture recognition, swallowing monitoring, and gait analysis. An amperometric sensor composed of a multiwall carbon nanotube (MWNT) functionalized nylon-6 mat to quantify the amount of sodium ions in sweat in real-time has been designed and developed [36]. Wearable micromachined sensors can be very powerful in providing accurate biomechanical analysis under ambulatory conditions [37]. The possibility of development of wearable skins that can monitor, sense, and interact with the world around us in a perpetual way, thus significantly enhancing ambient intelligence and quality of life has been discussed [38]. It is expected that the potential applications of wearable technologies will include the early diagnosis of diseases such as congestive heart failure, the prevention of chronic conditions such as diabetes, improved clinical management of neurodegenerative conditions such as Parkinson's disease, and the ability to promptly respond to emergency situations such as seizures in patients with epilepsy and cardiac arrest in subjects undergoing cardiovascular monitoring [39].

IV. Sensor Networks for Human Activity Monitoring

The architecture and the platform of the sensor networks of the HAM system play a significant role for continuous monitoring of physiological parameters especially of the elderly or chronic patient. The network should be selected based on cost, performance, ease of configuration, addition of extra sensor nodes, range and power consumption etc. A comparison of different IEEE protocols currently available is shown in Table I [40]. There may be different ad-hoc networks on which research are currently undergoing. A healthcare monitoring architecture combination of three network tiers providing pervasive, secure access to wearable sensor systems has been reported [41] in which the design of the wireless sensor motes involve a Bluetooth chip with enhanced security schemes. A few mobile health technologies including wearable sensors for electrodermal activity (EDA) and mobile plethysmography as well as mobile phones and the supporting wireless network architecture has been presented [42]. The development of a fall detection system based on a combination of sensor networks and home robots has been presented [43]. The sensor network architecture comprises of body worn sensors and ambient sensors distributed in the environment. The software architecture and conceptual design home robotic platform along with the performance of the sensor network in terms of latencies and battery lifetime are discussed. A mobile platform consists of a wearable sensor system for collecting algorithm training data in the lab, and a mobile phone application used to deliver therapeutic interventions as triggered by real-time sensor data for cognitive behavioral therapy (CBT) developed for an ongoing study for patients with drug-addiction and post-traumatic stress disorder (PTSD) has been presented [44]. A low-cost, low-power wireless sensor platform implemented using the IEEE 802.15.4 wireless standard, and describing the design of compact wearable sensors for long-term measurement of electrodermal activity, temperature, motor activity, and photoplethysmography has been described [45].

A Body Area Network based on wireless sensors has been optimized in for long-term recording and analysis of walking and running gaits under extreme conditions [46].

TABLE I
COMPARISON OF DIFFERENT IEEE COMMUNICATION PROTOCOLS [40]

Standard	ZigBee **(IEEE 802.15.4)**	Blue-Tooth **(IEEE 802.15.1 WPAN)**	WiFi **(IEEE 802.11 WLAN)**	WiMax **(IEEE 802.11 WWAN)**
Range	100 m	10 m	5 km	15 km
Data rate	250-500 kbps	1 Mbps-3 Mbps	1Mbps-450 Mbps	75 Mbps
Bandwidth	2.4 GHz	2.4 GHz	2.4, 3.7, and 5 GHz	2.3, 2.5 and 3.5 GHz
Network Topology	Star, Mesh, Cluster Tress	Star	Star, Tree, P2P	Star, Tree, P2P
Applications	Wireless Sensors (Monitoring and Control)	Wireless Sensors (Monitoring and Control)	PC based Data acquisition, Mobile Internet	Mobile internet

The optimization of the embedded software, the communication and time-synchronization protocols, and the low energy consumption of the devices has been carried out. A wearable sensor system for reading Braille uses a compact tactile sensor system, made up of a polyvinylidene fluoride (PVDF) film for the sensory receptor [47]. The sensor is mounted onto a fingertip and moved over Braille manually to obtain the output. A robust recognition system has been developed to analyze the waveforms of the signals obtained from the movements of the fingers. A new scheme to identify the locations of wearable sensor nodes in a wireless body area network (WBAN) automatically has been presented [48] enabling unassisted sensor nodes continuously monitor node locations without anchor nodes or beacons. The authors have experimentally demonstrated an enhancement of the scheme aiming to reduce false-positive (Type I) errors in conventional accelerometer-based on-body fall detection schemes. The authors have explored on-body energy management mechanisms in the context of emerging wireless body area networks [49]. It characterizes the dynamic nature of on body links with varying body postures which helps in developing a WBAN-specific dynamic power control mechanism for optimal power assignments. A multi-layer task model based on the concept of Virtual Sensors to improve architecture modularity and design reusability in Body Sensor Networks (BSNs) has been presented [50]. The developed model has been applied in the context of gait analysis through wearable sensors. Wireless Body Area Networks (WBAN) is seen as a great potential in improving healthcare quality, and consequently used a in a wide range of applications from ubiquitous health monitoring and range of computer assisted rehabilitation to emergency medical response systems [51]. The security and privacy protection of the WBAN is a major unsolved concern, with challenges coming from stringent resource constraints of WBAN devices, and the high demand for both security/privacy and practicality/usability. Though many researches on BSNs are reported, there is still a significant gap in the current research activities on BSNs to meet the requirements of medical monitoring applications. A secure and resource-aware BSN architecture enabling real-time healthcare monitoring, especially for secure wireless electrocardiogram (ECG) data streaming and monitoring has been presented [52]. A cross-layer framework has been developed based on unequal resource allocation to support biomedical data monitoring applications. In the developed framework important information (e.g., major ECG data) has been identified, and extra resources are allocated to protect its transmission. The reported work in [53] focuses on the Wireless Sensor Network (WSN) enhancements considering User Quality of Experience (QoE), mainly oriented to reduce energy consumption and required data transmission and consequently improving the autonomy and range of the sensors. It is seen that the sensor network is capable of handling the activities of person wearing sensors for monitoring different activities.

V. TYPES OF ACTIVITY MONITORING AND METHODOLOGIES

There can be a great number of activities to be monitored using wearable sensors and consequently the methodologies will also be different. The data from unobtrusive, light-weight, and power efficient wearable sensors can be used to recognize movement patterns while performing various activities. The usual methods for activity recognition rely on supervised learning requiring substantial amounts of labeled training data. It is a huge challenge to obtain accurate and detailed annotations of activities which prevents the applicability of these approaches in real-world settings. A new learning scheme based strategy for activity recognition that substantially reduces the required amount of annotation and effectively leverage such sparsely labeled data together with more easily obtainable unlabeled data has been reported [54]. One interesting area of wearable sensors in sports and exercise is to use the collected data to map real-world activities directly to the games, then, developing the recognition system in a fashion to produce an enjoyable game. It has been reported that the players with wearable sensors playing a game with near-realistic motions was shown to be an enjoyable, active video exergame for any environment [55]. Though wearable devices are now used in many applications, these devices have not penetrated into clinical practice, primarily due to a lack of research into “intelligent” analysis methods that are sufficiently robust to support large-scale deployment. One of the bottlenecks is the generation of large false-alarm rates, and an inability to cope with sensor artefact in a principled manner. A novel, patient-personalized system for analysis and inference in the presence of data uncertainty, typically caused by sensor artefact and data incompleteness has been presented [56]. The study has also demonstrated the method using a large-scale clinical study in which 200 patients have been monitored using the system [56]. A wearable ECG sensor in combination of an appropriate wireless protocol for data communication with capacitive ECG signal sensing and processing has been proposed [57]. The ANT protocol was used as a low-data-rate wireless module to reduce the power consumption and size of the sensor. An alternative approach for heart rate measurement using sound signals received from a microphone worn by a person has been presented [58]. The system can be used as an alternative to ECG system which requires skin-contact. On the other hand, recording of posture and self-propulsion data, as well as data on bulk movement of individuals or populations are very useful in biomechanics, neurosciences, ecology, and animal biology and so on. Data may include, for example, joint angles position, velocity, and acceleration of limbs, ground reaction forces and the overall motion of the body with respect to a reference frame of the ground. A long-term analysis of the performance of an athlete using a network of embedded wearable sensors has been developed and was tested during the 2010 "Sultan Marathon des Sables" desert race for six days of the competition [46]. Wireless body sensor networks can also be used to ubiquitously detect and monitor mental stress levels, enabling improved diagnosis, and early treatment. A new spectral feature of estimation of the balance of the autonomic nervous system by combining information from the power spectral density of respiration and heart rate variability has been presented [59]. Based on a logistic regression model the developed feature set is able to discriminate between two mental states with a success rate of 81% across subjects. In Parkinson's disease, essential tremor, dystonia, chronic pain, major depression and some other diseases sometimes Deep Brain Stimulation (DBS) method is used for the treatment of movement and affective disorders. Physicians determine the optimal settings for deep-brain stimulation by clinically testing different combinations of various stimulation parameters. Data from patient-worn sensors following the adjustment of stimulation settings could be the key in optimizing deep-brain stimulation and has been reported [60]. An Incremental Diagnosis method (IDM) comprised of a naive Bayes classifier generated by supervised training with Gaussian clustering has been reported to detect a medical condition with the minimum wearable sensor usage by dynamically adjusting the sensor set based on the patient's state in his/her natural environment [61]. Diagnosis and treatment of behaviorally based voice disorders can be improved using the data obtained from wearable sensors. The development of a new, versatile, and cost-effective clinical tool for mobile voice monitoring that acquires the high-bandwidth signal from an accelerometer sensor placed on the neck skin above the collarbone has been reported [62]. A smartphone has been used as a data acquisition platform for signal processing based on traditional ambulatory voice measures (f0, SPL, phonation time) and model-based estimation of glottal airflow properties. Wearable biophysiological sensors may enable us to measure how the environment and our experiences impact our physiology. An architecture and implementation of a system for the acquisition, processing, and visualization of biophysiological signals and contextual information has been presented [63]. The electrodermal activity wrist sensor worn by the users that measured their autonomic arousal. A novel ubiquitous upper-limb motion estimation algorithm has been proposed which concentrates on modeling the relationship between upper-arm movement and forearm movement [64]. A link structure with 5 degrees of freedom (DOF) to model the human upper-limb skeleton structure has been developed. Parameters are defined according to Denavit–Hartenberg convention, forward kinematics equations were derived, and an unscented Kalman filter has been deployed to estimate the defined parameters. The potential of incorporating a real-time biofeedback system with artificial intelligence for wobble board training, aimed at improving ankle proprioception has been reported [65]. The biofeedback system depended on Euler angular measurements of trunk and wobble board displacements and a fuzzy inference system was used to determine the quality of postural control. Wearable sensor technology has been reported in an unforgiving environment of the martial arts sparring ring [66] so that the piezoelectric force sensors on body protectors would help taekwondo judges and referees to score tournament matches. Overall, it is seen that the possibility of using wearable sensing technologies are enormous and more and more new applications and methodologies are reported.

VI. Design Challenges of Wearable Sensors for Human Activity Monitoring

The research and scientific communities are working hard to design and develop smart wearable devices to be used for continuous monitoring of different human activities for twenty four hours and seven days a week. There are several challenges faced on design, development, fabrication, implementation and utilization cum continuous monitoring. While designing wearable devices there are always design challenges from the hardware and software constraints arising from the form-factor, light-weight and low energy operations, as well as there are safety requirements such as avoidance of physical injury. The physical impact of a sensor operation needs to be taken into consideration and can be addressed by appropriate design of multiple sensor components such as processor, radio, and optimization of data algorithm. While the sensors are placed on the body, the risk of thermal injury to tissue may also be considered and can be reduced by limiting the sensing frequency as well as wireless frequency, the computation power, and the radio duty cycle of the body worn sensor. A novel non-linear optimization framework has been presented to consider safety and sustainability requirements that depend on the human physiology and derive system level design parameters for wearable sensors application [67]. In wireless wearable sensors different data sources generate time-varying traffic, the volume of which may be large resulting in intolerant latency. It is a huge challenge to ensure that the most significant data can always be delivered in a real-time fashion. Moreover, data transmission may suffer from deep fading and packets loss due to the dynamic on-body channel induced by movements and surrounding environment. So energy-efficient medium access control (MAC) is crucially needed to allocate transmission bandwidth and to ensure reliable transmission considering WBAN contexts, i.e., time-varying human and environment [68]. The most important requirements for an effective software framework, enabling efficient signal-processing applications have been reported [69]. Signal processing in node environment (SPINE), an open-source programming framework, designed to support rapid and flexible prototyping and management of sensor applications has been presented. It has been shown that SPINE efficiently addresses the identified requirements while providing performance analysis on the most common hardware/software sensor platforms. A health monitoring system consisting of wearable sensors such as ECG, temperature, skin humidity and accelerometer and smartphone based network has been reported to provide tele medical services [70]. The big challenge of the work is to have a comfortable wearable sensor system which can be worn by the patient or the individual continuously without any kind of discomfort. The issue of privacy, power consumption, reliable data collection, and patient identification also poses challenges towards the development of wearable sensing system for continuous activity monitoring. A nonlinear, reconfigurable architecture for the audio sensor interface has been proposed to address some of these challenges [71]. An overview of unobtrusive sensing platforms either in wearable form or integrated into environments is presented [72], [73]. Issues such as user acceptance, reduction of motion artifact, low power design, on-node processing, and distributed interference in wireless networks still need to be addressed to enhance the usability and functions of these devices for practical use. The challenges for design, development and fabrication of sensors for monitoring continuous activities in a home environment for determination of wellness of elderly are reported [74]–[88]. The enormous amount of data obtained from the sensors put a huge burden on the system in terms of storage, analysis and future use. The misuse of data may create a huge problem on the acceptability of the system in the society so the necessary security issues need to be addressed in the design of embedded wearable sensors [89] as well as interoperability, connectivity and energy management should be taken care [90]. The challenge to provide a continuous supply of energy for normal operation as well as communication of measured data to the central coordinator is to be solved to make it acceptable to wider community.

VII. Energy Harvesting Issues for Wearable Sensors

Continuous supply of energy is one of the paramount importance for making the wireless wearable electronics sustainable in long-term use. Although a huge amount of effort has been made to make the electronics sympathetic to power, the communication system is the main culprit to consume most of the energy. An energy harvesting scheme to feed power continuously to wearable sensors and electronics will make it more attractive and increase the acceptability. A flexible energy harvesting mechanism equipped with an ultralow power management circuit (PMC) specially designed on a flexible PCB to transfer near maximum electrical power from the input solar energy source to store in the supercapacitor for powering the wireless sensor node has been reported [91]. A flexible, robust and light weight antenna can play a significant role in wireless power transmission related to wearable sensors. A novel wideband polarized textile antenna for low-power transmission in the 2.45 GHz ISM band has been presented [92]. The wide impedance and axial ratio bandwidths make it suitable for low microwave power transmission to a wearable sensor system. Rechargeable battery along with some kind of energy harvester is becoming common to address the issue. If the battery can be eliminated from the system it can solve a huge problem. A low-power, battery-free tag for Body Sensor Networks has been reported [93]. It harvests RF energy from the environment using an external antenna and uses backscatter modulation to send data to a remote base station. It is extremely important to know how much is the requirement of energy which is difficult to measure as it depends on many factors such as data size, rate of communication and so on. A neural network based activity classification algorithm to estimate energy expenditure has been presented [94]. Two representative neural networks, a radial basis function network (RBFN) and a generalized regression neural network (GRNN), were employed as energy expenditure regression (EER) model for performance comparisons. Power Efficiency through Activity Recognition (PEAR) framework has been presented using an ECG-based body sensor network addressing real-world challenges in continuously monitoring physiological signals [95]. A patch-type healthcare sensor in combination with a health-monitoring chest band without expensive batteries and Ag/AgCl electrodes consuming only 12 μW of power supplied wirelessly has been reported [96], [97] and can be used for monitoring of health parameters continuously. Wearable sensors while designed need to take a holistic view as human body is a highly dynamic physical environment that creates constantly changing demands on sensing, actuation, and quality of service (QoS) [98], [99]. The network for wearable sensors must simultaneously deal with rapid changes to both top–down application requirements and bottom–up resource availability to make it sustainable for long-term monitoring.

VIII. Current Market Situation and Future Trends of Wearable Devices

Though the research and development on wearable devices has reached a stage where it can be used as normal household items, the high cost is still holding it back. From a commercial perspective, the prices of the product need to come down to a level so that people can afford them [100]. There will be a huge market in a growing aging population in Asian countries

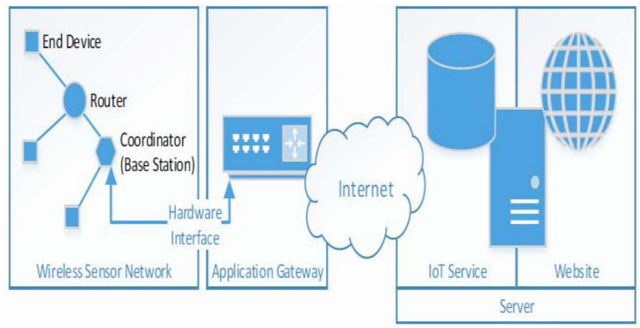

Fig. 5. The complete diagram of an implemented activity monitoring system [77], [78].

Fig. 6. Human emotion recognition system [97].

along with the developed countries but the price point has to come down. As per the estimate [100], the wearable consumer devices such as fitness trackers, smart glasses and smart watches will be sold over 40 million in 2014 and will be approximately 100 million in 2015. The other challenge for wearable electronics to be successful is to sustain the interest so that it is not only being considered as only a shiny object but also a useful one with adequate functionality. The consumers need to be convinced that it is not only notification but beyond that. The data from the wearable sensors may be used for long-term health monitoring and may predict the future health condition. The necessary block diagram representation in such a system is shown in figure 5 [77], [78]. The security issue needs to be properly addressed to make the monitoring system acceptable to the wider community without any fear and/or anxiety.

In light of the above discussion, there is a huge glimpse of hope that wearable device, Apple Watch, will be with us which will be like strapping a computer on our arm [101]. The watch is expected to be personal and intimate and is based on technology attempting to colonize our bodies. It is designed to track our movement, listen to our heartbeat and puts our whole body on line. The data from the wearable devices may be used to determine the emotion of the person Under monitoring too, an experimental platform as shown in figure 6 has been reported [102]. Or, may be the time will come when the whole computer may be fabricated in such a way that it will be possible for the human to wear it as a small device [103].

IX. Conclusion

The paper has reviewed the reported literature on wearable sensors and devices for monitoring human activities. The human activity monitoring is a vibrant area of research and a lot of commercial development are reported. It is expected that many more light-weight, high-performance wearable devices will be available for monitoring a wide range of activities. The challenges faced by the current design will also be addressed in future devices. The development of light-weight physiological sensors will lead to comfortable wearable devices to monitor different ranges of activities of inhabitants. Formal and Informal survey predicts an increase of interest and consequent usages of wearable devices in near future, the cost of the devices is also expected to fall resulting in of wide application in the society.

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