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Increasing trend of wearables and multimodal interface for human activity monitoring: A review

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ABSTRACT

Activity recognition technology is one of the most important technologies for life-logging and for the care of elderly persons. Elderly people prefer to live in their own houses, within their own locality. If, they are capable to do so, several benefits can follow in terms of society and economy. However, living alone may have high risks. Wearable sensors have been developed to overcome these risks and these sensors are supposed to be ready for medical uses. It can help in monitoring the wellness of elderly persons living alone by unobtrusively monitoring their daily activities. The study aims to review the increasing trends of wearable devices and need of multimodal recognition for continuous or discontinuous monitoring of human activity, biological signals such as Electroencephalogram (EEG), Electrooculogram (EOG), Electromyogram (EMG), Electrocardiogram (ECG) and parameters along with other symptoms. This can provide necessary assistance in times of ominous need, which is crucial for the advancement of disease-diagnosis and treatment. Shared control architecture with multimodal interface can be used for application in more complex environment where more number of commands is to be used to control with better results in terms of controlling.

1. Introduction

Activity monitoring aims to monitor the actions of agents obtained from a number of observations on the actions of agents and conditions of the environment. Activity recognition plays an important role in ambient living environments to assess changes from the normal behavior of elderly people (Uslu et al., 2013). The objective of activity monitoring is to analyze or interpret the ongoing events from data automatically. Since 1980s, this field has grasped the attention of many researchers due to its ability to provide personalized support for several applications which include patient monitoring, surveillance and many different varieties of systems involving interactions between machines and persons such as Brain-Computer Interfaces (BCI).

Activity monitoring includes two processes: data acquisition followed by classification of acquired data. The acquisition of data includes acquiring the bio-signals and signal preprocessing. The bio-signals can be EEG, EOG, EMG or ECG depending upon the application. Signal preprocessing includes amplifying, filtering, averaging, extracting relevant features to be used as training data for classifier etc. For classification, various methods are used such as least squares (Marquardt, 1963), Knearest neighbors (k-NN) (Cunningham and Delany, 2007), hidden Markov method, artificial neural networks (ANN) (Hopfield, 1988) decision tree classification and support vector machines (SVM) (Gunn, 1998). Data acquisition process has two different approaches: one is the traditional approach which uses external sensors such as cameras or other monitoring devices (Lin, 2009) and the second one is the newly introduced approach which uses wearable wireless sensors. Both the approaches use different types of electrodes to acquire the physiological signals. These electrodes can be active or passive electrodes as per requirement and the positions of the electrode placement can be signal-dependent as well as application-dependent. For example, to acquire the EOG signal for vertical movement of eyeballs, electrodes are placed above and below the eyes and for horizontal movement of eyeballs, electrodes are placed on right side of right eye and left side of left eye. For EEG recording, electrodes are placed according to the 10–20 International system. In the traditional approach, sensors are fixed at predetermined places, so the conjectures are fully based on the discretionary interaction between person under monitoring and sensors used. Examples of external sensing approach are Intelligent Homes (Englebienne and Krose, 2010; Tolstikov et al., 2011; Yang et al., 2011; Sarkar et al., 2011). However, in the second approach, sensors are attached to the human body. Human Activity Recognition (HAR) systems based on wearable sensors can be categorized in two stages. One is learning approach, may be supervised, unsupervised or semi-supervised. In the second stage, depending on the response time, these approaches may be either offline or online.

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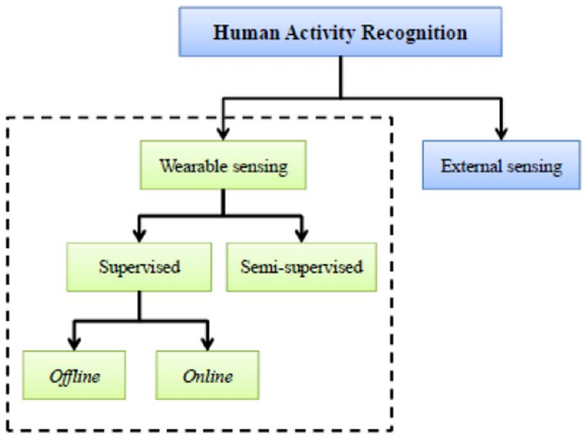


Fig. 1. Approaches of Human Activity Monitoring (Lara and Labrador, 2013).

Online approaches immediately recognize the action performed and give feedback accordingly. While offline schemes require more time to respond to the actions performed. Offline scheme demands high computation and is suitable for applications that do not demand immediate feedback in real-time. The hierarchy of these two approaches has been shown in Fig. 1. These two approaches of HAR systems are used for different purposes and both are having different challenges (Lara and Labrador, 2013). Continuous increase in population besides a consequent aging portion has forced rapid rises in health-care and health maintenance costs. Apart from that, there are many technical challenges at the designing point of view of activity monitoring systems. As even the same person does not act in the same way for the same reason every time and some different activities may show similar behavior. Due to these uncertainties and randomness, recognition accuracy decreases significantly. To overcome this problem, the healthcare or HAR system is searching for some systems having wearable wireless sensors in which continuous monitoring of patients is possible in real time even without hospitalization. This may be a complete transformation of existing healthcare system. There are various applications of real-time activity monitoring systems. In clinical applications, continuous monitoring of physically or mentally disabled inhabitants has become important for their safety. Similarly, interactive or virtual games like simulators may improve person's experience and can produce more enjoyable game virtually.

The block diagram of a simplest architecture of the HAR system is represented in Fig. 2. A number of sensors are used to handle different monitoring tasks (Malhi, 2010). Sensors may be used to measure attributes such as motion, location, temperature, ECG (Iglesias et al., 2011; Choujaa and Dulay, 2008; Juha et al., 2006; Jatobá et al., 2008). Sensor data is collected and after analysis of acquired data, made these data available to the patients, caretakers, wearers or healthcare professionals. The goal is to improve the management and care-delivery, to engage patients and encourage independent living (Rodgers et al., 2015).

2. Wearable Sensors

Wearable sensors are typically wireless tiny sensors enclosed in bandages or some patches or something that can be worn. It may be a ring, shirt, skin patches, watch, or exoskeletons. Ring sensor and smart shirt are shown in Fig. 3(a) and Fig. 3(b). Sensitive biological elements, transducer, and associated electronics are the components of wearable biosensors. Calorimetric, Potentiometric, Amperometric, Optical, Piezo-electric biosensors and immunosensors are different types of wearable sensors. The data acquired from these wearable sensors are processed as per requirement for a particular application. Wearable sensors are completely unobtrusive devices that help physicians to overwhelm the restrictions of traditional technologies. Through wearable systems, biological signals can be continuously acquired wirelessly and thus patients can be monitored remotely. These sensors have applications for the persons suffering from severe diseases like Parkinson disease or heart-attack (Mariani et al., 2013; Chen et al., 2011). For example, ring sensor shown in Fig. 3(a) is used to monitor heart rate and oxygen saturation. It is an optical biosensor based pulse oximetry sensor. Every time when the heart muscle contracts, a pressure pulse is passed through circulatory system. This pressure pulse causes displacement in vessel walls when the pulse travels through the vessels. This displacement changes by photoelectric method and can be measured at different points on the human body to detect pulsatile blood volume. Light is emitted from LED placed on the wearable ring sensor shown in Fig. 3(a) and travelled through artery. Blood is forced to extreme points with every heart contraction and blood flow amount increases in the finger. As a result, optical density of transmitted light through the finger reduces. Therefore, functioning of heart is monitored just by measuring alteration in this optical density. Ring sensor also has a trans-receiver for bidirectional communication and for uploading the data at a point. However, ring sensor has a major disadvantage that a limited number of physiological parameters can be monitored with this sensor.

A wearable smart shirt shown in Fig. 3(b) is a device which tracks some vital analytes of human body such as breathing rate, body temperature, respiration rate etc. by using optical and electrical fibers. These fibers are conductive and are woven into the fabric of the shirt. The biological sensors are used to sense the presence as well as concentration of a substance to be monitored. It can be very useful for sports performance monitoring, medical care, hazardous applica-

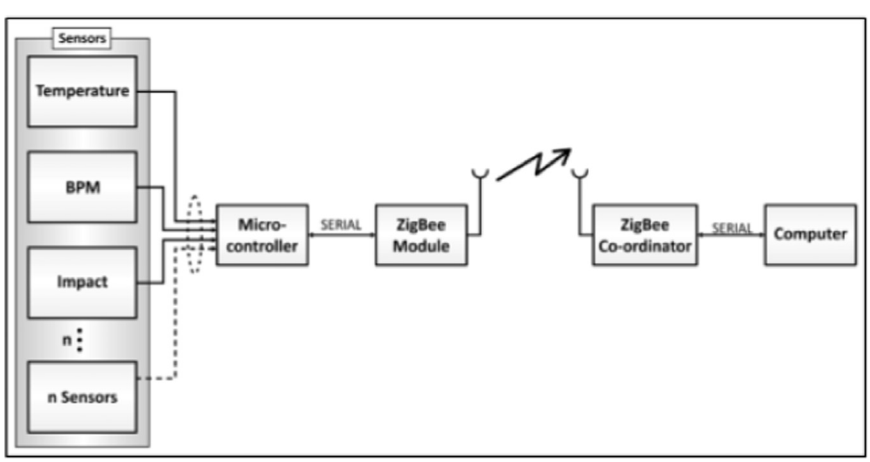
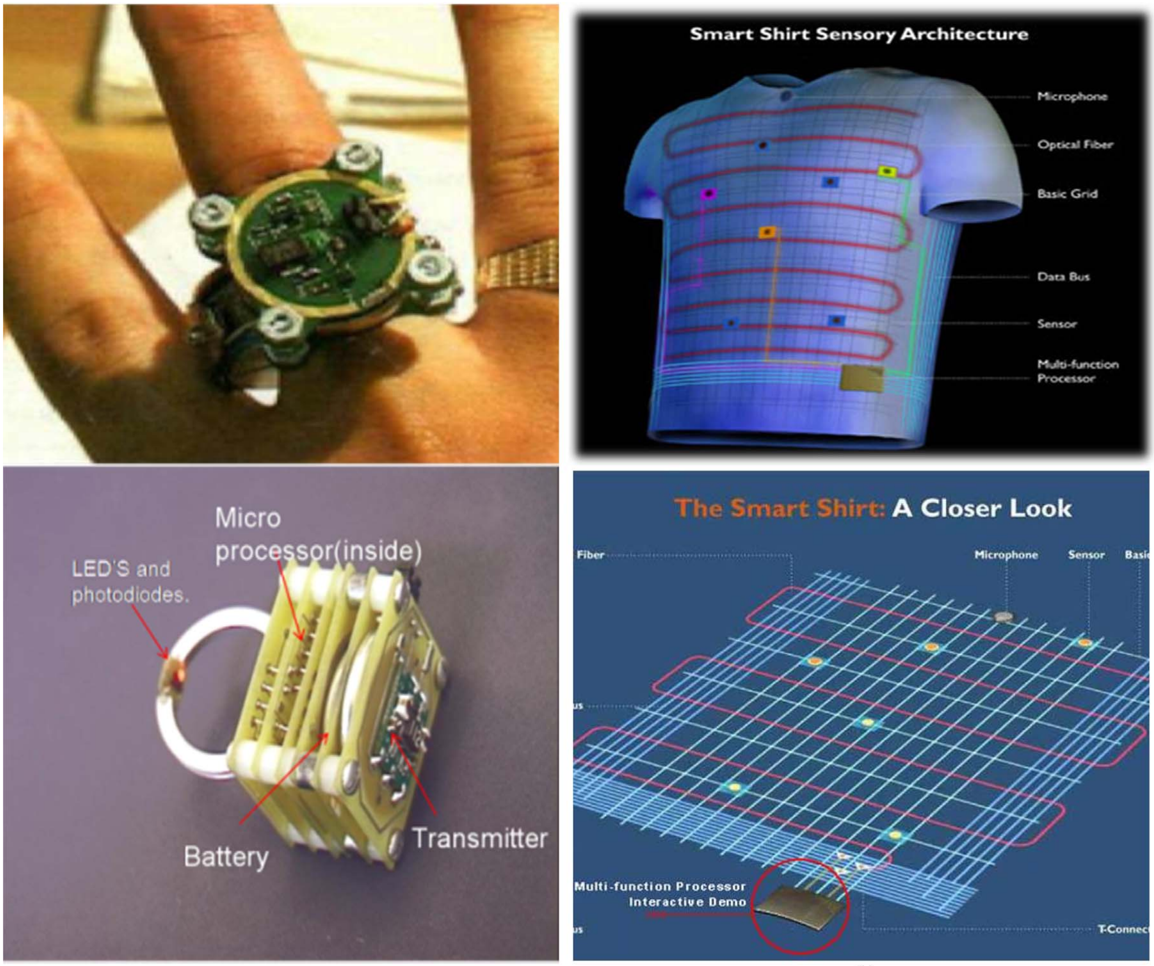


Fig. 2. Representation of Human Activity Recognition (HAR) system in block diagram (Malhi, 2010).



(a) (b)

Fig. 3. (a). Ring Sensor & its Schematic Diagram. (b). Smart Shirt and its Sensory Architecture.

tions, fireman cloths, diving cloths or cloths for any specific function we want.

Other applications in health care are biofeedback respiratory system (Liu et al., 2011), mental stress assessment (Seoane et al., 2014), rehabilitation system (Patel et al., 2012), weight lifting exercise (Velloso et al., 2013), vision sensor in real-time (Peixoto et al., 2001), posture & movement wearable sensor (Ugulino et al., 2012). Apart from health-care systems, wearables are widely used in various other fields such as to provide training support for athletes, to monitor the persons who work at hazardous places. It also facilitates physically-disabled people to continue enjoying their independence for longer time span. It can give mental peace to the elderly persons through a simple panic button (Versel, 2012; Alert Devices for the Elderly, 2016; Mobile phones to come with panic button from, 2017, 2016) and provides assurance to family members and friends.

2.1. Basic requirements of a wearable device

Before developing a wearable system, it is essential to have a clear idea about the basic requirements and designing challenges for any wearable device. There are always hardware and software constraints beginning from low-energy operations, light-weight and safety requirements. While person is placing the wearable sensor on his/her body, the chances of thermal injury must be considered and should be reduced by controlling the sensing and wireless frequency and radio duty cycle of wearable sensor. A novel optimization framework has been proposed for considering safety requirements as well as sustainability requirements based on the human physiology and system level design parameters have been derived (Bagade et al., 2014). Some basic requirements are discussed below:

2.1.1. Aesthetics

Appearance is so important that many top companies are working in partnership with the fashion industry to make these wearable devices fashionable and more attractive.

2.1.2. Size

Wearable devices must be compact enough so that they can easily fit onto the human body. It should be comfortable to the wearer as well as they must have more features integrated into the same space.

2.1.3. Water tolerance

As the wearable device has to go everywhere along with human body, it should be tolerant of the environmental conditions such as temperature, water droplets, moisture, and sweat for continuous monitoring of the human behavior.

2.1.4. Power consumption

Wearable devices are powered by a battery. For monitoring of human behavior continuously 24×7, power requirement will be very high. Among all the system-components, communication system consumes most of the energy. An autonomous wireless wearable sensor node having flexible energy harvesting mechanism has been presented which is equipped with ultralow power management circuit. This flexible power management circuit can transfer maximum electrical power from solar energy to give power to the wireless sensor node (Toh et al., 2014). Reduction of power consumption of these devices poses requirement of special features in Micro Controller Unit and firmware algorithms. ARM architecture is very popular for wearable systems because of its best performance. Also, ANT+, Bluetooth Low Energy (BLE) are energy efficient wireless technologies.

2.1.5. Wireless communication

For continuous monitoring of human behavior, wireless connectivity is essential, as the person or the wearer cannot move freely so far with wires. Also, the person will not feel comfortable being surrounded by wires. Apart from this, they may need to interact with more than one device. According to the type and features offered, the device may support different wireless protocols such as Wi-Fi, ANT+, and IEEE 802.15.4 based protocol. Different data source may generate heavy time-varying traffic which may lead to intolerant abeyancy in wireless wearable sensors. Moreover, delivery of data in real-time, packet loss and fading in data transmission induced by movement as well as surrounding environment is a big challenge.

2.1.6. Operating system

Sometimes, the wearable device may need a specific operating system such as Android depending on the features being offered. For example, a smart watch designed to be an extension of a mobile phone needs to run a specific advanced operating system.

Day by day, new trends can be seen in the field of Wearable system which has enhanced features. For example, shirt or other cloths with all-fabric keyboard made by conductive thread can be washed in the machine same as ordinary cloths. So, it is water durable which is one of the basic requirements for a wearable device. Computerized cloths can be the next generation for computers and other devices which does not require strap of electronics into our body. Although a huge amount of effort is being made in the wearable sensors, challenges like user-acceptance, low power consumption, interference in wireless systems are still to be resolved for better usability and functionality of these wearable devices.

3. Architecture of wearable system

Architecture of wearable system can be explained with the help of a block diagram representation as shown in Fig. 4. It consists of different blocks namely: Power supply, display, wireless connectivity, motion sensing and application processor. Micro-Electro-Mechanical Systems (MEMS) sensors monitor the movement of a human body in every dimension. The examples of motion sensor or MEMS sensor may include accelerometers, magnetometers, and gyroscopes. Analogue sensors are biometric sensors such as heart rate monitors and EEG, EMG. Analogue Front End (AFE) basically preprocessed the data acquired from sensors. It contains operational amplifiers, filters, and A/D Convertors. User Interface (UI) systems are used for interaction between human being and wearable device which is an important consideration.

Capacitive touch sensing is the most preferred User Interface available today. UI elements are indicators used for alerts implementation from the device to the user as well as from user to the device. Pulse width modulation (PWM) is used to drive these UI elements. Among all these components of wearable system, one of the most important components is application processor and is selected very carefully. The selection of application processor depends on the type, features and characteristics of the device. The latest microcontrollers are compatible with most of the wearable systems. MCUs are compact and can integrate a number of functions on a single chip which is very important to reduce the overall size and cost of a wearable device. For example, 32 bit ARM architecture is a very popular Central processing Unit (CPU) technology for wearable systems as it shows best performance in terms of computation and energy efficiency (Ramasamy et al., 2014). For Some advanced applications, wearable systems may need a separate co-processor to offload the sensor data from the main processor. This is needed when the system has to load the sensor data and at the same time, it has to analyze it together in real time, requiring full CPU attention. This function is known as '**sensor hub**' or 'sensor fusion'.

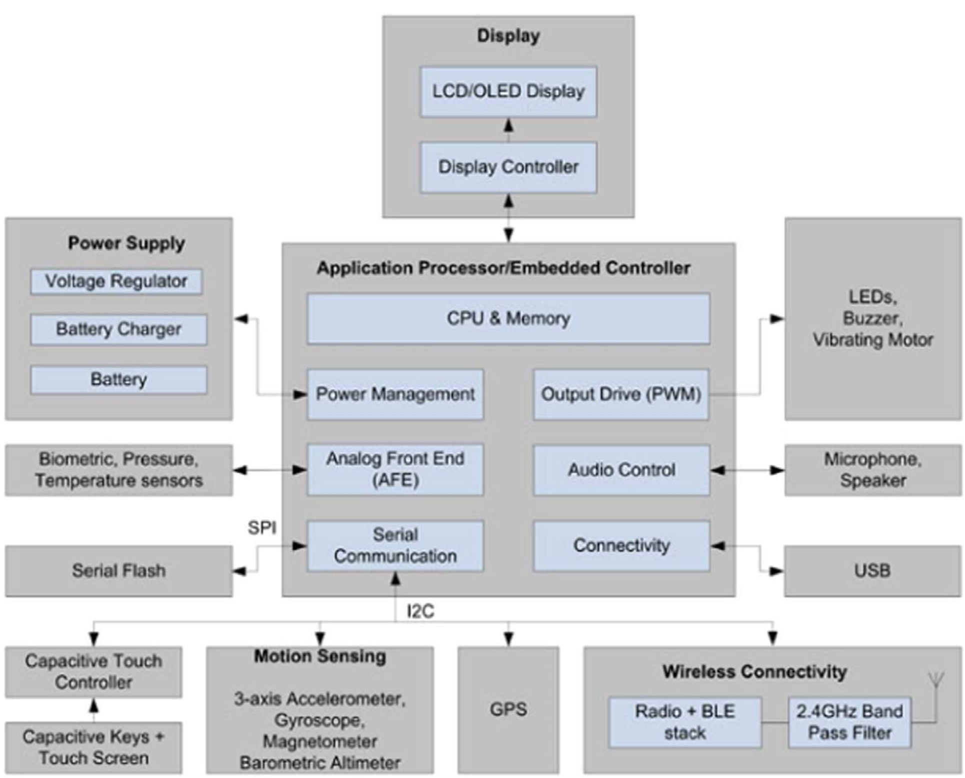


Fig. 4. Block diagram representation of a wireless wearable system (Ramasamy et al., 2014).

4. Current market situation and future trend of wearable devices

Wearable technology broadly concerns electronic devices, apparel and textiles. The Fig. 5 shows two types of wearable technology and its characteristics developed by many big companies. The wearable device business has been already grown up. IDTechEx has been already grown up. IDTechEx has examined and explained leading signs of future wearable technology sales like Google Trends, reduced cost of these technologies, continuous increase in most promising features, user-friendliness and starting sales of newly launched smart wrist-wears (for example Samsung watch, fitness monitors). All of these show that very fast growth is in prospect.

There are a number of big names namely Google, Apple, Adidas, Nike, Samsung, and Intel behind the most advanced and promising new developments in the field of wearable technology (Hayward et al., 2015). The market for wearable technology is entering into a rapid growth phase. However, the healthcare sector will remain dominant which includes wellness and medical fitness. At the end of the next decade, advanced technologies such as wearable electronics will be matched with the healthcare market, having new healthcare-informatics devices challenging sales potential in billion dollars.

The pie chart in Fig. 6 shows that North America is more forward towards wearable electronics developers and manufacturers for medical purpose, fitness and wellness as compared to other territories like Europe, East Asia.

A report provided by IDTechEx (Hayward and Chansin, 2016) shows detailed description about sensor types which is a dominating component of any wearable technology products. The relative market size by wearable sensor types in 2020 is shown in Fig. 7. With the most

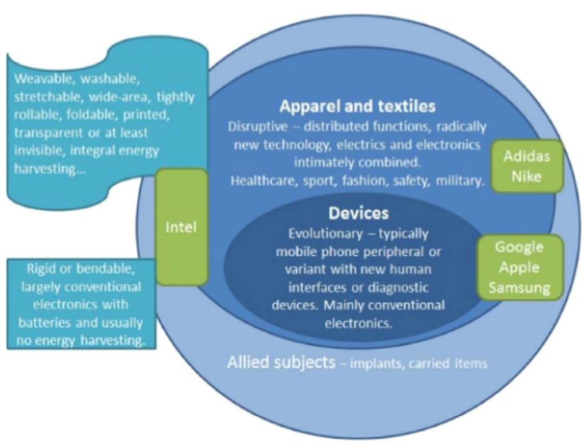


Fig. 5. The two main types of wearable technology and their characteristics (Hayward et al., 2015).

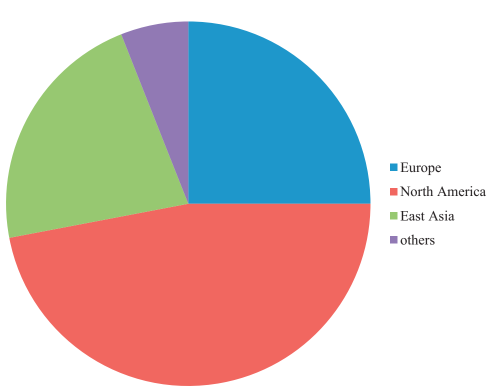


Fig. 6. A comparison of different territories in the field of development and manufacture of wearable electronics for healthcare (Hayward et al., 2015).

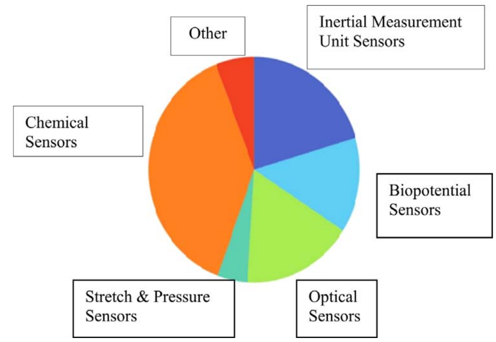


Fig. 7. The Relative Market Size by wearable sensor types in 2020 (Hayward and Chansin, 2016).

featured and promising sensor options, the report concluded that there will be approximately 3 billion wearable sensors by 2025 and most of them will be newly emerged.

5. Recent developments in human activity monitoring using wearable sensors and bio-potential signals

Wearable sensors have vast scope in different areas such as medical services, surveillance training support for athletes, automation industry, connected smart homes, robot control, and security systems. However, at designing end, there are some challenges including user acceptance, small and comfortable to wear (wearability), hardware design, development, and support, prototyping, manufacturing, and deployment, real-time data collection and processing (reliable communication), large-scale user studies (interoperability), cost effective, energy consumption, privacy and security problems. To clear these hurdles, many research works are going on. Few of them are discussed here. Considering the power/energy consumption requirements of wireless sensor networks, Patel et al. (2009) have developed a wearable system integrated with some algorithms to diagnose the severity of diseases and motor difficulties in patients. This proposed configuration allows monitoring patients for many days, once the batteries of the Body Sensor Network (BSN) nodes are fully charged. P. Bonato has talked about the new trends in combining wearable technology and robots (Bonato, 2010). Integrating robots and wearable technology seem like a key step in the direction of achieving the goal of monitoring patients at home, effectively. These systems are complex and are able to monitor the status of the subjects and provide a tool which is invaluable to tackle the emergency situations. A wearable ECG signal sensing and processing system have been proposed. The wearable sensor is combined with a wireless protocol (ANT protocol) for data transfer. To reduce the power requirement and effective sensor-size, the wireless protocol was used as a low data rate module (Nemati et al., 2012). The proposed system can be fixed on a T-shirt and the size of the electrodes was smaller than many recent works. A wearable module and artificial neural network (ANN) based activity/ behavior classification algorithm has been presented by (Lin et al., 2012) to estimate energy expenditure. The purpose of the design was to classify human body activities with similar intensity levels and then to develop energy expenditure regression models using ANN for optimization of the estimation performance. The categorization of human body activities use the accelerometer data and ECG signal data acquired by wearable sensor modules. A human emotion recognition system is shown in Fig. 8.

Quazi (2012) has reported in his M.S. thesis that the data from the wearable devices may also be used to determine different emotions of the person under monitoring. The system was based on information provided by the physiological signals obtained from a skin-temperature and skin-conductance sensor. The physiological signals obtained from these sensors were amplified and filtered. After all preprocessing, the signals were input to a microcontroller for final processing. The basic

Fig. 8. Human Emotion Recognition System (Quazi, 2012).

emotions considered in this work were happy, sad, angry, relaxed. The concept of smart skins has been proposed in some recent works (Cook et al., 2013). Smart skins are intelligent cognitive skins that sense, wirelessly communicate, and will be capable of modifying environmental or physiological parameters using very simple passive RFID technology sticker in the future. Smart skins are zero-power devices meaning they rummage their own energy using ambient energy such as electromagnetic, solar, mechanical, thermal, or RFID/Radar-based inquisition techniques. The concept can also be extended as body-wearable skins for continuous monitoring. One interesting application of wearable sensors in sports and exercise is to use the data collected from sensors for mapping real-world activities to the games, then, developing the activity monitoring system in such a way that it can produce an enjoyable game. Some authors have proposed the development of a truly virtual mobile sports environment game "tablet-based exergame with wearable human body sensors" (Mortazavi et al., 2014). There was a time when sweat rate measurement for athletes was possible only in laboratories. Now, it is possible to measure sweat rate using wearable devices outside the laboratories also (Ermes et al., 2008; Salvo et al., 2010; Strohrmann et al., 2012). It has been found that exergames can be helpful to strengthen the children with autism spectrum disorders physically and mentally. A novel wearable sensor based Automatic Ingestion Monitoring (AIM) system has been reported for unbiased monitoring of ingestive activity/behavior in normal life (Fontana et al., 2014). It integrates three sensor modalities namely a sensor for jaw motion, a sensor for hand gesture recognition, and an accelerometer. These sensors interface to a smartphone through wireless network. The development was aimed to correct known ingestive behaviors causing weight gain with the help of a novel behavioral modification tool. It will also help the patients with eating disorders by studying their free-living food consumption. The possibility of wearable computers has been discussed which could share thoughts and sensations (Bleicher, 2014). It would be like wearing a computer on our arm. This will be personal and intimate and will be based on technologies that attempt to colonize our whole body. It may track our body movements, listen to our heartbeat and put our body on line. A patent "MD-based Brain Sentry" represents a crucial concept of wearable sensors which uses accelerometers to measure acceleration during physical activity. The Brain Sentry helmet-mounted sensors give an alert alarm when an athlete suffers an unusual rapid and potentially dangerous acceleration of the head. The alarm indicates possible injury in the head of the player. The sensor is compact enough and weighs only one ounce. It is waterproof and the batteries are long-lasting. It can work for a whole year without charging, meaning no maintenance by the person (Boyle, 2014). "Mindful" wearables have been designed for improving physical health as well as mental well-being. Meditation apps together with conventional EEG are being designed with the aim to help in concentration build-up and self-regulation skills (Fernandez, 2015). To recognize the facial expression of human being, Step-wise Linear Discriminant Analysis (LDA) and Hidden Conditional Random Fields (HCRF) had been used and validated offline. However, in real-world environment, its performance is not investigated till now. To solve these problems, a robust, real-time subdivision technique may be needed. Furthermore, in an actual environment, the facial frames may have different angles and side views. Therefore, there is a need for further research for improving the recognition rate of facial expressions with various angles and litter of face (Siddiqi et al., 2015). Human body movement can be recognised and separated with the use of Principle Component Analysis (PCA) and Micro-Doppler (m-D) effect but, its effectiveness is still to be verified for real-time application (Shi et al., 2016; Mukhopadhyay, 2015). Human activity recognition has been in some way, individualized. It means, the most of the systems can be used only for a single user at a time. Although social networks give information effective to recognize collective activities (Lane et al., 2011) which can be considered one step further. A flexible force sensor was developed to assess the feasibility of detection of improper sitting posture. The sensor was based on piezo-resistive capacitive film (Lee and Shin, 2016). The study can be further extended in order to increase the resolution with the increase in number of sensors and the area of measurement. The sensor platform can be optimized by determining the size and position of the sensor. A wearable EEG was introduced based on the In-Ear-EEG recording concept.

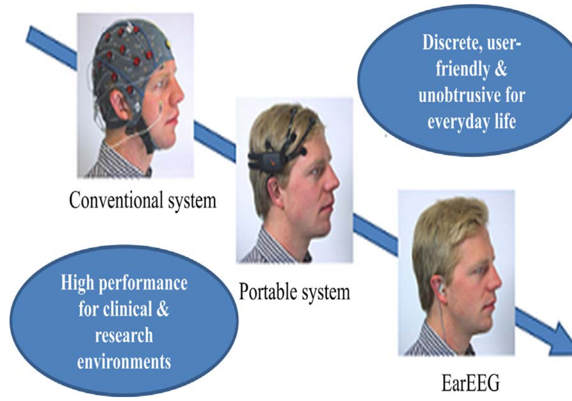


Fig. 9. Evolution of EEG from conventional system to In-Ear-EEG.

It was a generic device and can be used to record all the responses that may be acquired from standard EEG (Goverdovsky et al., 2016). Fig. 9 shows the evaluation of EEG system from conventional to In-Ear-EEG.

Recently, a multi-tasking wearable device is developed which monitors the health of person's heart as well as assess the position of the person (Mao et al., 2008). To monitor dental cavities and other dental plaque, a health monitoring apparatus is designed. It is an oral monitoring system (Nanjundappa et al., 2016). A data fusion algorithm based fall detection wearable system is developed for elderly persons. The developed device uses MEMS, Kalman filter, Code Division Multiple Access (CDMA) network to achieve efficient detection (Wang and Qin, 2016). In very recent years, people are working on resolving all these above mentioned major challenges for wearable computing such as power line interference removal, selection of best wearing location (Chimeno and Pallàs-areny, 2000). For continuous monitoring of physiological signals with wearable devices,

Power Line interference (PLI) removal is of important consideration. Keeping this in mind, a work has been presented for evaluation of different techniques of PLI filtering to acquire better quality in heterogeneous physiological signals (Tomasini et al., 2016).

A number of neurological disorders can be diagnosed with bio-potential signals EEG, EOG, and EMG. For ECG recording, we have many wireless systems as shown in Table 1. However, for bio-potential signals such as EEG, EOG, and EMG recording, most of the platforms provide wired system. Only few manufacturers such as Compumedics provide Bluetooth system and Siesta's Ethernet radio link. A list is shown in Table 2.

Sometimes, wearing these add-on devices in public places may be uneasy or uncomfortable to the user (Knight and Baber, 2005). In a

Table 1
Commercial ECG recording platforms (Varadan et al., 2016).

Manufactures	Product Name	No. of channels	Storage	Wire less
Phillips	Page writer TC50 ECG	12 channels of ECG	USB memory stick (upto 16 GB)	No
GE Healthcare	MARS Ambulatory ECG System (SEER 12, SEER light)	3–12 channels of ECG	1 GB internal and optical DVD storage	No
Imec	Secure Digital Input Output	1channel ECG	16 GB	Yes
AliveCor®	AliveCor	1 channel ECG	16 GB	Yes
Phillips	EASI (Philips DigiTrak XT)	4 channels ECG	256–512 MB	No

study, some common wearing locations were investigated. According to statistical results, a noticeable alteration in elderly people's attitudes is observed towards these add-on devices attached to different locations on their body. The wrist was the most acceptable location for wearable device by the users (Fang and Chang, 2016).

Many medical research also points to the importance of doctor-patient interaction (Chaudhry et al., 2006; "Cloudy Forecast: Predictions for Big Data in Large and Small Medical Practices", 2013; Niksch et al., 2014). Whether the use of wearables by patients might affect the doctor-patient interaction or whether this would influence patient behaviors too and therefore health results are important questions (Loos and Davidson, 2016).

Neurological disorders like sleep disorder, drowsiness can also be monitored by wearable wireless systems. According to National Institute of Health (NIH), millions of Americans suffer from sleep disorders (Shen et al., 2006). For diagnosing sleep disorders, different approaches are used such as polysomnography (PSG) and home sleep test (HST). PSG is considered as a standard approach for monitoring sleep disorders or sleep patterns. But this approach has many disadvantages like: cost involved is very high, the patient has to stay in the laboratory for the whole night which may cause discomfort or inconvenience to the patient and that may also affect the test. Also the waiting time for the test is very long due to unavailability of sufficient capacity of sleep laboratories (Flemons et al., 2004). The HST is performed at home. So, it has overcome the problem of inconvenience of patient, long waiting time and cost involved. But it has lack of real time (RT) monitoring of sleep patterns and less physiological information. The real time monitoring of signals from remote locations can be achieved by the concept of combining two wireless communication standards, on is for building WPAN (Wireless Personal Area Network)/ WBAN (Wireless Body Area Network) and other is for WAN (Wide Area Network). Wireless wearable biosensors can also be used to monitor drowsiness which is very useful in improving safety. People, like security guards, night shift workers, drivers who need to stay awake during night need drowsiness monitoring systems. According to National Highway Traffic safety Administration (NHTSA), approximately 25% of road accidents involve some form of drowsiness, inattention, sleep or fatigue (Ranney et al., n.d.; The Role of Driver Fatigue in Commercial Road Transport Crashes, 2001). Psychomotor Vigilance Test (PVT) is one of the tests used to assess the quality of sleep (Kamen, 2004). In a study, it has been found that continuous eye gaze triggers the Autonomic nervous system (ANS) which causes hormones release in blood stream and alters blood pressure and heart rate. This eye gaze-induced stress level can be evaluated by monitoring bio potential signals ECG and EOG (Aggarwal et al., 2014). To help the elderly or disabled persons, a real-time EOG based alarm system has been designed. Further, the work can be extended to various other control applications for needy people (Bobade and Khirwadkar, 2016). EOG technique is used to measure the resting potential of retina (Mala and Latha, 2014). Wide applications of EOG also include activity recognition (Bulling et al., 2011), virtual key board (Usakli and Gurkan, 2010), controlling of expert multitask gadget (Gandhi et al., 2010) and many more.

Now a days, monitoring of human activity through fusion of a number of bio potential signals are very much popular. A multimodal fusion of EOG and EEG information has been shown as a robust approach for recognition of reading activity in day-to-day life (Bulling et al., 2012). For driving fatigue detection, a fusion of EEG signal and forehead EOG signal (Huo et al., 2016) has been used which shows better performance than solely using EEG (Wang et al., 2016) and forehead EOG signal (Zhang et al., 2015). A wearable wireless brain-computer interface system was developed for hybrid control of a robot based on EEG and EOG signals (Oh et al., 2012). In this system, speed and stopping of the robot were controlled by brain signals (EEG) and right and left movements were controlled by EOG signals. A human-machine interface system was developed which was based on wearable sensor and only one channel EOG. The usability of the system is much higher as it can enhance the comfort and wearability of the system (Guo et al., 2016). In this work, individually optimized threshold for each subject improved the classification performance, but the obtained classification accuracy (84%) and Information Transfer Rate (ITR) (13 bits/min) was not sufficient to use this system for real-world applications. Electrooculogram (EOG), electromyogram (EMG), and glossokinetic potential (GKP) based multimodal interface was used for human-computer interface to improve the information capacity. These kinds of multimodal interface approach may improve the information capacity as well as its robustness and usability. The author (Nam et al., 2014) himself has suggested that the performance and the capacity of the developed system can further be enhanced if it is integrated with other modalities such as EEG. A robot control system was developed using two modalities Electrooculography and Electromyogram. EOG is using for moving the robot joint angles and EMG is using for object grasping. However, it was found that the EOG and EMG signals are hard to discriminate for the robot control system (Sasaki et al., 2015).

Table 2
Commercial EEG, EOG and EMG recording platforms (Varadan et al., 2016).

Manufactures	Product Name	Number of channels	Storage	Wireless
Philips/Respironics	Alice PDx	21channelwith optional ECG and EEG	1 GB SD card	No
Embla	EmblettaX 100	12- channel with X100 proxy	128 MB internal memory	No
Compumedics	SomtePSG	16- channel	2 GB Compact Flash	Bluetooth
Compumedics	Siesta	32- amplified channel	Compact Flash	Siesta's Ethernet radio link
Cleveland Medical	Sleep Scout	9-channel	SD card	2.4–2.484 GHz
ResMed	ApneaLink Plus	4-channel	15 MB internal memory	No
CareFusion	Nox-T3	14- channel	1 GB SD card	No

The combination of EOG interface with RFID technology in shared control architecture was used in an assistive robot. With this approach, interaction with objects can be possible without using any kind of motor related movement and the number of commands were increased that can be generated by the EOG interface alone (Iáñez et al., 2012).

6. Conclusions

It can be concluded from the above discussion that human activity recognition is an emerging area of research which is moving towards the development of an intelligent and smart Healthcare Platform Integrated in small devices for providing comfort to the patients as well as elderly persons, for their well-being and independent living. A significant commercial development and progress have been already reported. Still, we have many challenges and unsolved issues. Presently available wearable sensors have solved the purpose to some extent. However, they are also not very much cost effective and efficient from all the aspects which have been discussed in this paper. These unsolved issues motivate the development of new wearables having some new techniques which can be applicable in health-care systems or HAR systems and solve the purpose efficiently for more realistic environments. It is expected from previous studies that many more user-acceptable, high-performance, low cost wearable devices will be available for recognition of variety of activities. Surveys also predict that the interest, and consequently, the use of wearable devices will be increased in near future. At the same time, the cost of wearable devices is expected to fall due to its wide applications in real-time. As much as technology will mature, novelty in medical science will be increased, further increase in integration of medical sensors and electronics instruments will be witnessed and consequently, wearables will be further smaller. It will support home based physiological data collection, preventive healthcare programs and also facilitate remote care. The future of medical sciences is likely to be packed in the huge prospective of the world's smallest sensors and wearable devices – where technology shorten to lengthen, and a generation lifted on gadgets waste away. To provide a better alternative to the healthcare system, development of comfortable, low cost wearable devices are needed that can measure and continuously record the electrical activity of human body as well as can transmit the obtained data wirelessly to a computer, where it will be displayed in real time. If activity samples of a significant number of users from a predefined area like a city, or a state could be gathered as samples, the information obtained from these samples could be used to estimate health conditions, early diagnosis of some disorders, exercise habits. Hence further, this type of participatory human-centered application would be free from economic-incentive-based method. The users will participate willingly in the system since they would be receiving the suggestions, information related to their health conditions and exercises to improve their physiological performance. Such gathered data from a sufficient number of users can be used to train machine learning classification algorithms or soft computing techniques to enhance the overall accuracy and consequently, to improve health diagnosis. EOG signal has wide applications in clinic as well as in engineering such as diagnosis of eye injuries, eye diseases, eye-controlled engineering devices viz. cursor mouse. In spite of that, the use of an EOG interface is still not enough capable of performing tasks involving complex control commands to guide an external device optimally. One solution for these limitations is shared control approach. E.g. combining EOG and Radio-frequency identification (RFID) technology. Shared control has a wide range of applications. In robotics, it is used with multi-agent systems on cooperative tasks. Shared control is also useful for disabled people, e.g., to aid blind people and to improve mobility. In future research, one can have the opportunity to work for minimization of positions of EOG electrodes and design of real time wearable devices based on EOG signal. To increase the performance of recognition, more multimodal fusion of physiological signals is sought, since a single physiological signal cannot have all the information required for a particular task.

7. Scope of future work

There are a lot of works centered in solving accessibility issues using rehabilitation robotics or developing alternative communication methods with the environment. Human–machine interfaces are used to interact with external devices aimed at helping handicapped people or elderly persons. Ocular movements can be used to generate commands to control external devices as in progressive neurodegenerative diseases, the brain and spinal cord nerve cells are affected but the eye movements remain intact. Since most completely paralyzed people can still move their eyes, EOG is a signal that can be practically used for controlling the prosthetic devices. The advantage of EOG in terms of accuracy and complexity is quite important so it is one of the most commonly used methods to detect eye movement. The combination of an EOG interface with Radio-frequency identification (RFID) technology in shared control architecture is used in recent research works. However, a single EMG, EEG or EOG-based system can only manage one certain kind of task. It is rather difficult to have a universally robust system applicable to different situations. Therefore, multimodal system will be a more effective approach. Shared control with multimodal interface can be a better approach for generating complex control commands to optimally guide an external device or application. Wearable systems can be designed to control the different kind of objects based on multimodal interface and shared control architecture where multimodal interface can take decisions about the movement of a robot for a particular application and the interaction with objects can be assisted by RFID technology. More modalities can be added in future to further enhance the controlling commands and make the product more feasible and usable.

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