International Journal of Computer Information Systems and Industrial Management Applications.
ISSN 2150-7988 Volume 10(2018) pp. 261-271

Submitted: 22 Dec, 2017; Accepted: 27 Feb, 2018; Publish: 7 Oct, 2018

Internet of Things and Ambient Intelligence for Mobile Health Monitoring: A Review of a Decade of Research

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Abstract: **Due to increase in chronic disease, aging, and medical costs, we are approaching a world where basic healthcare would become out of reach to most people. Fortunately modern technologies like Ambient Intelligence (AmI) and Internet of things (IoT) offer unparalleled benefits, which could improve the quality and efficiency of treatments and accordingly improve the health of the patients. The idea is to bring down the hospital management, drugs and healthcare costs and also make it more accessible. Real-time monitoring using sensors can save lives in event of a medical emergency like heart failure, diabetes, etc. and for terminally ill patients, who needs continuous monitoring. IoT enables interoperability, machine-to-machine communication, information exchange, and data movement that makes healthcare service delivery effective. Mobile healthcare helps monitor / check the patients and identify anomalies instantly besides reducing hospital management costs. This paper presents a survey about infrastructure, technologies and methodologies used in IoT - AmI for mobile health monitoring. We focused on the methodologies utilized to detect and monitor health status of patients and how Ambient Intelligence can greatly effect our lives.**

Keywords: Ambient intelligence, health care, IoT, mobile health, activity recognition, wearable sensors.

I. Introduction

As reported by [98] "Between 2000 and 2050, the proportion of the world's population over 60 years will double". The Europeans population over 60 years represent more than 25% of the population [21]. The rising number of aging population will be accompanied with big increase age-related chronic diseases such as Asthma, heart diseases, Diabetes and Alzheimer. By 2050, over 13 million people will be affected per Alzheimer's disease [21]. According to US National Vital Statistic Report, chronic diseases are among the 15 leading cause of death in 2015 like heart diseases, Diabetes, Alzheimer's and chronic lower respiratory disease. In EU countries, Circulatory and Respiratory system diseases are reaching 1.8 million and 382 thousand deaths in 2014 [94]. Globally, 425 million adults suffer from Diabetes [95]. Also, chronic diseases in turn have massive costs to society as a whole. In the United States the cost of health care was estimated $2.4 trillion [96]. People with chronic illnesses need a routine check, so traditional hospital or medical center services will be costly and inefficient solution.

The decisive human need to use ambient intelligence for mobile health care to support older and disabled people and person with chronic disease. It aims to improve the quality of life and to move health care services from traditional systems to a new paradigm without increasing financial or care burdens with low cost. The AmI's vision can be seen as the convergence and integration of at least three areas of computing: ubiquitous computing, sensor networks and Artificial Intelligence (AI). Thus Ambient Intelligence is a novel challenge of AI.

A. *What is AmI?*

The European Commission Information Society Technologies Advisory Group (ISTAG) first introduced the concept of Ambient Intelligence [93]. Thus, AmI is not new but it becomes more real by reason of the computer's evolution, seen the miniaturization of microprocessors and nanotechnology, as well as the cost-effectiveness of storage capabilities and communication bandwidths. It also proposes a new way of interaction between people and systems [18], where a human behaves spontaneously while machines and artificial intelligence act in background to improve his comfort and to reduce the risks he may face. An AmI system is particularly identified by several characteristics: [3]

- "Context Aware: It exploits the contextual and situational information."
- "Personalized: It is personalized and tailored to the

needs of each individual."

- "Anticipatory: It can anticipate the needs of an individual without the conscious mediation of the individual."
- "Adaptive: It adapts to the changing needs of individuals."
- "Ubiquity: It is embedded and integrated into our everyday environments."
- "Transparency: It recedes into the background of our daily life in an unobtrusive way."

AmI works in a seamless, unobtrusive and an invisible way. It is an emerging domain based on ubiquitous computing and makes a vast modification of the protocol's design, communications devices, etc [2]. Therefore, it is made possible by the flourish of Wireless Sensor Networks (WSN) [30]. WSN is used to provide the AmI systems with data about the user's quotidian activities without human intervention. The wide spread of WSN technologies used are Bluetooth, Zigbee and Radio Frequency Identification (RFID). But, the most important characteristic of AmI is the intelligence side because it uses several machine learning, data mining techniques and algorithms to analyze sensor data [39]. Using artificial intelligence, AmI can be more personalized, anticipatory, ubiquitous and adaptive. Ambient intelligence is a mature system and we can find it in many applications in our lives. In this paper, we will just present the AmI for healthcare monitoring.
In this paper, we survey about infrastructure, technologies and methodologies used in AmI for mobile health monitoring. The rest of the paper is organized as follows: Section 2 summarizes some of the main technology infrastructures used in AmI for health monitoring. Section 3 presents several methodologies utilized to detect and monitor health status of the user. Section 4 presents the applications in which Ambient Intelligence can greatly affect our lives. Sections 5 and 6 highlight future research and conclude the paper.

II. Technologies infrastructure

A. Body Area Networks

The pervasive availability of technological resources and miniaturization of sensors sparked the realization of Body Area Networks (BAN). Typically, in this network, sensors are placed on or into the human body and under clothing [4] to monitor the health situation of wearer and give real-time feedback to the user or medical staff [5]. We use body sensors to observe vital signs [6]. Since body sensor devices are becoming wearable, smaller and lighter, AmI systems integrate our daily life in an unobtrusive way. As a result, WBAN is the key of several important and innovative applications such as telemedicine and remote patients, monitoring to deliver many health care services without constraining their quotidian activities with low cost and ambient assisted living for elderly people or people with physical or cognitive disabilities to contact the assistant if there is an emergency case [7]. Several typical body sensors are introduced below.

Table 1: Sensors Used to Detect Vital Signs.

Name	Purpose	Data Format
Accelerometer	Measure acceleration, fall detection, location and posture	Time series
Gyroscopes	Measure orientation, motion detection	Time series
GPS	Motion detection and location tracking	Categorical
ECG	Monitor cardiac activity	Analog signal
EEG	Measure of brain waves	Analog signal
EOG	Monitor eye movement	Analog signal
EMG	Monitor muscle activity	Analog signal
PPG	Heart rate and blood velocity	Analog signal
Pulse oximeter	Measure blood oxygen saturation	Analog signal
Blood pressure	Measure blood pressure	Numerical
SKT	Skin temperature	Numerical

- Accelerometers/Gyroscopes: Accelerometers are body sensor used in the health care system. They play a leading role to detect daily activities and predict falls [63]. But, using Accelerometers in isolation may not be enough to be accurate. So we need to combine with Gyroscopes. Gyroscopes are used to measure angular velocity of rotation.
- Global positioning systems (GPS): Is used as wearable sensors to provide context aware location data [9].
- Electrocardiography (ECG): Gives the ability to personal digital assistant (PDA) to diagnose different heart diseases. It is the electrical representation of the contractile activity of the heart over time, which can be recorded using non-invasive electrodes on the chest or hand. ECG provides massive information about the state of heart [64].
- Electroencephalography (EEG): Is beyond ideal for patients suffering from brain diseases. It is used to monitor brain activities and any abnormal activities within the brain by fixing small electrodes on the human scalp on multiple locations [9]. The EEG acquisition system consists of three electrodes, one to obtain the EEG signal from the ear and two electrodes behind the ear acting as a reference electrode.
- Electrooculography (EOG): Is used to monitor and track eye movement. EOG is achieved by placing two electrodes on the outer side of the eyes to detect horizontal movement and two others above and below the eyes to detect vertical movement [10].
- Electromyography (EMG): Is used as a diagnostic tool to identify neuromuscular diseases and movement disorders by examining and recording the activity of bioelectric signals of the body [65].
- Photo-Plethysmogram (PPG): Is used to detect and record the variations in blood flow and blood volume in the body. It is achieved by a detector pulse wave that circulates in the body [66].
- Pulse oximeter: Is placed in the human body to sense the oxygen saturation value. It uses two technologies:

Table 2: Ambient sensors used in smart environments.

Name	Purpose	Data Format
Light	Measure intensity of light	Time series
PIR	Identify user location	Categorical
Temperature	Measure room temperature and body temperature	Time series
Pressure	Identify inhabitant location	Numerical
Switch sensor	Open/close door detection	Categorical
RFID	Object and people identification	Categorical
Ultrasonic	Location tracking	Numerical
Power	Calculate power usage	Numerical
Humidity	Measure room humidity	Time series

Spectro photometry to measure hemoglobin oxygen saturation and optical plethysmography to measure pulsatile changes in arterial blood volume at the sensor site [67].

- Blood pressure sensors: Are used in the field of health care in recognizing behavioral, detecting energy expenditure and providing data for pressure analysis by monitoring the pressure variation below the foot in a real time way [11].

- Skin temperature sensors (SKT): Are used to provide body's accurate temperature measurements

Table 1 summarizes the various body sensors that detect vital signals of a user.

B. Sensor Networks for Smart Living Environments

An interesting application of sensor networks for intelligent living environment is smart house. Smart environment sensors are placed in different stuff at home to gather information about the user's environment [8], and have the potential to revolutionize the remote monitoring for persons with chronic disease and elderly people [34]. It aims to detect motion current location and monitor environment of the user, such as the orientation of the body, weather condition, location by ambient sounds and by lamps (i.e. light) [6], to observe and identify quotidian activities and behavior of the user [9] to enhance the quality of life.

- Passive InfraRed (PIR): Is used to monitor the resident in different locations (bedroom, kitchen, etc.) [77] and detect daily living activities [31].

- Radio-Frequency IDentification (RFID): Is employed to identify object and users of the smart environment [32].

- Ultrasonic/Pressure: Are widely used to track motion and identify the location of the resident [35].

- Humidity and Temperature sensors: They are used to measure the temperature of the user's body and the temperature/ or the humidity of the environment around the resident.

- Light sensors: The light sensor is an electronic device. It is employed to measure the illumination density of the user environment.

- Power sensors: Are utilized to manage energy consumption and calculate power usage in a specific place by the identification of the active devices [33].

- Switch sensor: Contact switch is used to detect user interaction with objects such as closing/opening door or window and so on, so it can track human daily activities.

With these sensors, AmI's system can offer a large number of applications such as smart home [35], smart cities [37] and so on. In smart home the sensors are placed in different stuff to gather information about the home conditions [8]. The Gator Tech Smart House was developed to monitor older people and individuals with chronic disease. This home is equipped with a high number of sensors which collect massive volumes of data [36]. Otherwise, Santander city includes more than 12,500 sensors. It focuses to implement smart transportation through congestion management, outdoor parking management, driver guidance, etc [38].

C. Recent Trends

There are many technologies used to upgrade the quality of AmI in health care services. The technology trends are:

- Internet of Things (IoT): According to [60], Internet of Things semantically means "a world-wide network of interconnected objects uniquely addressable, based on standard communication protocols". IoT is a novel network concept, interrelated computing device, machine, object and people which have a unique identifier associated with them. It can sense and transfer data without human intervention. Thus, the "Internet of Thing" has the ability to make everything communicate, interact and identifiable anywhere and anytime, to get life less difficult and more comfortable.

  It is one of the most existing trends and innovation in the recent history of technological advancement. With cloud computing, connectivity and big data there has been an explosion of IoT based application solution in diversified field like healthcare systems. In healthcare domain IoT has made huge inroads, for example, in [91] authors Implemented IoT functionalities for unobtrusive and continuous Heart Rate (HR) monitor such that HR data are recorded from Pulse-Glasses, visualized on Android smartphone, and stored seamlessly on the cloud. Also, in [92] authors used a smart Glove with Fog-Driven IoT to assist people with Parkinson's disease in tracking the effectiveness of medications that relieve motor symptoms and to transmit motion data into a personal, patient oriented app.

- Cloud Computing: According to [87], cloud computing can be defined as "A computing paradigm which is a pool of abstracted, virtualized, dynamically scalable, managing, computing, power storage platforms and services for on demand delivery over the Internet". Using cloud computing for healthcare present promising opportunities to healthcare service delivery. It provides a strong infrastructure to support health services with high quality and lowest cost "pay-as-you-use". There are several benefits of using cloud computing for healthcare [56] such as (a) better patient care: The medical record of the patient is available for healthcare providers anytime and anywhere, (b) reduced cost: It reduces the operational and maintenance costs means pay for actual resource utilization and without hardware costs, (c) information sharing: Healthcare providers can share part of their data with others like health research institutes, hospitals. Many researchers have worked on cloud computing for healthcare system. For example, in [88] authors propose a solution to automate the process of gathering patient data through the use of sensors connected to medical devices and convey this information to the medical centers "cloud" for storage, processing and distribution. It facilitates the deployment process, means without cabling, and provides real-time data collecting all the time. Also, in [57] authors developed a cloud-based system for clients with a mobile device or web browser for hosting ECG analysis service for real-time ECG monitoring and analysis.

- Big Data analysis in healthcare: These days, large data volume is generated from heterogeneous sources such as social networks, internet and health care system. This is owing the use of several technology trends, like the spread of smart device, Internet of Things and the prevalence of cloud computing.

  Generally, healthcare systems generate tremendous data that are difficult to store, process and interpret [55]. Because this data can be structured, semi-structured and unstructured [86], is impossible to manage it with traditional database management. Consequently, there is a huge need to use big data in health care systems. Big data has the potential to improve the quality of care by the use of past and current healthcare data to make quality healthcare decision [54]. The four main characteristics that define big data are:

  1. Volume: Massive data collected through enormous sensor devices, Electronic Patient Record, Electronic Health Record, etc [55].
  2. Velocity: Refers the speed of processing the data in real time such as telemedicine, remote health monitoring and virtual human on mobile platforms [62].
  3. Variety: The data can take heterogeneous form (structured, semi-structured and unstructured) such as photo, video, sensor data and so on.
  4. Veracity: Treat the quality of the data captured.

- Machine learning: There are many machine learning techniques used to analyze sensor data for healthcare systems. These techniques improve the work of medical expert, assisted healthcare monitoring and make the system more accurate. In [59] authors have presented a comparison of different classifiers and Meta classifiers. Then combining algorithms to develop novel intelligent ensemble healthcare and decision support. This ensemble was constructed on Meta classifiers voting with three base classifiers Random Tree, J48 and Random Forest algorithms. Also, machine learning algorithms identify the anomalies and enable continuous diagnosis. For example, in [89] authors use bagging algorithm to determine the cautionary signs of heart disease of the patient and compare this outcome with the decision tree algorithm. In [90] predictive models for breast cancer survivability presented, using C5 algorithm with bagging are proposed. As well, in [99] authors presented an application of inductive machine learning techniques in the medical diagnosis of stroke. They use See5 algorithm (new version of C4.5 [58]) which is capable of "learning from example" by constructing a decision tree that can be transformed to IF/THEN rules.

III. Algorithms and methodology

Ambient intelligence is the combination of environment and body sensors with algorithm and methodologies. In this section we focus on these algorithms.

A. Activity Recognition

The contribution that sensors offer is the ability to collect daily activities which occurred in an intelligence environments such as "the user goes to bed at 09:00 pm". Therefore, it performs a decisive role in AmI environment. Activity recognition is used in several applications such as health care [40], ambient assisted living [42], surveillance and security [43] and smart home [41]. The Neural Network House, Intelligent Home, the House_n and mavHome project monitor the health condition by location's prediction and activities recognition [8] at home. the activities are divided into two categories, the first is recognized by sensors which are placed on the body, such as walking, standing up and lying. The second category is recognized by looking for pattern in how people move thing [68]. Human behavior in quotidian activities is complex and highly diverse. Hence, controlling these activities is a big challenge. These challenges are: (a) recognizing concurrent activities: Doing different activities at the same time, (b) recognizing interleaved activities: activities that overlap with others, (c) ambiguity of interpretation: similar activities can be explicated differently, (d) support multiple residents: recognizing the activities perform in parallel by the resident in a group [50].
According to [12], activity recognition involves different steps from gathering data using the body and ambient sensors to know the current activity of the user. These steps are preprocessing, feature extraction, classification and interpretation. For the classification we have two categories; supervised and unsupervised learning. For supervised learning, we can cite Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) algorithm. For unsupervised classification techniques we can cite K-means algorithm and Gaussian Mixture Model (GMM) approach [13]. We use an unsupervised approach when the context of activity recognition is difficult to specify.
Smartphones are becoming the main platform for human activity recognition [44]. Since the mobile phone is used on a daily basis and equipped with several sensors (Accelerometer, GPS, Barometer, Thermometer, Pedometer, Troximity sensor, Light sensor etc.) [45], it is a suitable tool for continuous monitoring the user's activities. In [78] the authors

present a mobile application for identifying physical activities and calculating the amount of daily calorie expenditure using triaxial accelerometer. Also, in [79] authors develop ActiServ system to support activity recognition on mobile phones for common users.

B. Behavioral Pattern Discovery

Human activity understanding includes activity recognition and behavioral pattern discovery. Activity recognition focuses on precise detection of the human activities based on a predefined activity model. But, the behavioral pattern discovery aims to find some unknown behavior from sensor data without any predefined models. In a remote monitoring, the system needs to gather massive information on several daily behavior patterns. Through human behavior the system can detect anomaly and provides personalized service due to the discovery of the preference and habits of the users. To know the behavioral pattern of the user, we should use various sensors. Some sensors provide information about the user's activities. Some sensors provide information about user activities, other provide information about the environment of the user and other type of sensors provides information about the health status of the user.

C. Anomaly Detection

The main task of smart health environment is to detect abnormal activity or emergency situation which requires intervention of caregivers. Anomaly detection is a critical problem in the field of health care and needs a high degree of accuracy. It has several benefits for smart environment such as: Enhancing life's quality of older persons, promoting the difference between standard data, raw data and feedback control [15], to distinguish between normal and abnormal behavior of elderly persons. Anomaly detection refers to detecting patterns that does not conform to habitual behavior. The non-conforming pattern is often referred as a deviation or an anomaly [82]. The goal of anomaly detection is translating data anomalies to significant and actionable information in a wide variety of application domains [46]. It is used in several applications such as fraud detection for credit card, health care, military surveillance for enemy activity, intrusion detection for cyber-security and detection in safety critical systems.
Hence, many systems developed to detect anomaly in health care systems. For instance, RFID-based approach used to detect abnormal activities in a smart home [16]. This approach presents the system architecture for RFID of data collection, preprocessing, clustering for anomaly detection and experimental result. Also, in [47] and [80], authors propose new systems of anomaly detection for mild cognitive impairment. According to the rules defined by experts, the anomaly is detected as an activity containing a deviation from normal behavior. As well, in [81], the authors use One Class Support Vector Machines (OCSVM) techniques to identify the behavior model of the resident. In addition, there are different anomaly detection techniques used in health care services such as Neural Networks [71], Bayesian Network [72], Rule Based System [73] and Nearest Neighbor based technique [74].

D. Decision support systems

According to [61], Decision Support System (DSS) is "an interactive, flexible, and adaptable computer based information system, developed especially for better decision making as it supports the solution of a non structured management problem. It utilizes data which provides an easy-to-use interface, and allows for the decision maker's own insights". DSS have been widely used in the health care system. The decision support system plays a principal role in the diagnosis and treatment of multiple diseases, improves the safety of the elderly and the quality of medical care and provides accurate diagnosis that leads to make a quick decision on the anomaly detected [17]. For example, in [48] the authors propose a decision support system that can detect renal cell cancer using abdominal images of healthy and renal cell cancer tissues, by the use of support vector machines as a classifier. Also, in [100] the authors developed new discriminant temporal pattern mining algorithm which aims to identify the association between hospitalization for seizure and anti-epileptic drug to improve the work of medical staff and make their decision more efficient and accurate.
Current Health care systems generate large volume of data because it is used every time, daily and everywhere. In this area, data mining is important to detect disease and identify the situation of the patient. It converts information to knowledge, supports decision makers to understand several situations and predict future events by the use of several algorithms. [19].

E. Anonymization and Privacy Preserving Techniques

As ambient intelligence system is integrated into our everyday environment, more data is gathered about the user. These data need to be secure and private. Security and trust are the main issues in ambient intelligence visions [49]. Thus, protecting personal privacy is one of the most challenges of AmI in health care systems. There is a huge need to use some protection mechanisms as data anonymization. It modifies the data and makes difficult to identify the concerned person. The popular anonymization techniques are generalization and bucketization [20]. The main difference between these techniques is that bucketization does not change Quasi Identifiers.

IV. Application

There are many fields in which ambient intelligence can maximize the comfort of our life. This section presents AmI applications for healthcare.

A. Health Monitoring

The Europeans beyond the 60 years age represent more than 25% of the population. By 2040 over 11 million will suffer from Alzheimer disease [21]. Also, people over 85 years require need routine check. In United State the cost of health care is $2.4 trillion. These figures show that traditional health care services are inefficient to handle classical diseases we can prevent in advance. Thus, AmI for health monitoring may be an effective solution to control elderly, disabled and people with chronic illness anytime, anywhere and in an un-

obtrusive way with low cost. With the development of supporting technologies, older people and people with disabilities can have an independent life in their home with the assistance of health monitoring. AmI methodologies presented in previous section support this goal.
Various systems for monitoring health status of elders have been developed such as the proactive group at Intel develop technology to enhance and facilitate life's quality of the older persons [75]. In [22] authors propose new continuous e-health monitoring system that predicts the future status and its deterioration before more complication. In addition, in this field, there are other works use RFID, and environmental sensors [24] [25].

B. Assisted Living

Ambient Assisted Living (AAL) [51] is an efficient solution which enables the elderly population to maintain independence for a longer time. It has been defined as a service that aims to form an intelligent environment to support the user in their work place and home. AAL can help people with various types of physical disability. Many projects are developed or in developing stage in this field. For example, in [83] the authors proposed health smart home system for disabled person that can alert them about accidents that can occur somewhere in the house by the use of low-cost technologies such as Raspberry Pi, cameras, motion sensors and the central computer. This system has the ability to call a healthcare provider and the fire brigade in emergency situation. Furthermore, in [84] authors proposed a novel obstacle detection system to assist the visually impaired using 3D sensors. Also, in [85] authors present mobile health care (mHealth) to compensate for any impaired movement of smart wheelchairs using emerging IoT technologies. In addition, in [53] authors described the development of VIVOCA project, which is intended to recognize and interpret an individual's disordered speech and deliver the required message in clear synthesized speech.

C. Smart hospital

In traditional hospitals the staff must navigate the hospital to gather information about patients and control their status. However, doctors and nurses have several parallel activities. Thus the control of the patient becomes more difficult and makes the service insufficient. AmI in hospital enhances the quality of service, improves the security of patient and the personal of hospital can monitor the situation of sufferers. Smart hospitals can promote the communication and support the staff and the patient.
In [52] authors present a different scenario to understand how AmI can improve the work in hospitals. For instance, "Dr. Garcia is checking the patient in bed 234, his personal digital assistant (PDA) alerts him that a new message has arrived. His handheld displays a hospital floor map informing him that the X-ray results of patient in bed 225 are available. Before, Dr.Garcia visits this patient, he approaches the nearest public display that detects the physician's presence and provides him with a personalized view of the hospital information system. In particular, it shows a personalized floor map highlighting recent additions to clinical records of patients he is in charge of, messages addressed to him, and the services most relevant to his current work activities. Dr. Garcia selects the message on a bed 225, which opens windows displaying the patient medical record and the X-ray image recently taken. Aware of the context of the situation (patients original diagnosis, the fact that X-rays were just taken from the patients hand, etc.), the system automatically opens a window with the hospitals medical guide that relates to the patient's current diagnosis, and an additional one with previous similar cases to support the physician's analysis. While Dr. Garcia is analyzing the X-ray image, he notices on the map that a resident physician is nearby and calls him up to show him this interesting clinical case. The resident physician notices that this is indeed a special case not considered by the medical guide and decides to make a short note on his handheld computer by linking both the X-ray image and the medical guide. He can use these links later on to study the case in more detail or discuss it with other colleagues from any computer within the hospital."
Going back to smart hospital work, such as activity recognition from the smart hospital. In [26] authors develops an approach for automatically estimating hospital-staff activities by training Hidden Markov Model (HMM) to map contextual information in a user activity. In addition, GerAmI is another project developed for Alzheimer patient [23]. It is an intelligent environment using multi agent system, mobile device, RFID and WiFi to facilitate the integration and the use of the system.

D. Therapy and Rehabilitation

According to the Disability and Rehabilitation Team at the World Health Organization (WHO), the number of people who need rehabilitation service is 1.5% of the world population [97]. AmI in therapy rehabilitation can help people who required remote systems [3]. It offers personalized, transparent service and used everywhere. The use of AmI in the health care system, especially in rehabilitation is based on sensor networks [27]. In [76] authors present the system used in the ubiquitous rehabilitation center, which integrates a Zigbee-based wireless network with sensors that monitor patient and rehabilitation machines. These sensors interface with Zigbee motes which in turn interface with a server application that manage all aspects of the rehabilitation center and allows rehabilitation specialists to assign prescriptions to patients. In [28] authors presented multi agent system which developed to provide people with Acquired Brain Injury (ABI) and with physical therapies for the rehabilitation by using specific devices to monitor the patient's movements and some physiological responses, such as the variation of the heart rate, during the rehabilitation process.

V. Ongoing Challenges and Future Research Directions

As ambient intelligence is used everywhere, every time to facilitate our daily activities, there are still many challenges. Based on this survey, we present in this section some AmI challenges, issues facing health monitoring systems and future research. Heart rate, temperature and movement's control are not enough. In the future, AmI system should listen and understand the conversation of users. In addition, there is a huge need to improve the recognizing activity systems of multiple users. Despite there are several algorithms to monitor more than patient, the accuracy and robustness of their result are still relatively far from to give efficient service. Also, security of sensor data is a crucial issue in WSN. The security of sensor data either stored data while inside the wireless sensor network or during the transmission of the data outside the WSN. Storing the data in the WSN is a big challenge because usually we use sensors node to capture and not to stored who is captured. In addition, there is a threats are trying to break the security of the delivery data at the base station because channels are open to anyone [70]. According to Maslow's hierarchy of needs, security is the second need of people. Thus, researchers should solve the issues related to AmI's security and privacy. Furthermore, the use of sensors in our daily life needs a huge amount of energy. The energy is provided by small batteries. These batteries should be small because the little size of the sensors. Further, the batteries need to be recharged or replaced after each period. But, it can be burdensome because of demographic condition, the forget or because the user is old [69]. So, one of the major challenges is the battery life of the sensors. In [29] authors start to develop battery-free solution. But, this solution needs much work to be used in AmI intelligence for health care. According to [14], the principal reason of energy waste found at the Medium Access Control (MAC) layer such as collision, control packet overhead and idle listening. Thus, researchers in this area should develop more solutions to solve these issues and on top of that to improve the use of the human physiology as heart beat to guarantee time synchronization to analyze the data correctly and predict accurately user behavior.

VI. Conclusion

Ambient intelligence enhances the quality of health care monitoring systems. This paper presented a survey about infrastructure, technologies and methodologies used in IoT - AmI for mobile health monitoring. We focused on the methodologies utilized to detect and monitor health status of patients and how Ambient Intelligence can greatly affect our lives.

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