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A Review of Ambient Intelligence Assisted Healthcare Monitoring

Abdelhamid Salih Mohamed Salih
Sudan University of Science and Technology
Faculty of Computer Science
Khartoum, Sudan
Hamidsalih39@yahoo.com

Ajith Abraham
Machine Intelligence Research Labs (MIR Labs)
Scientific Network for Innovation and Research Excellence, Washington 98071, USA
Email: ajith.abraham@ieee.org

Abstract*: There is growing need to supply constant Health Care Monitoring (HCM) and support to patients with Chronic Diseases (CD) especially the disabled, and elderly. Ambient Intelligence (AmI) for healthcare monitoring and personalized healthcare is a promising solution to provide efficient medical services, which could significantly lower down the healthcare cost. The aim of this review paper is to summarize recent developments in the field of AmI for HCM. The paper focused on the concepts of AmI and Artificial Intelligence (AI) methods and data mining techniques used in AmI applications of wearable sensors technology to monitor older, adults and patient with CD in the home and community settings. A short description of key enabling technologies Wireless sensor networks (WSNs), wearable sensor technology, and communication technology, that have allowed researchers to implement wearable systems is followed by a detailed description have been reviewed. Applications described in this review paper include those that focus on health and wellness, home rehabilitation, assessment of treatment. Various architectures and platforms of AmI application have been reviewed. The integration of wearable and ambient sensors is discussed in the context of achieving home monitoring of older adults and patient with chronic diseases. We aim with this review paper not to criticize, but to serve as a reference for researchers and developers in this scientific area and to provide direction for future research improvements.

Keywords: Ambient intelligence, artificial intelligence, Healthcare monitoring , wearable sensors Network.

1. INTRODUCTION

Traditional healthcare and services are usually offered within hospitals or medical centers. CD is becoming the major causes of the death. In EU countries, the heart disease is the most common cause of death [1]. According to US National Center for Health Statistics, major CD such as heart disease, cerebrovascular disease, and diabetes account for 35.6% of death in US in the year 2005 [2]. In Sudan according to the latest WHO [3] data published in April 2011, Coronary Heart Disease (CHD) deaths reached 10.67% of total deaths. There is an ever-growing need to supply constant care and support to patients with CD, disabled, and elderly. The drive to find more effective ways of providing, such care has become a major challenge for the scientific community [4]. Also people in post-surgery state need continuous monitoring of their health condition, especially the vital signs, until their health status becomes stable. Patients, as well as their families, also need to collaborate with their doctor and medical professionals to get informed about their states. Until now, the monitoring of the health condition of such people is usually accomplished within medical centers or hospital environments. As a result, measurements of vital signs and the corresponding diagnosis are carried out in controlled environments. However, this solution is costly, inefficient and inconvenient for the people with the need of routine checks, since the patients need to frequently visit the hospital, sometimes on a daily basis, or even worse, need a long-stay. There are huge requirements to move the routine medical check and healthcare services from hospital to the home environment, thus release the hospital beds and other limited resources to the people with urgent needs. Ambient Intelligence (AmI) for healthcare monitoring and personalized healthcare is a promising solution to provide efficient medical services, which could significantly lower down the healthcare cost. AmI [5] is an emerging multidisciplinary area based on ubiquitous computing, which influences the design of protocols, communications, systems, devices, etc. [6]. Ami proposes new ways of interaction between people and technology, making it suited to the needs of individuals and the environment that surrounds those. AmI [7] tries to adapt the technology to the people's needs by means of omnipresent computing elements which communicate amongst them in a ubiquitous way, It also proposes a new way to interact between people and technology, where this last one is adapted to individuals and their context. The context includes both the users and the environment information. The information may consist of many different Parameters such as the building status (e.g. temperature or light), vital signs (e.g. heart rhythm or blood pressure), etc. Wireless sensor networks (WSNs) are used for gathering the information needed by Ami environments. Some examples of possible WSN technologies are Radio Frequency Identification (RFID), ZigBee or Bluetooth. Gather information about the context is not enough. However information must be processed, analyzed, reasoning and decision making, since the quality of decision making depends of quality of information by using dynamic mechanisms and methods. In this sense various Architectures and models have been used for development of Ami systems. This review paper presents a review of the applications of AmI for HCM. The paper is organized as following: the next section briefly describes some of the main concepts and definitions and motivation. Section 3 presents review of some AI methods used in AmI. Section 4 depicts a review of the Technologies used in AmI. Section 5 presents a review of AmI applications and Section 6 presents Architectures used by AmI and finally the conclusions of this paper.

II. Ambient Intelligence

The European Commission's Information Society Technologies Advisory Group (ISTAG) [8-10] has introduced the concept of AmI. Researchers have defined AmI in different ways as given below. These definitions are summarized and highlight the features that are expected in AmI technologies: sensitive, responsive, adaptive, transparent, ubiquitous, and intelligent.

- AmI is an emerging multidisciplinary area based on ubiquitous computing which influences the design of protocols, communications, systems, devices, etc. [5].
- AmI proposes new ways of interaction between people and technology, making it suited to the needs of individuals and the environment that surrounds those [6].
- AmI tries to adapt the technology to the people's needs by means of omnipresent computing elements, which communicate amongst them in a ubiquitous way [7].
- A developing technology that will increasingly make our everyday environment sensitive and responsive to our needs [11].
- A potential future in which we will be surrounded by intelligent objects and in which the environment will recognize the presence of persons and will respond to it in an undetectable manner [12].
- AmI implies intelligence that is all around us [13].
- The presence of a digital environment that is sensitive, adaptive, and responsive to the presence of people [14].
- A new research area for distributed, non-intrusive, and intelligent software systems [15].
- A digital environment that supports people in their daily lives in a nonintrusive way [16].

A) Areas related with AmI

AmI inherits aspects of many areas of Computer Science, see Figure 1, but should not be confused with any of those in particular. Networks, Sensors, Human Computer Interfaces (HCI), Pervasive Ubiquitous Computing and Artificial Intelligence (AI) are all relevant and interrelated but none of them conceptually covers the full scope of AmI. AmI puts together all these resources to provide flexible and intelligent services to users acting in their environments [17].

B) Motivation

We can expect a greater demand for services and applications oriented toward people with Chronic diseases. These demands include providing services for those who suffer from various illnesses and the need for constant healthcare monitoring such as: diabetes, arthritis, senile dementia, Alzheimer, heart-related diseases among many others.

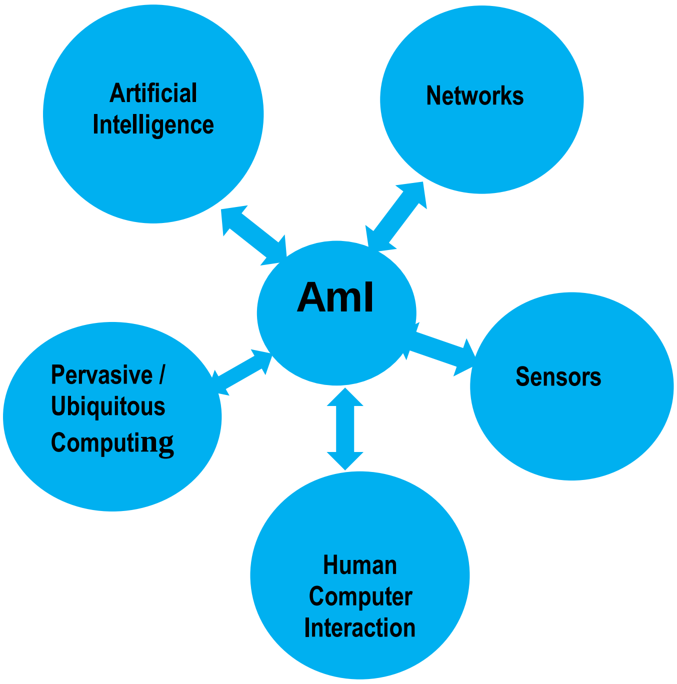

Figure 1: Areas related with AmI

Ami and the emergence of new types of mobile and embedded computing devices, developments in wireless networking, smart sensors, and others, gives us the tools and methods to come up with innovative applications to better assist users, and therefore, improve their lifestyle. We believe that support for people with chronic diseases and elderly through Ami infrastructures is the most naturally appropriate. Not just because of its evident social impact, but because of the characteristics of its special requirements. The objective of Ambient Intelligence is to develop intelligent and intuitive systems and interfaces, capable of recognizing and responding to the user's necessities in a ubiquitous way, providing capabilities for ubiquitous computation and communication, considering people in the center of the development, and creating technologically complex environments in medical, domestic, academic and other fields [12].

III. Technologies

Wireless sensor networks (WSNs) are used for gathering the information needed by AmI environments. WSN research has become a popular area of research in recent years. Asada et al

[18], and also Pottie and Kaiser [19]. The WSN community has explored applications such as environmental monitoring, situational awareness, and structural safety monitoring. Gaynor et al [20] and Martinez et al. [21]. Lewis [22] and Edgar [23] have described different topologies for different scenarios.

Sensors	Observation
ECG	Heart rate, heart rate variability (HRT)
EMG	Muscle activities and fatigue
Temperature	Skin temperature, health State (fever)
Respiration	Breathing rate, physical activity
Blood oxygen	Status of the cardiovascular System, heart rate
Blood pressure	Status of the Cardiovascular hypertension.

Table 1: Sensors Used to Detect Vital Signs [26].

The main topologies used in WSN are Start Network and Mesh Network. Some examples of possible WSN technologies are radio RFID, ZigBee or Bluetooth. ZigBee [24]. However ZigBee is a low-cost, low-power, wireless mesh networking standard. The low cost allows the technology to be widely deployed in wireless control and monitoring applications, the low power usage allows longer life with smaller batteries, and the mesh networking provides high reliability and larger range. The principal device in a WSN is the network node, also called mote. This device, battery powered, has the RFID for the transmission and the reception of the information, an interface between the module and the sensor and a microcontroller. The context is defined as any information used to characterize the situation of an entity, which can be a person, a place or an object. [25]. This information is important for defining the interaction between users and the technology that surround them. For these reasons, it is necessary to continuously keep track of information about the users and their environment. The information may consist of many different parameters (sensors) such as location, the building status (e.g. temperature or light), vital signs (e.g. heart rhythm or blood pressure), etc. Thus, most of the context information can be collected by distributed sensors throughout the environment and even the users themselves. WSNs are used for gathering the information needed by AmI environments, whether in home automation, educational applications or healthcare monitoring [6]. The same can be said about a Body Area Network (BAN) that allows the monitoring of vital sign parameters of a user. A combination of both networks is also possible including mobile nodes in the body of a person that can be directly connected with the fixed mesh network in the environment. Moreover, it is necessary the integration and the interoperability of these networks with the Personal, Local, Metropolitan and Wide area networks used in the "classic" applications. The same WSN used in the connection of sensors, allow the transmission of commands and data to actuators in the environment (engines, lights, etc.) and user body (vibrator, leds, etc.). Table 1 highlight the sensors used to detect vital signs and and Table 2 higlight sensors used to detect motion and location.

Sensors	Observation
Accelerometer	Motion patterns of the body and limbs
Microphone	Speaker recognition, localization by ambient sound, activity detection, speech features
Visible light sensor	Location of Light sources
Rotation	Body movement
Compass	Orientation of the body and head.
Air Pressure	Vertical motion in elevator or staircase
Light sensor	Sunshine, location of lamps
Environment temperature	Outdoor, indoor.
Wlan/ GSM/ CDMA	Location, user environment.
Bluetooth, ZigBee	Services and devices nearby.

Table 2: Sensors Used to detect motion and location [26].

IV. AI methods and techniques Used in AmI

When analyzing sensor data, AmI systems may employ a centralized or distributed model [27]. Sensors in the centralized model transmit data to a central server, which fuses and analyzes the data it receives. In the distributed model, each sensor has onboard processing capabilities and performs local computation before communicating partial results to other nodes in the sensor network. The choice of model will have a dramatic effect on the computational architecture and type of sensor that is used for the task as described by Benini and Poncino [28] and also by Jayasimha et al. [29]. In both cases, sensor data is collected from disparate sources and later analyzed to produce information that is more accurate, more complete, or more insightful than the individual pieces. There are several AI and data mining methods and Techniques used in analyzing sensors data in AmI such like Neural networks, fuzzy Rules, Reasoning, Decision making, and spatial-temporal reasoning and machine learning. These methods and techniques can help accomplish many important tasks in AmI assisted healthcare monitoring and make the system more efficient.

A. Artificial Neural Networks (ANNs)

Jafari et al. [30] proposed an ANN based activity recognition system in order to determine the occurrence of falls. Their system works with single sensor placed on to the chest of the subjects. However ANN Require more tuning parameters than support vector machines, and also ANN is sensitive to noise (a validation set may help here) and missing values in the training samples need to be replaced or removed. Also

Yang et al. [31] presented multilayer feed forward neural networks (FNNs) as activity classifiers and recognize 8 daily activities with an overall performance of 95%. However Multilayer FNNs need enough training samples and hidden nodes to be able to approximate any function, providing.

B. Fuzzy Rules

Hagras et al. [32] have used of fuzzy logic-based techniques to learn user preferences in an ordinary living environment. They have devised an experimental intelligent inhabited environment, called the iDorm (intelligent dormitory) at the University of Essex, UK. The iDorm contains space for various activities such as sleeping, working, and entertaining, and contains various items of furniture such as bed, desk, etc. The sensors can sense temperature, occupancy. iDorm deals with two types of rules, static (user-independent) rules such as how to react in an emergency, and to lower the lights and temperature when the room is unoccupied, and learned rules reflecting the user preferences. The learning uses a fuzzy logic-based technique called Incremental Synchronous Learning (ISL). After monitoring and learning, the iDorm agent can take control of the environment. If the user behavior changes, the learning system may need to modify some of the rules, so it will go back to learning phase in which there can be a repeated learning process.

C. Event-Condition-Action(ECA) Rules

Augusto et al. [33-37, 41-45] used ECA rules and various extensions of them for applications in Smart Homes and supported living for the elderly. The intuitive reading of such rules is that on detecting certain events, if certain conditions are true then certain actions should be executed. The event part (first line) is the trigger of the ECA rule. The rule is triggered if an event occurs that matches the event part of the rule. Then if the condition (second line) of a triggered rule is true the rule fires, requiring execution of the action (third line).

An example of such is the work has been done by Augusto et al. [38] is by looking into the use of Event – Condition – Action rules (ECA). These are proposed to fulfill two criteria. Monitoring of patients for safety, long term monitoring of patients for profiling and learning behavioral patterns. Bager et al. [39] developed another Smart Home application and area of testing, for the Medical Automation Research Center. This system uses probabilistic methods to determine patterns in behavior. Based on a series of sensors, one in each room, the system monitors the duration of time that the user spends in each room. Although these systems have shown improvements over other systems of its type. However it is still lacking in one major area. Both of the above systems deal with the elderly living alone. This is due to the fact that there is no identifier on the person using the system, also Kleinberger et at. [40] developed single person home for the elderly this assumes no partner, no visitors, no health care providers and no maintenance people entering the house. Any one else entering the house will cause the systems to gather false data. Corchado et al. [41] developed GerAmI system that has got around this problem. The GerAmI system was developed in conjunction with the Alzheimer Sant ́ısima Trinidad Residence of Salamanca, an institute with multiple stories, multiple rooms and upwards of 40 residents. As with all previously mentioned for AmI systems, the GerAmI uses sensors to record patient and user data. However rather than sensors using motion or heat to track users, each resident and staff wears a bracelet containing a unique radio frequency identification chip (RFID). As each bracelet's RFID is unique it allows all of the residents and staff to be tracked individually without false data being recorded. This system is unique in that it also tracks the movements of the staff members, this is a major benefit in a system such as this when the medical care providers are on hand as it allows faster reactions to emergencies by alerting staff that are on duty and also located closer to the source of the problem. If intervention or assistance is required a message is sent to the staff members PDA. The message contains the name or identifier of the patient in question, the problem that has occurred as well as information from the database about the best way to deal with the situation based on previous events.

D. Reasoning

Sensing and acting provide links between Data mining algorithms and environment, a number of Methods of reasoning must take place to make such algorithms responsive, adaptive, and beneficial to users. These include user modeling, activity prediction and recognition, decision making, and spatial-temporal reasoning. The following we summarize these methods.

Modeling

The most common data source for model building is low-level sensor information. This data is easy to collect and process. However, one challenge in using such low-level data is the voluminous nature of the data collection. Youngblood [42] developed the MavHome smart home project, for example, in this project collected motion and lighting information alone results in an average of 10,310 events each day. In their project, a data mining pre-processor identifies common sequential patterns in this data, then uses the patterns to build a hierarchical model of resident behavior. Loke [43] relied upon this sensor data to determine the resident action and device state, and then pulls information from similar situations to provide a context-aware environment. Like the MavHome project. Doctor et al. [44] have developed the iDorm research conducted focuses on automating a living environment. However, instead of a Markov model, they model resident behavior by learning fuzzy rules that map sensor state to actuator readings representing resident actions. The amount of data created by sensors can create a computational challenge for modeling algorithms. However, the challenge is even greater for researchers who incorporate audio and visual data into the resident model. Luhr [45] used video data and intertransaction (sequential) association rules in resident actions.

Activity Prediction and Recognition

DeVaul and Dunn [46] used accelerometer data to identify different kinds of activities like walking, running, climbing stairs. All these approaches rely on offline data analysis to learn “typical” contexts. VanLaerhoven and Cakmakci. [47] proposed a method based on Kohonen Self Organizing Maps (KSOMs) and k-Means clustering, which is able to identify typical motion profiles. This approach relies on active training, used to construct a supervised context transition profile based on a first order Markov process to make the KSOM training procedure converge, the neighborhood radius of the learning neurons must decrease over time [48]. However KSOM have strong dependence of the initialization and is has too unbalanced classes, and also K- Means clustering has problems when clusters are of differing sizes, densities, non-globular shapes, and empty clusters. Duda et al. [49] presented Critical events that can be detected using classification algorithms, for which Bayes classifiers are known to provide good results. However, traditional classifiers do not allow meaningful interruption until the entire model has been evaluated, which is crucial in mobile devices due to limited resources. Limited processing power and high data rates limit the time available for processing one set of sensor values. To overcome this limitation therefore they employ a novel anytime Bayes classifier was implemented by Duda et al. [49] in a two-phase architecture. On the back-end server a full index structure is stored, which is an extension of previous work was presented by Assent et al. [50] for anytime stream classification. It is trained by sequences of sensor measurements which correspond to normal situations. Shyamal et al. [51] have implemented Support Vector Machines (SVM’s) to predict clinical scores of the severity of data obtained from wearable sensors in patients with Parkinson’s disease. Vapnik [52] has selected SVM’s due to their success in many classification problems, SVM’s success can be attributed to several properties. SVM’s optimize an objective function that is convex, hence guaranteed to find an optimal solution. However many other classification algorithms only guarantee that local optima be reached. SVM’s have the ability to generate nonlinear decision boundaries, by mapping the feature space into a higher dimensional space (using kernels) where classes are linearly separable. However SVM’s take long training times but high accuracy because the decision boundaries can be highly complex and Extension to classification of more than two classes is usually time- consuming. Reasoning algorithms offer is the ability to predict and recognize activities that occur in AmI environments. Much of this work has occurred in smart environments research. Cook and Das [53] presented AmI application, which is focused on a single environment, which has outfitted with sensors and designed to improve the experience of the resident in the environment, Mozer [54] presented the Neural Network House, and MIT [55] has presented the House network and the MavHome was been presented by Das and Cook. [56]. Youngblood et al. [57] developed projects adaptively control home environments by anticipating the location, routes and activities of the residents (i.e., a person moving within an AmI space). Roy et al. [58] have developed prediction algorithms as multiple types. Also Roy et al. [59] developed resident cases. Helal et al. [60] developed predicting resident locations, and even resident actions that allow the AmI system to anticipate the resident's needs and assist with (or possibly automate) performing the action. The modeling techniques described so far can be characterized as unsupervised learning approaches. However, if resident activity data is available, then supervised learning approaches can be used to build a model of resident activity and use it to recognize observed activities. Tapia et al. [61] employed a naive Bayes learner to identify resident activity from among a set of 35 possible classes, based on collected sensor data. However Naïve Bayes is simple probabilistic classifier based on the assumption that the features for a given class are mutually independent, which means that the decisions are made as if all features are equally important. Liao et al. [62] used just location information. Philipose et al. [63] enhanced the model with object interaction data.

Decision Making

Over the last few years, supporting technologies for AmI have emerged. Automated decision-making and control techniques are available for Building a fully automated AmI application. Simpson et al. [64] have discussed how AI planning systems could be employed to not only remind individuals of their typical next daily activity, but also to complete a task if needed. Augusto and Nugent [65] have described the use of temporal reasoning with a rule-based system to identify hazardous situations and return an environment to a safe state while contacting the resident. Few fully implemented applications decision-making technologies have been implemented. Youngblood et al. [66] also have used a reinforcement learner to automate physical environments with volunteer residents, in the MavPad apartment and the MavLab workplace. Hagras et al. [67] presented the iDorm, which is another of these notable projects that uses fuzzy rules learned through observation of resident behavior. These rules can be added, modified, and deleted as necessary, which allows the environment to adapt to changing behavior. However, unlike the reinforcement learner approaches, automation is based on imitating resident behavior and therefore is more difficult to employ for alternative goals such as energy efficiency. Amigoni et al. [68] have employed a Hierarchical Task Network (HTN) planner to generate sequences of actions and contingency plans that will achieve the goal of the AmI algorithm. For example, the AmI system may respond to a sensed health need by calling a medical specialist and sending health vitals using any available device (cell phone, email, or fax). If there is no response from the specialist, the AmI system would phone the nearest hospital and request ambulance assistance. University of Washington [69] has developed novel computer systems enhancing the quality of life of people suffering from Alzheimer's disease and similar disorders, that help an individual perform daily tasks by sensing the individual's location and environment, learning to recognize patterns of behavior, offering audible and physical help, and decision making to alerting caregivers in case of danger. Beck and Pauker [70] described dynamic sequential decision making in medicine using Markov-based approach originally described in terms of medical decision-making. Xiang and Poh [71] utilized dynamic influence diagrams. There are also others approaches for example. Leong [72] and Stahl [73] have utilized decision trees to model temporal decisions. In all cases, the goal is to determine optimal sequences of decisions. Markov decision processes (MDPs) is an efficient technique for determining optimal sequential decisions (termed a “policy”) in dynamic and uncertain environments have been used by both Schaefer et al [74] and Alagoz et al. [75].

Ensemble Model

Others researchers have utilized ensemble models in AmI assisted health care monitoring. Fatima et al. [76] presented Classifier Ensemble Optimization method for activity recognition they have been proposed by optimizing the output of multiple classifiers with evolutionary algorithm. They have combined the measurement level output of different classifiers in terms of weights for each activity class to make up the ensemble. Classifier ensemble learner generates activity rules by optimizing the prediction accuracy of weighted feature vectors to obtain significant improvement over raw classification. Tan and Gilbert [77] have presented a comparison of single supervised machine learning and ensemble methods in classifying seven publicly available cancerous data. The experimental results indicate that ensemble methods consistently perform well over all the datasets in terms of their specificity. A combinational feature selection and ensemble neural network method is introduced by Liu et al. [78] for classification of biomedical data. Many individual algorithms such as self-organizing maps (SOM), learning vector quantization (LVQ), multi-layer perceptrons (MLPs), neural-fuzzy systems, and SVMs were applied to ECG signals. However, these methods have been typically applied to distinguish normal signals from abnormal signals across patients. This is difficult because of the substantial variation in the morphologies of ECG signals across patients. For this reason, Li et al [79] implemented an ensemble consisting of a standard SVM designed to distinguish normal signals from abnormal signals across patients and a set of one-class SVMs, presented by Scholkopf et al. [80] (one per patient) to distinguish normal signals for a given patient from all other signals [86].

Spatial and Temporal Reasoning

Spatial and temporal reasoning are two well-established areas of AI. Galton [81]. They have been the subjects of intense research for a couple of decades and there are well-known formalisms and algorithms to deal with spatial, temporal, and spatial-temporal reasoning. Gottfried et al. [82] has shown how the traditional frameworks for spatial reasoning and for temporal reasoning can be used to have a better understanding of the activities in an AmI application. Augusto and Nugent [83] used such a language to integrate both concepts in the same formalism and to obtain spatial temporal reasoning combined with active databases in the identification of interesting situations. Allen and Ferguson [84] presented an alternative formalism for reasoning about time based on Allen's temporal logic.

VI. Ambient Intelligence Architecture

The development of AmI-based software requires creating increasingly complex and flexible applications, so there is a trend toward reusing resources and share compatible platforms or architectures. There are several agent frameworks and platforms. One of the most prevalent alternatives in distributed architectures is software agent and Multi agent systems (MAS). Bajo and Corchado [85] presented THOMAS architecture, which basically consists of a set of modular services. THOMAS feeds initially on the FIPA [86] architecture, it expands its capabilities to deal with organizations, and to boost its services abilities. THOMAS is specifically addresses to design organizational structures for multi-agent systems. Agents have access to the THOMAS infrastructure through a range of services included on different modules or components. Agents that are capable of autonomous decision making, incorporate learning mechanisms, and are able to respond to events by planning and preplanning in execution time. THOMAS is an open architecture that can easily incorporate any type of agent. Fraile et al. [26] presented Marv architecture is MAS that has evolved from the THOMAS architecture which have been presented by Bajo and Corchado [85] to facilitate the integration of agents and smart wearable devices via wireless networks and mobile technology. The MaRV MAS is based on a belief, desire, and intention (BDI) model have been developed by Corchado et al. [87], in which the agent’s function as controllers and coordinators for various medical care tasks. The MaRV MAS is a specialized feature of the THOMAS architecture for intelligent environments that can address the need to improve techniques for obtaining resident and patient data, as well as assign diagnoses in hospital centers and geriatric facilities, and monitor all types of patients. The agents can initiate services on demand, or according to planned actions. The MaRV MAS is a distributed agent platform that uses a ZigBee [31][24] WSN to establish remote communication between patients and caregivers. All smart wearable devices in MaRV are based on RFID technology. Recent years have given way to a number of multi-agent architectures that utilize data merging to improve their output and efficiency. Gonzalez and Corcha [88] presented Alzheimer multi-agent system (ALZ-MAS), which is a MAS aimed at enhancing the assistance and healthcare for Alzheimer patients. The main functionalities in the system include reasoning and planning mechanisms. That is embedded into the agents, and the use of several context aware technologies to acquire information from users and their environment. Alonso et al. [89] developed Telemonitoring homecare, a telemonitoring system aimed at enhancing remote healthcare of dependent people at their homes, the main contribution of this development is the use of an experimental architecture developed by Tapia et al. [90], that allows the interconnection of heterogeneous WSNs (i.e. multiple technologies) and is based on the AmI paradigm. This architecture formalizes the integration of services, communications and wireless technologies to automatically obtain information from users and the environment in an evenly distributed way, focusing on the characteristics of ubiquity, awareness, intelligence and mobility. Shnayder et al. [91] presented CodeBlue developed at Harvard University. CodeBlue is hardware and software platform. The hardware design part includes the design and development of a mote-base pulse oximeter, two-lead ECG, and a motion analysis sensor board. The software architecture is based on a publish /subscribe routing framework. CodeBlue aims to provide coordination and communication among wireless medical devices in an ad hoc manner. The sensors do not publish data at an arbitrary rate, because the wireless channel's bandwidth is limited and they filter the data locally. Moreover, when publishers and subscribers are not within radio range, multi-hop routing is used. Since the publishers and subscribers are mobile. Also, a discovery protocol is used for CodeBlue nodes to discover each other and determine the capabilities of their sensor devices. Moreover, the system integrates a localization system called MoteTrack. Lorincz and Welsh [92] developed an RF-based localization system used for locating the patients and healthcare professionals.

VII. Ambient Intelligence Applications

AmI has potential applications in many areas of life, including in the home, healthcare system, elderly, transport, and industry, safety systems, and supported living of many different variations. We focus in this paper on healthcare and elderly systems. HEARTFAID have been developed by HEARTFAID project [93], which aims at defining efficient and effective health care. Wood et al. [94] developed ALARM-NET, which is an Assisted-Living and Residential Monitoring Network for pervasive, adaptive healthcare developed at the University of Virginia. It integrates environmental and physiological sensors in a scalable, heterogeneous architecture, which supports real-time collection and processing of sensor data. Communication is secured end-to-end to protect sensitive medical and operational information. In the SAPHIRE project [95] presented by Banu et al. [96], the patient monitoring is achieved by using agent technology complemented with intelligent decision support systems based on clinical practice guidelines. The observations received from wireless medical sensors together with the patient medical history will be used in the reasoning process. The patient's history stored in medical information systems will be accessed through semantically enriched Web services to tackle the interoperability problem. In order to guarantee long term patient monitoring and successful execution of clinical decision support systems

VIII. Conclusions

In this review paper, we reviewed the concepts of AmI, including the motivation and the areas of sciences related to AmI. Furthermore, in the context of AmI we have looked at several data mining and AI methods and Techniques used in AmI for HCM. We have looked at how various current technologies are being used and what extensions are thought to be necessary. For example WSNs are used for gathering the information needed by AmI environments. Some examples of possible WSN technologies are RFID, ZigBee or Bluetooth also BAN that allows the monitoring of vital sign parameters of a user. We also looked at several approaches to use Agents and Multi-Agents, for example as abstraction tools, for modeling devices and their interactions, and as middleware. We then considered the role of affective computing and patient in AmI. Also we have reviewed different approaches to monitoring and classifying patients. We have reviewed several application areas of AmI healthcare monitoring. Furthermore, in the context of AmI architectures we looked at several architectures that have the primary aim of allowing agents to enter and leave the system, and for the goals of the system to be achieved by organizations of agents that form dynamically. Several concluding observations can be made from this review paper. One is, there are two broad approaches regarding AmI. One is that much of the functionality is realizable through advances in hardware and sensor technologies, functioning with simple data and simple reasoning mechanisms. The other is that the full potential of AmI cannot be realized without sophisticated knowledge representation, reasoning, and AI and agent-oriented technologies. In this review paper, we focus on the second approach. It has explored what AI and agent technologies can offer in processing, and in making decisions on the data provided by the sensors. Second, is the agreement of the construction of plans in the context of the currently available devices and their capabilities. Most of healthcare and elder care systems looked at decides what action(s) to perform in the context of the current circumstances, or to suggest a new schedule of activities to compensate for disturbances in previous schedules. Third, is the variety of different techniques proposed for achieving context-sensitivity, which are very similar and almost interchangeable in formalizing the same concepts. The most obviously related techniques are rules, production rules, decision trees, case-based reasoning and hybrid CBR-BID. Fourth, most authors broadly share similar views of the features required for AmI applications. The key features here are intelligence and embedding. Moreover, the potential impact of AmI on and its challenges for researchers and development are undoubtedly enormous and exciting.

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