A survey of Ambient Assisted Living systems: challenges and opportunities

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***Abstract*—As the research in Ambient Assisted Living (AAL) matures, we expect that data generated from AAL IoT devices will benefit from analysis by well established machine learning techniques. There is also potential that new research in ML and Artificial Intelligence (AI) can be used on data generated from the sensors used in AAL. In this paper we present a survey of the research in the related topics, identify its shortcomings and propose future work that will integrate these fields by collecting ambient sensor data and process the data by ML framework which can detect and classify activities.**

Keywords*—*Ambient Assisted Living, Machine Learning, Pervasive Computing, Ambient Intelligence, Wearable sensors, Environmental sensors

I. Introduction

With advancement of technology and medical science the average lifespan of people has increased. This aging phenomenon already has implications on the society and health care providers, because there are increased number of elderly people requiring better quality of life and affordable health care [1]. AAL seems to be promising approach in facilitating the elderly to live longer in their family residential environments [2]. AAL is a term that appeared for the first time in the European Framework Program for research funding. Within the AAL field, we can find several systems, proposals, and investigations, most of which present definitions and ideas. Very few present real implementations or even simulations [3].

In this paper we will investigate the research related to AAL. We will provide overview of selection of papers, provide classification based on the focus of the research and we'll also investigate ML and its use in activity recognition and classification.

The methodology used for the selection and processing of the research papers in this paper is similar to [4]. We searched the IEEEXplore database and the ACM database for papers containing the phrase "Ambient Assisted Living". From the found papers in the database we selected only papers that are newer than 2008. The number of papers that were screened was 40 papers. The papers were selected based on the topics that justify more attention but at the moment are not sufficiently addressed. A systematic review was performed on the selected paper and the reviewed papers were classified based on their content.

II. Related Work for AAL

A well documented introduction to the field of AAL is provided in [3]. This paper describes the challenges of AAL and gives overview of used technologies such as the wireless protocols. It also provides a high level architectural design of AAL applications listing their essential features and scenarios that need to be addressed. The architecture uses communication technologies such as device-to-device, machine-to-machine and sensor-actuator. For researchers starting in this field this paper provides detailed overview of the issues and challenges in the application of AAL systems.

A dependability analysis for AAL domain is presented in [5]. The authors start by providing activity diagram which then is converted to a Prism language that can present the activity as state machine diagram where each node has probability of failure and the system as a whole is evaluated. The authors do not provide empirical probability for the nodes but demonstrate how a system dependability can be calculated knowing the dependability of individual actions in an AAL work Flow. The authors do not provide empirical probability for the nodes but rather base the calculations on a sample value of 99.99% up-time. This calculation, even though cannot give valid dependability of the system, demonstrate how a system dependability can be calculated knowing the dependability of individual actions in an AAL work-flow.

Any sufficiently complex system, such as Ambient Intelligence, which includes AAL consisting of many components (multiple sensors, processors, actuators and subsystems), in order to be effective, must have a way to make all components work together. This can be accomplished using some middleware communication system. One such system is proposed in [6]. The author proposes the use of Physically Embedded Intelligent System Ecology (PIES-Ecology). If some of the objects in the environment are not active components, such as kitchenware and furniture, but the system should be aware of them, the author uses RFID tags and proxy nodes that will share data on behalf of the inactive objects. All active components use the PIES kernel, which enables communication between all components. As some of these devices, such as dedicated sensors or actuators, have limited processing capabilities, the author has provided a Tiny-PIES kernel capable of running on more constrained systems.

The design of low power acquisition electronics is evaluated to be worthless by the authors of [1], as the main power drainer is usually the wireless communication module. Their paper analyses data rate and power consumption of Wi-Fi, Zig-Bee and a proprietary technology module. The Wi-Fi has higher energy consumption, but because of its higher data rate it can be a viable solution for systems that can have data transmitted in burst after some period of collection. Zig-Bee has lower energy consumption and is a good choice for mobile systems that cannot carry large battery and need constant data link such as body sensors.

Jara et. al. in [7] evaluate NFC communication to perform continuous monitoring of electrocardiogram (ECG). The data is collected from ECG module on Android based phone. The paper evaluates the feasibility of real time data transmission and concludes that the bandwidth is insufficient to transmit raw data. The proposed solution is to use pre-processing module named YOAPY, which compresses and analyses vital signs, making possible continuous and real-time transmission.

The proliferation of smart phones has had impact on AAL research as well. In the previous paper the authors use the phone as data receiver. In [8] the authors focus on the various sensors present in modern phones and elaborate an event-based smart phone processing. The events come from internal and external sensors (like Bluetooth connected physiological monitoring sensors), as well as from other software, the operating system or communication interfaces. In the conclusion it is pointed that the innovation of the proposed approach is to transfer the sensor processing to mobile devices. For some applications this approach should be considered as alternative to the cloud processing of data where smart phones are regarded simply as communication or sensory devices.

Internet of Things (IoT) is a popular research field as well as industry discipline. A great hope has been placed in this industry to bring improvement in daily lives of people. An impact that this field has had in the research is demonstrated also in AAL.

The authors of [9] evaluate the application of IoT for AAL. They first provide introduction to IoT and AAL and then they describe two methods of IoT for AAL. The first method is Keep in Touch and it uses RFID equipped medical devices, such as blood pressure meter and NFC equipped mobile phones. which are utilized as universal communication terminal for medical devices or smart objects. Combined together they provide easy way to collect medical sensor data and provide it to health providers. The second method is Closed Loop Healthcare Services, which is the process of collecting data and obtaining feedback. This, unlike merely collecting and storing data, provides a way for care providers to act upon the patient's status by setting thresholds for physiological parameters.

An IoT based personal device for diabetes therapy management has been proposed in [10]. This paper also presents an integrated system with AAL environment and web based diabetes management portal. The AAL environment is consisted of several modules such as glucometers, RFID tags and cards, LCD touchscreen, AAL Gateway, and a mobile node at the center of it. This system will be used by caretakers, patients and family members.

Another paper dealing with the issue of diabetes is [11] and it applies service value network (SVN) approach to automatically match medical practice recommendations based on patient sensory data to health care services provided by network of service providers. Based on medical guidelines related to treatment of patients with Type 2 Diabetes, a set of rules is extracted. This approach was evaluated by a case study consisting of 493 patient profiles and 111 rules where profiles could trigger multiple rules. This paper addresses an important aspect of AAL which is having rules to provide response for different situations or physiological parameters that are detected. While this approach is based on preset recommendations we can easily envision a machine learning system that can generate the rules based on large dataset of issues, physiological parameters, treatments and outcomes.

Segarra and Andre in [2] propose self-adaptive distributed model as a way to build context-aware AAL application. They use a previously designed framework that help developers implement adaptive applications. Their adaptation model is validated on AAL application which encapsulates a data consistency management service (CMS).

Trajkovik et. al. provide a system architecture model for AAL [12]. This paper summarize related work on many system topics of AAL such as logical and physical architecture, usability, reliability, data accuracy, cost and security. The paper determines possibilities for various assisted living system deployments, based on this architecture, by providing five use case scenarios.

A different architecture of AAL system based on multi-agent architecture responsible for analyzing the data produced by different types of sensors and inferring what contexts can be associated to the monitored person is presented in [13]. This architecture is organized into three layers: event management, context, and assessment. In this multi-agent system each agent supports its point of view about the person's context trough arguments. This approach is used to address the ambiguous or inconsistent representation of the observed situation by the data provided from AAL infrastructure.

Another paper that deals with a multi-agent system is [14] and it proposes a system consisting of sensor, context, intervention, interface, and profile agent. These agents communicate with each other as well as with user interface, sensors and databases. Trough mutual interactions they can provide assistance during routine activities of the person in the house, as well as identify events that deviate from the ordinary events and even trigger alarms. The advantage that the multi-agent system offers in the area of context aware systems is to self configure and tailor interventions.

III. Feature extraction and machine learning in AAL systems

Applying machine learning algorithms for learning based on the collected data is a composite part of AAL systems. In this section we review the algorithms that have been successfully applied for classification and recognition of posture and activities of humans.

Much of the vast literature on time series classification makes several assumptions about data which in practice are usually unwarranted [15]. For example, many research efforts assume that the beginning and ending points of the pattern of interest can be correctly identified, during both the training phase and later deployment. The authors show that the task of correctly extracting individual gait cycles, heartbeats, gestures, behaviors, etc., is generally much more difficult than the task of actually classifying those patterns. They propose to mitigate these problems by introducing an alignment-free time series classification framework.

In [16], the systems that analyze human motion and facilitate automatic classification using on-body accelerometers are reviewed, with a major emphasis devoted to the computational algorithms employed for this purpose. The authors review the achieved predictive performance of various algorithms and papers that use them for activity recognition. Finally they illustrate and discuss a use case of accelerator time series for human posture and action recognition.

Authors in [17] perform comparison of state-of-the-art algorithms using a benchmark dataset for classification of daily life activities (DLAs). The authors identify that state-of-the-art human physical activity classification systems differ in the number and kind of sensors, the performed activities, and the sampling rate. To help in the evaluation of different approaches they have generated a publicly available benchmark data-set for the classification of DLAs. They have compared their approach to other approaches for detecting similar activities in terms of used features, classifiers and performance. Authors also identify which features from the time and frequency domains are useful for successfully training ML algorithms and additionally point out that SVMs (Support Vector Machines) provide best performance compared to CART (Classification And Regression Trees), AdaBoost and kNN (k-Nearest Neighbors).

In [18] activity detection method is proposed that uses non intrusive sensors. The authors evaluate the proposed method on several DLAs and obtain very high accuracy in the detection of the DLAs. The proposed method can be used as a part of any AAL system that needs to record user activities and consider user privacy, technology acceptance and system accuracy. Similarly to the previous paper, this one also identifies informative time domain features (mean, minimum, maximum, standard deviation, variance, range, root-mean-square, correlation, difference, etc.) and frequency domain features (spectral energy, spectral entropy, key coefficient, etc.). They also propose the use of SVMs for classification.

In [19] the authors use simple posture classification based on time of flight (TOF) cameras to detect if the user is sitting, standing, walking etc. The users posture is classified based on a nearest neighbor approach. They use a component called Activity Monitor to monitor if the action has started, is ongoing or has finished. The simpler actions are used with the Bayesian Network based classifier to infer more complex actions. Both simple and complex actions are described using semantic representation.

Authors in [20] demonstrate that only with one chest-mounted accelerometer and a small feature set a Random Forest classifier or AdaBoost can give over 90% accuracy in prediction of 5 actions.

IV. Classification of papers

In this section we will classify papers by assigning relevant properties and topics. We will accomplish this by creating a matrix which will identify the property or topic and all the papers that address it. We will use the following groups of properties for classification:

1) *Research fields or technologies*. We note if a papers evaluates other research fields or technologies: A) IoT; B) Wi-Fi; C) Multi-agent systems.
2) *AAL system properties*. This group is related to properties of AAL systems, such as: D) Security; E) Availability/Dependability etc.
3) *Paper structure*. These qualitative properties identify specific aspects of the paper structure, for example if/how the paper evaluates the proposed approach on empirical data: F) Conceptual design; G) Simulation; H) Working system / experiment; I) Presented results; J) Statistical analysis of results.
4) *Types of Machine learning algorithms* We classify the papers based on the ML approaches used. K) Decision Boundary based (SVM, k-NN, ANN, Clustering etc.); L) Probabilistic (Naive Bayes, Bayesian Networks, Hidden Markov Model); and M) Decision trees (Random forest, Random trees etc.)

Since AAL is broad field that can include many technologies and relate to many other research fields we have narrowed this list to several topics that are key to one or more of the considered papers. We should note that the criteria to fit papers to a particular property is significantly related to the paper's point.

A) Internet of Things
B) WiFi technologies
C) Multi-agent systems
D) Security
E) Availability / Dependability
F) Conceptual design
G) Simulation
H) Working system / experiment
I) Presented results
J) Statistical analysis of results
K) Decision boundary based
L) Probabilistic
M) Decision trees

1
2
3
4

The matrix that matches papers to paper properties is presented in table I. It should be noted that this classification does not judge the quality and does not rank papers. The purpose of this classification is to present the state of the research and serve for quick reference for researchers in this area.

TABLE I. Paper properties matrix

Paper	A	B	C	D	E	F	G	H	I	J	K	L	M
[1]	✓								✓				
[2]						✓							
[3]	✓				✓	✓		✓					
[5]					✓	✓	✓						
[6]					✓	✓		✓					
[7]	✓	✓						✓	✓	✓			
[8]						✓							
[9]	✓					✓							
[10]	✓	✓				✓		✓					
[11]								✓	✓				
[12]				✓		✓							
[13]			✓		✓	✓			✓				
[14]			✓			✓			✓				
[15]							✓		✓	✓	✓		
[16]							✓		✓	✓	✓	✓	
[17]								✓	✓	✓	✓	✓	✓
[18]		✓		✓	✓			✓	✓	✓	✓		
[19]	✓					✓	✓	✓	✓		✓	✓	
[20]						✓	✓	✓	✓				✓

V. Conclusion

From the sample of research work analyzed here we can conclude that most of AAL research is currently focused on conceptual design with significantly less research that is experimental or data driven. While the field of topics covered is quite large and current research shows that AAL can benefit from multiple fields in computer science, from the presented survey we show that experimental research, gathering of data and statistical analysis is represented only in a fraction of the papers.

We have identified that current AAL research lacks experimental results with data from continuous monitoring. Attempts to draw benefits from ML will require that AAL research is more data driven. Based on this survey we identify that AAL is a field that has potential to benefit from ML based on the collected data. In order to create a supportive environment that will not stigmatize the elderly, focus should be given on non intrusive ambient sensor data gathering. As it is difficult to manually predetermine all activities and risks in the AAL environment, we propose to use a combination of unsupervised and supervised ML in order to identify new or unknown conditions and also to better train the system to give correct responses. In cases when there are some experimental results that verify different approaches, there are usually some assumptions about the nature of the data, reliability of data flows and sensors, which in practice are are often violated. Therefore the research in this area need to also consider the realistic assumptions of the AAL systems.

Apparently, there are successful applications of different ML algorithms and efficient feature extraction techniques. Additionally, there need to be defined standards and thresholds that state which performance is acceptable for different AAL scenarios. Also the data-sets used in the reviewed works are with limited size and do not correspond to a realistic application of AAL where there can be thousands of users generating data in real time. In reality, this is also a significant challenge.

Another conclusion that presents itself is that topics such as security and privacy are not properly addressed in research given the importance and sensitivity of the data generated in AAL systems. Same can be said for availability and dependability.

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