A Survey on Ambient-Assisted Living Tools for Older Adults

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***Abstract*—In recent years, we have witnessed a rapid surge in assisted living technologies due to a rapidly aging society. The aging population, the increasing cost of formal health care, the caregiver burden, and the importance that the individuals place on living independently, all motivate development of innovative-assisted living technologies for safe and independent aging. In this survey, we will summarize the emergence of 'ambient-assisted living" (AAL) tools for older adults based on ambient intelligence paradigm. We will summarize the state-of-the-art AAL technologies, tools, and techniques, and we will look at current and future challenges.**

***Index Terms*—Context awareness, decision support systems, intelligent systems, mobile computing, sensors.**

I. Introduction

RECENT advances in medicine allow people to live longer and healthier compared to the previous generations. In fact, approximately 20% of the world population will be age 60 or older by 2050 [1]. Aging brings many challenges to older adults due to their cognitive decline, chronic age-related diseases, as well as limitations in physical activity, vision, and hearing. In the U.S., about 80% of those over 65 are living with at least one chronic disease, and an estimated 5.4 million senior citizens are suffering from Alzheimers disease [2].

The increasing aging population will also result in many challenges for society and the health care system.

1) *Increase in diseases*: There will be an increase in age-related diseases, such as the Alzheimer's disease or Parkinson's disease for which we currently have no cure.
2) *Increase in health care costs:* There will be rising health care costs. Currently, senior citizens use more than 40% of the U.S. health care budget, while accounting for only 13% of the U.S. population. Therefore, the current model of health care is going to become strained as the aging population increases in the next decades.
3) *Shortage of caregivers:* There will be a shortage of professionals trained to work with the aging population, which means more family members have to take the role of informal caregivers. Caring for dependent individuals at home will result in many complications for the informal caregivers, such as higher levels of emotional distress and physical health problems.
4) *Dependency:* With an increase in age-related diseases, there will also be a rise in individuals unable to live independently. As the population ages, it becomes a question of how are we going to pay for the quality care for the elderly and how are we going to deliver quality care to our aging population.
5) *Larger impact on society:* Economist believe that as a society, we will be unable to build, staff, and pay for the older individuals to live in assisted living or skilled nursing facilities. It is also estimated that annual loss to employers of various working family care givers is about \$33 billion (\$2100 per employee) for absenteeism, workplace disruptions, and reduced work status [3].

Given the fact that 89% of the older adults prefer to stay in the comfort of their own homes, and given the costs of nursing home care [4], it is imperative to develop technologies that help older adults to age in place.

In recent years, researchers have developed a variety of assistive technologies based on a new paradigm called "ambient intelligence." Ambient intelligence is a new paradigm in information technology aimed at empowering people's capabilities by the means of digital environments that are sensitive, adaptive, and responsive to human needs [5], [6]. This vision of daily environments will enable innovative human–machine interactions characterized by pervasive, unobtrusive, and anticipatory communications.

Assisted living technologies based on ambient intelligence are called ambient-assisted living (AAL) tools. AAL can be used for preventing, curing, and improving wellness and health conditions of older adults. AAL tools such as medication management tools and medication reminders allow the older adults to take control of their heath conditions [7], [8]. AAL technologies can also provide more safety for the elderly, using mobile emergency response systems [9], fall detection systems [10], and video surveillance systems [11]. Other AAL technologies provide help with daily activities, based on monitoring activities of daily living (ADL) and issuing reminders [12], as well as helping with mobility and automation [13]. Finally, such technologies can allow older adults to better connect and communicate with their peers, as well as with their family and friends [14], [15].

In this survey paper, we will summarize the state-of-the-art AAL technologies, tools, and techniques. We will also explore successful case studies and deployed systems. Finally, we will identify the important current and future challenges.

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TABLE I
AMBIENT SENSORS USED IN SMART ENVIRONMENTS

Sensor	Measurement	Data Format
PIR [1]	Motion	Categorical
Active Infrared	Motion/Identification	Categorical
RFID [2]	Object Information	Categorical
Pressure	Pressure on Mat, Chair, etc.	Numeric
Smart Tiles	Pressure on Floor	Numeric
Magnetic Switches	Door/Cabinet Openning/Closing	Categorical
Ultrasonic	Motion	Numeric
Camera	Activity	Image
Microphone	Activity	Sound

[1]Passive Infrared Motion Sensor.
[2]Radio Frequency Identification.

TABLE II
ASSISTIVE SMART HOME PROJECTS

Project	Institution	Reference
Aging In Place	U. Of Missouri	Ranz [17]
Aware Home	Georgia Tech	Abowd [19]
CareLab	Germany	Nick [23]
CareNet(MIDAS)	U. of Wales, UK	Williams [24]
CASAS	Washington State U.	Cook [16]
DOMUS	U. de Sherbrooke	Giroux [21]
Elite Care	OHSU	Adami [18]
ENABLE	Netherlands	Van Berlo [25]
Gator Tech	UF	Helal [26]
HIS	Grenoble U., France	Noury [27]
MavHome	U. of Texas at Arlington	Cook [28]
Millennium Home	Brunel U.	Perry [29]
ProSAFE	LAAS, France	Chan [30]
SELF	ETL, Japan	Nishida [31]
Smart Medical Home	Rochester U.	Allen [32]
Ubiquitous Home	UCG, Japan	Yamazaki [33]
WTH	JMITI, Japan	Tamura [34]
-	UNSW, Australia	Celler [35]

II. TOOLS AND TECHNOLOGIES

Recent advancements in several technological areas have helped the vision of AAL to become a reality. These technologies include smart homes, assistive robotics, e-textile, and mobile and wearable sensors. In the following sections, we will examine each technology in more detail.

A. Smart Home

A smart home is a regular home which has been augmented with various types of sensors and actuators. Some of the most widely used smart home sensors are summarized in Table I. Rich context information can be obtained by analyzing and fusing various types of sensor data [16]. Most smart homes utilize such knowledge for automation and providing more comfort for the residents, as well as for assessing the cognitive and physical health of the residents.

Table II summarizes several smart home projects aimed at assisted living. For example, CASAS [16] project at Washington State University provides a noninvasive assistive environment for dementia patients at home. The "Aging in Place" project at the University of Missouri aims to provide a long-term care model for seniors in terms of supportive health [17]. Elite care is an assisted living facility equipped with sensors to monitor indicators such as time in bed, bodyweight, and sleep restlessness using various sensors [18]. The Aware Home project at Georgia Tech [19], [20] employs a variety of sensors such as smart floor sensors, as well as assistive robots for monitoring and helping elderly. Other notable smart home testbeds include DOMUS [21] at the University de Sherbrooke, and House_n project at the MIT [22].

TABLE III
TYPICAL WEARABLE AND MOBILE SENSORS

Sensor	Measurement	Data Rate
Accelerometer	Acceleration	High
Gyroscope	Orientation	High
Glucometer	Blood Glucose	High
Pressure	Blood Pressure	Low
Co_2 Gas	Respiration	Very Low
ECG (Electrocardiography)	Cardiac Activity	High
EEG (Electroencephalography)	Brain Activity	High
EMG (Electromyography)	Muscle Activity	Very High
EOG (Electrooculography)	Eye Movement	Very High
Pulse Oximeter	Blood Oxygen Saturation	Low
GSR (Galvanic Skin Response)	Perspiration	Very Low
Thermal	Body Temperature	Very Low

Some smart home projects in Europe include iDorm [36], Grenoble Health Smart Home [27], Gloucester Smart House [37], PROSAFE [30], ENABLE [38], and CareLab [23]. There are also related joint initiatives such as the "Ambient Assisted Living Joint Programme" supported by the European commission with the goal of enhancing the quality of life of older people across Europe through the use of AAL technologies [39]. In Asia, also some smart home projects have been developed, such as the early "Welfare Techno House" project, which measured indicators such as ECG, body weight, and urinary volume using sensors placed in the bathroom and bathtub [34]. The Ubiquitous Home project [33] is another smart home project in Japan, which uses passive infrared (PIR) sensors, cameras, microphones, pressure sensors, and radiofrequency identification (RFID) technology for monitoring the older adults. For a more thorough review of the smart home technology, refer to related survey papers [40].

B. Mobile and Wearable Sensors

Today, most smart phones are equipped with various sensors such as accelerometer, gyroscope, proximity sensor, and global positioning system (GPS), which can be used for detecting user activity and mobility. Also, recent advances in epidermal electronics and MEMS technology[1] promise a new era of health-related sensor technology. Researchers have already developed noninvasive sensors in form of patches, small Holter-type devices, body-worn devices, and smart garments to monitor health signals. For example, blood glucose, blood pressure, and cardiac activity can be measured through wearable sensors using techniques such as infrared sensing, optical sensing, and oscillometric (see Table III). Some other measurements such as EEG still require invasive sensors such as electrodes. Also, depending on the captured physiological signal, high or low data sampling rate might be needed. For example, accelerometer and gyroscope capture acceleration and orientation; therefore, a high sampling rate is required to detect activities such as running. On the other hand, some other physiological measurements such

[1]Microelectro mechanical systems

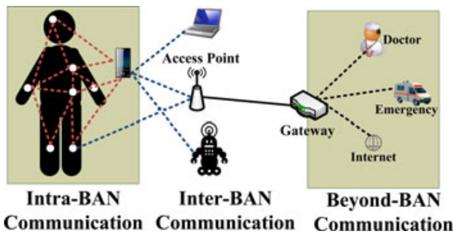

Fig. 1. Communications in a three-tier BAN.

as body temperature will not change abruptly; therefore, occasional data sampling will suffice.

Smart garments or E-textiles promise the most noninvasive form of health monitoring. The fabric sensor integration technology is categorized into several categories [41]. "Garment level" refers to a late-stage visible sensor integration, while "fabric level" refers to a more subtle sensor integration process during production. The ultimate goal is "fiber level" integration to achieve a seamless sensor-fiber integration.

Most sensors adopt a combination of TinyOS operating system and IEEE 802.15.4 (ZigBee) as the radio interface. Sensors generally rely on a network architecture known as the body area network (BAN) [42]. BANs enable wireless communication in or around a human body in three different tiers, as depicted in Fig. 1.

Intra-BAN communications refer to communications between body sensors. Several schemas have been proposed to achieve energy efficient communication with QoS provisioning, including MITHrill [43], SMART [44], and CodeBlue [45]. Recent advances such as inductive links and intrabody links promise alternative communication technologies by using body tissue as a transmission medium. To transmit data from on-body sensors to handheld devices, various IEEE 802.15 standards can be used. Popular choices include Bluetooth (IEEE 802.15.1) with a max data rate of 1 Mb/s and a range of less than 10 m, ZigBee (IEEE 802.15.4) as a low power and low rate protocol with a max data rate of 250 kb/s and a range of less than 20 m, and WiMedia (IEEE 802.15.3) as a more recent technology with a max data rate of 480 Mb/s and a typical range of less than 10 m.

The inter-BAN communications include communicating data from personal devices such as smart phones to the access points, either in an infrastructure-based manner or in an *ad hoc* manner. Various technologies can be employed for inter-BAN communication, including WLAN, Bluetooth, ZigBee, cellular, 3G/4G, etc. The most popular choice is ZigBee protocol due to its ability to support mesh networks, low energy consumption, low duty cycle, low latency communication, and 128-bit security. More recent technologies such as "Bluetooth Low Energy" (BLE) will provide other alternatives in the future by decreasing the communication overhead.

Finally, the beyond-BAN tier connects the access points to the internet and other networks. A database is usually part of the infrastructure to hold collected data and information about users. A Web interface also might be provided to facilitate communication between users and care providers.

C. Robotics

Assistive robots allow the older adults to overcome their physical limitations by helping them in their daily activities. Assistive robots can be categorized into three categories: robots assisting with ADL activities, robots assisting with instrumental activities of daily living (IADL), and robots assisting with enhanced activities of daily living (EADL). ADL tasks include self-maintenance activities, such as feeding, dressing, grooming, etc. IADL tasks include the ability to use instruments in daily living, such as the successful use of the telephone, preparing food, etc. EADLs include participation in social activities, such as engaging in hobbies.

The majority of the ADL assistive robots [46] assist elderly by reducing the need to move such as by fetching objects [47]–[49], or by assisting with typical ADL tasks such as feeding, grooming, bathing, and dressing. For example, Dusty robot helps the older adults by retrieving dropped objects from floor (motor impaired elderly drop objects an average of 5.5 times a day) [50]. Care-O-bot, developed by Fraunhofer IPA at Germany, is able to move safely among humans, to detect and grasp typical household objects, and to safely exchange them with humans [47]. RIBA robot realizes a series of patient transfer operations including lifting up and transferring the elderly from a bed or a wheelchair [49].

IADL assistive robots mostly help with activities such as housekeeping [51], meal preparation, medication management, laundry, shopping, and telephone use [46]. For example, robots such as uBot5 [52] and PerMMA [53] are able to assist elderly by using their manipulator arms to compensate for impaired upper extremity function. PerMMA can assist the user with personal hygiene, meal preparation/consumption, shopping, and mobility. uBot5 also can help with a variety of daily tasks and it even can use a stethoscope to check vitals.

Robots might also assist with EADL tasks such as hobbies, social communication, and new learning [46]. EADL-assistive robots are categorized into service and companion robots [54]. Service robots facilitate a persons interaction with the robot (e.g., Care-O-bot [47]). Companion robots enhance emotional well-being by playing the role of a companion (e.g., Paro [55]).

Besides assisting older adults with ADL, IADL, and EADL tasks, robots might also prove helpful in monitoring [56], interfacing with technology [57], tele-presence (Care-O-bot [47], reminding older adults of location of objects (e.g., Mamoru [58]), or tasks such as taking medication (e.g., Pearl [59]).

III. Algorithms

AAL tools are supported by various algorithms and computational techniques such as activity recognition, context modeling, location identification, planning, and anomaly detection. In the following sections, we will review some of the most frequently encountered techniques.

A. Activity Recognition

One of the most important components in AAL systems is "human activity recognition" component or HAR. A HAR

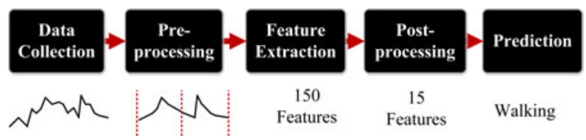

Fig. 2. Processing activity time-series data.

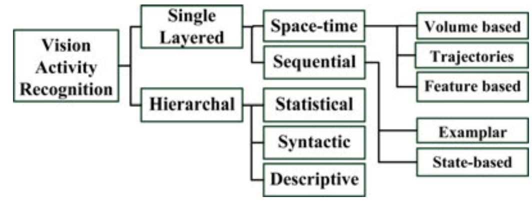

Fig. 3. Vision-based activity recognition approaches [96].

component is responsible for recognizing human activity patterns from various types of low-level sensor data. Different sensors produce different types of data. For example, data collected from most wearable sensors such as accelerometer or gyroscope are in the form of time series, ambient sensors such as motion sensors produce numerical or categorical data, and cameras and thermographic devices record image/video data. The activity itself can be represented and recognized at different resolutions, such as a single movement, action, activity, group activity, and crowd activity.

1) Mobile Activity Recognition: Data from most mobile sensors such as accelerometer and gyroscope are in the form of time series. A time series is a sequence of data points typically measured at regular periods [60], [61]. Most simple actions such as walking, jogging, and running can be represented in the form of distinct, periodic time-series patterns. Recognizing such activities can be useful in many applications, for example, for detecting physical activity level, for promoting health and fitness, and for monitoring hazardous events such as falling.

In general, processing time-series data from sensors such as accelerometer and gyroscope is a multistage process, as shown in Fig. 2. First, sensor data are recorded at a specific frequency, for example, according to the Nyquist criterion. Then, preprocessing tasks are performed on data. For example, data are filtered to remove high-frequency noises and is segmented into shorter segments. Next, statistical and morphological features are extracted from the signal segments, including mean, standard deviation, peak-to-peak amplitude, fast Fourier transform (FFT) coefficients, or wavelet features [62], [63]. The postprocessing step reduces the number of features by applying feature selection and dimensionality reduction techniques. Finally, the classification step predicts the class of activity according to the features. If on-chip processing is required, then efficient techniques should be used because of limited computational resources. For example, extracting Fourier and wavelet features can be implemented on-chip using fast algorithms such as FFT [61]. On the other hand, most dimensionality reduction methods, especially the nonlinear dimensionality reduction methods, cannot be implemented on-chip.

Besides typical supervised models, some researchers use unsupervised models such as "motif discovery" to automatically discover activity patterns [64], [65]. Activity motif discovery differs from typical motif discovery, as activity motifs tend to be sparsely distributed, vary in length, and may exhibit intra-motif similarity only after appropriate time warping [65].

2) Ambient Activity Recognition: To recognize more complex activities, a network of ambient sensors is used to model resident activities in the environment, as a sequence of sensor events. The majority of ambient activity recognition algorithms are supervised, and rely on labeled data for training [66], including decision trees [67], neural networks [68], case-based reasoning [69], mixture models [70], and the popular graphical models [71]. A graphical model uses a graph to represent the conditional independence among observed random variables (sensor observations) to infer about queried random variables (activities). Most graphical models are able to deal with the sequential nature of data, including Markov chains [72], Dynamic Bayesian network [73]–[75], hidden Markov model (HMM) [71], and conditional random fields (CRFs) [76], [77]. HMMs are one of the most popular graphical models for activity recognition, and many extensions have been proposed such as the coupled HMM for recognizing multiresident activities [78], hierarchal HMM for providing hierarchal definitions of activities [79], [80], hidden semi Markov model for modeling activity duration [81], and partially observable Markov decision process for modeling sequential decision processes [82].

Despite their prevalence, supervised methods might not scale well in real world. First, the assumption of consistent predefined activities does not hold in reality. Due to physical, mental, cultural, and lifestyle differences, not all individuals perform the same set of tasks. Also, annotating activity data is a very time consuming and laborious task. To tackle these problems, data-mining methods are used such as the frequent sensor mining [83], simultaneous frequent-periodic activity pattern mining [16], activity stream mining [84], activity episode discovery [85], activity modeling based on low-dimensional eigenspaces [86], sequential activity mining [87]–[89], and using Web mining to retrieve activities' definitions [90], [91]. In addition, techniques such as semisupervised learning [92], active learning [93], and transfer learning [94], [95] have also been applied to the sparsely labeled human activity data.

3) Vision-Based Activity Recognition: Vision-based activity recognition techniques provide very detailed context information. However, they also face difficulties such as tremendous variations in natural settings, algorithmic complexity, and privacy concerns. Typically, data are first preprocessed by applying techniques such as foreground–background segmentation, and then activities are recognized from preprocessed video frames. Vision-based activity recognition techniques consist of two general categories: single layer approaches and hierarchal approaches (see Fig. 3) [96]. Single-layered approaches recognize human activities directly from a sequence of images, and are more appropriate for recognizing gestures or simple actions. Hierarchical approaches represent high-level human activities in terms of simpler activities or actions; therefore, such techniques are appropriate for recognizing more complex activities. Single-layer approaches are further categorized into space-time approaches and sequential approaches. Space-time approaches view an input video as a 3-D (XYT) volume, while sequential approaches interpret it as a sequence of observations. Hierarchal approaches are also further categorized into statistical, syntactic, and description-based approaches. Statistical approaches construct statistical state-based models in a hierarchical fashion (e.g., hierarchal HMM). Syntactic approaches use grammar syntax such as stochastic context-free grammar to model sequential activities, and description-based approaches represent human activities in terms of logical structures. For a more comprehensive review of such techniques, refer to related surveys [96].

B. Context Modeling

AAL systems need to represent many different types of context information, such as sensor information, activities structure, user profiles & preferences, temporal information such as the medical history, and spatial information such as the residence layout and its surrounding [97]. Context-aware system represents context information using approaches such as key-value based models [98], markup-based models [99], situation modeling languages [100], [101], and uncertain context models based on metadata information such as freshness, confidence, and resolution [102], [103]. Also, several ubiquitous ontology models have been proposed such as COMANTO [104], SOPRANO [105], SSH [106], SOUPA [107], and GAIA [108]. Ontology models are particularly interesting, as they provide an explicit commonly agreed upon representation of concepts in a hierarchal manner, using shared properties, subclass, and superclass. Ontology-based markup languages provide a portable specification coupled with reasoning mechanism. To deal with incomplete information in complex real-world ontology models, some researchers have used online resources such as eHow or WordNet to determine the similarity between known concepts and unknown concepts [109], [110].

C. Anomaly Detection

Anomaly detection refers to the problem of finding patterns in data that do not conform to the expected behavior [111]. Many anomaly detection techniques have been proposed in the literature, such as clustering-based methods, statistical methods, and information theoretic methods, among others [111]. In the context of AAL systems, anomaly detection has been used for detecting anomalies in daily activities or medication compliance, by using rule-based techniques, similarity-based techniques, and temporal relation discovery techniques [29], [112]–[114]. Anomaly detection also has been used for detecting wandering patterns or hazardous situations using heuristic methods based on using spatiotemporal information [115], classification [116], and goal analysis [117].

D. Location and Identity Identification

Indoor location identification is another useful component in AAL applications that allows to track, to monitor, and to provide fine-grained location-based services to the elderly. GPS has limited usage in indoor settings due to its limited accuracy and buildings impacting received signals. Therefore, a number of alternative indoor positioning systems have been proposed in the literature, as summarized in Table IV. Smart floor technology uses pressure sensors to detect presence of inhabitants [118]. PIR sensors, which are an unobtrusive popular choice among researchers, detect motion when an infrared source such as human passes through the sensor field. RFID-based systems such as SpotOn [119] and LANDMARC [120] employ RFID readers to detect signal from user's badge. The WiFi-based systems such as RADAR [121] work in two phases. In the offline phase, information about the strength of the signal is collected as a function of user's location, and in the real-time phase, the signal strength is classified based on collected information. Ultrasonic systems use 'time of flight" to measure location information [122]. Active badge systems detect the infrared signal emitted by user's badge [123].

TABLE IV
INDOOR POSITIONING SYSTEMS

Technology	Advantage	Disadvantage
Smart floor	Accurate	Physical reconstruction required
PIR	Cheap, unobtrusive	Inaccurate, sensing motion (not presence), relative position is important
Vision-based	Rich Information	Privacy concerns
Active badge	Accurate	Direct sight required
Ultrasonic	Accurate	Expensive
RFID Tags	Auxiliary data	Limited range, readers position is important
WiFi	Availability	Interference, inaccurate

A related topic is resident identification, e.g., identifying who is currently passing through the hallway or taking the medications. To distinguish residents from one other, two general approaches have been taken by the researchers. The active identification approach uses tools such as RFID badges to identify the residents [78], while the anonymous approach uses machine learning methods to build unique motion models of each resident [124], [125]. Active identification methods are more accurate. On the other hand, the anonymous methods provide a more viable and less obtrusive solution in the long term, as the user is not required to carry a badge.

E. Planning

Automatic planning and scheduling is another important component in many AAL systems. For instance, planning makes it possible to schedule daily plans and to create flexible daily reminders to help dementia patients to carry out their daily activities [126]. Planning and scheduling techniques can be categorized into classical approaches such as forward and backward search or graph-based analysis, the decision-theoretic techniques like Markov decision processes, and the hierarchical techniques [127]. As AAL systems deal with human activities with an uncertain nature, more specialized approaches have been used in AAL systems, such as temporal planning, anytime planning, knowledge-based planning, heuristic planning, reactive planning, and mixed-initiative planning [127]. The plan details might be provided to the system by designers (e.g., COACH [72], or Autominder [126]) or might be learned or adapted based on observations [128].

TABLE V
AAL APPLICATION AREAS

Application Area	Examples
Cognitive Orthotics	Daily Reminders, Medication Reminders, Navigators, Wandering prevention Tools, Planners
Continuous Health Monitoring	Vital Signs Monitoring, Sleep Monitoring, ADL [1]Monitoring
Therapy	Tele-Health Systems, Tele-Rehabilitation Systems
Emergency Detection	Fall Detection, Medical Emergency Detection, Hazard Detection
Emotional Wellbeing	Social Connectedness, Facilitating Communication
Persuasive Applications	Well-being Promotion, Medical Compliance

[1]Activities of Daily Living.

A related issue is when to remind and what to remind. This is an important issue in order to avoid: issuing too many prompts (which might result in user annoyance), issuing lower priority prompts, issuing incorrect prompts (which might result in injury or rejection of the system), or issuing prompt at inappropriate times. It should be noted that over-reliance on the system might also have undesirable effects; therefore; minimum guidance should be provided, if possible. Researchers have addressed such problems using inference, planning, and reinforcement learning to learn user's preferences regarding prompts timing, frequency, or content [12], [126], [129].

IV. Applications

In this section, we will review some of the AAL application areas shown in Table V, such as monitoring tools, wandering prevention tools, and cognitive orthotics devices.

A. Health and Activity Monitoring Tools

A large number of AAL systems aim to monitor daily activities for sustaining independent living, continual naturalistic assessment of health and cognitive status, automated assistance, and decreasing caregiver burden. Some researchers monitor a single activity such as walking or watching TV. Nambu *et al.* [130] monitor watching TV for diagnosing health conditions. Wu *et al.* have developed a smart cane that classifies cane usage and walking patterns, and informs the elderly in case of high risk of falling [131]. The majority of research projects monitor a subset of ADL tasks. For example, CASAS project [16] monitors a subset of ADL tasks to identify consistency and completeness in daily activities. IADL tasks also have been monitored, e.g., IMMED project monitors IADL tasks in dementia patients using a wearable camera [132]. Other researchers have worked on recognizing social activity, especially in nursing homes [79], [133]. Identifying any changes in activities might be an indicator of cognitive or physical decline. For example, indicators such as changes in movement patterns, walking speed, number of outgoings, and sleep rhythm have been identified as early signs of dementia [112], [134], [135].

Continuous vital signs monitoring is another important application area and various wearable and e-textile sensors have been developed for this purpose (see Table VI). AMON is a wearable health monitoring system developed at ETH Zurich University [136]. HealthBuddy by Bosch [137], TeleStation by Philips [138], HealthGuide by Intel [139], and Genesis by Honeywell [140] are examples of commercially available tele-health devices. WEALTHY [141], BIOTEX [142], and MagIC [143] are examples of e-textile projects. The BIOTEX project aims to integrate sensors in textiles for applications such as sore monitoring based on detecting pH changes or inflammatory proteins concentration [142]. Healthy Aims is another project that plans to develop a range of medical implants to help the aging population [144]. Some researchers have also devised other unobtrusive health monitoring techniques. For example, Masuda *et al.* [145] measure heart and respiratory rates based on using an air-filled mat and measuring perturbations in the air pressure by exploiting the low-frequency characteristics of heart and respiratory rates. Similarly, Andoh *et al.* have developed a sleep monitoring mattress that analyzes breathing, heart rate, snoring, and body movement [146]. The SELF smart home project also monitors posture, body movement, breathing, oxygen in the blood, airflow at mouth and nose and apnea, using pressure sensor arrays, cameras, and microphones [31].

TABLE VI
WEARABLE AND E-TEXTILE HEALTH MONITORING SYSTEMS

Project	Description
Vivago [147]	Implantable radiotelemetry platform
LifeShirt [148]	First commercially available smart shirt
HealthVest [149]	Knitted sensor structures
BioHarness [150]	Sensors embbedded in a chest belt
MagIC [143]	Textile electrodes
AMON [136]	Wearable medical monitoring and alert system
BIOTEX [142]	Sensors in textiles for medical applications such as sore monitoring
Healthy Aims [144]	Medical implants for the aging population
WEALTHY [141]	Textile sensors in jacket
CodeBlue [151]	Custom sensor wearable motes

Fall detection is another important application area, as falls constitute an important cause of morbidity and mortality in the elderly. Various types of fall detection systems have been developed. Fall detection methods can be categorized into three categories: wearable device based, ambience sensor based, and camera (vision) based [152]. Wearable fall detection systems measure posture and motion using sensors such as accelerometer and gyroscope [153], [154]. Ambient fall detection systems rely on sensors such as PIR sensors, pressure sensors, as well as floor vibration detection and audio analysis [155], [156]. The vision based fall detection systems rely on video features such as 3-D motion, shape, and inactivity to detect falls [157], [158].

B. Wandering Prevention Tools

AAL tools can be useful for preventing wandering behavior of dementia patients. There are a number of outdoor wandering prevention tools. KopAL [159] and OutCare [160] support disoriented elderly by alerting the caretakers in case of deviating from predefined routes or daily signature routes. Comfort Zone [161], EmFinder [162], QuestGuard [163], and GPSShoes [164] are examples of commercial outdoor wandering prevention tools relying on GPS technology. In the case of indoor stray, Lin *et al.* [165] use RFID technology to detect if an elderly person has approached a dangerous area, and Crombag [166] proposes using virtual indoor fencing in potentially harmful situations.

Some commercially available products for wandering prevention include safeDoor and SafetyBed [162], for example, safeDoor raise alarm if a person walks out a door without opening it, to prevent nighttime wandering.

Machine learning algorithms have also been used for detecting wandering behavior. Vuong *et al.* [167] automatically classify wandering patterns of dementia patients based on the Martino–Saltzman typology [168] into direct, random, pacing, and lapping patterns. Kim *et al.* [115] try to distinguish wandering patterns from normal patterns in a nursing home by using time and location information. Campo *et al.* [116] have developed methods for determining normal trajectory classes and triggering alarms when the trajectories are unusual. They compare each extracted path to all types of trajectories in order to classify them using a neural network. Also, Gottfried *et al.* [117] discuss several artificial intelligence (AI) techniques for analyzing trajectory patterns and classifying them as goal-oriented or erratic.

Navigation assistance tools have also been developed to help elderly suffering from early signs of dementia. "Opportunity Knocks" is a mobile application that provides public transit system guidance by learning user's routes [169]. Mahmud *et al.* [170] describe design and development of an interactive aid tool for dementia patients by utilizing time, location, and social network information. Hossain *et al.* [171] also develop a tool to predict individual walking routes of elders and to assist them to get back on track, if they get lost.

C. Cognitive Orthotics

Cognitive orthotics tools can prove very useful in case of older adults suffering from cognitive decline, as family members usually find it embarrassing and upsetting to provide cues and prompts to their loved ones, due to privacy invasion and role reversal issues [72]. The idea of cognitive orthotics has been around since 1960s [172]. Later, those ideas evolved into simple activity reminder tools such as NeuroPager [173], MAPS [174], "Visual Assistant" [175], MEMOS [176], MemoJog [177], and ISAAC [178]. Cognitive orthotics tools can be useful in case of medication management, for example, by using automatic mediation dispenser systems coupled with reminders [179], or using small wearable medication management devices [180]. Cognitive orthotics tools can also be used for cognitive rehabilitation. SenseCam, which is developed by Microsoft, captures a digital record of the wearer's day in terms of a series of images and a log of sensor data [181]. It helps the wearer recollect aspects of earlier experiences that have subsequently been forgotten, thereby acting as a retrospective memory aid. Hoey *et al.* [182] also describe the development of a cognitive rehabilitation tool to assist art therapists working with older adults with dementia.

There also have been more advanced cognitive orthotics tools using advanced machine learning and AI techniques. An example early cognitive orthotics tool is PEAT [183], which maintains a detailed model of the daily plan in terms of hierarchal events, and tracks their execution. Autominder by Pollack *et al.* [126] provides users with reminders about their daily activities by reasoning about any disparities between what the client is supposed to do and what she is doing, and makes decisions about whether and when to issue reminders. Mihailidis *et al.* [72] also have developed a prototype prompting system based on vision techniques named COACH, to guide users while washing their hands. Medication compliance is another area that can benefit from more advanced algorithms, for example, Jakkula and Cook [114] propose temporal relations for detecting anomaly in medicine compliance of elderly.

V. Design Issues

Designing AAL systems for the elderly requires special attention, because of their cognitive, perceptual, or physical limitations. In general, AAL systems should not rely on user's effort. This design concept is in accordance with an emerging class of technology called zero-effort technologies that requires little or no effort from the people who use it, by relying on advanced computational techniques to autonomously learn about users needs [184]. In the case of AAL system with a user interface, the user interface should be kept as simple as possible. For example, the possibility of error should be limited, cognitive overload should be avoided by limiting possible options, the dialogs should be linear, and parallel tasks should be avoided [185]. Also, metaphor interfaces might be more intuitive for the elderly. An example of a metaphoric interface is the "UbiFit Garden" by Consolvo *et al.* [186] that uses the metaphor of a garden that blooms throughout the week with different types of flowers representing activities that are important to a well-balanced routine.

Sensors and other equipments also require special attention when designing AAL systems. As the sensors are usually in direct contact with the body, their size and compatibility with human body tissue is very important. An implication of small size devices is reducing the battery size while maintaining efficiency. To avoid battery usage problems, energy harvesting or short-range wireless energy submission can be used in the future. The physical interference of sensors with movement also should be minimized and any potential difficulties in removing and placing sensors should be eliminated. The sensors should be lightweight, and the frequency and difficulty of related maintenance tasks such as charging and cleaning should be minimal. Another important issue is to consider related social and fashion concerns, for example, by using common devices such as smart phones to avoid drawing attention and possible stigmatization [187]. In the case of more complicated systems such as smart homes, some other guidelines include providing control over the system to override the automation if necessary, and avoiding excessive guidance as people should not become reliant on ambient technology [188]. AAL systems for the elderly should also be adaptive to the context and their needs. For example, in the case of a daily task reminder, day and night require different types of content, given that the person might have different levels of consciousness and alertness [189].

Finally, it should be noted that the elderly are not the only beneficiaries of AAL systems; rather, other stakeholder should also be taken into account, such as the formal onsite and offsite caregivers, informal onsite and offsite caregivers, and technical personnel. For example, visualization tools should be designed to allow the caregiver to easily view the daily activities and health information of the older adult.

VI. Social and Ethical Issues

One of the big hurdles for deploying AAL system in real world is technology acceptance by the older adults. As van Bronswijk *et al.* [190] point out, "the reluctance of older adults to adopt technological change may be described by the ancient proverb: Better a known devil than an unknown god. Older adults may view the technological option as "gilding the lily," replacing a perfectly good and well-known alternative with an unnecessarily complicated one, which offers slight or no advantage." Also, Zagler *et al.* [188] note that elderly often want a "guardian-angel," but without any sensors, which is of course a paradox. A 2011 study on adoption of health-related information and communication technology among older adults found that healthier older people being far more likely to use computers than their unhealthy coevals, showing that the adoption of technology by the older adults is still lingering [191]. The authors suggest that systems designed for the elderly should be kept simple, and special attention should be paid to training and support.

Preserving privacy and confidentiality is another important issue and privacy should be considered in design specifications of AAL devices (privacy by design [192]). All communications should be encrypted and secure, and the involved parties should ensure confidentiality. This is especially important in the case of wireless communication which are easier to intercept. Personal monitoring devices should authenticate the identity of the older adult using unobtrusive biometrics or possibly key physiological signs to avoid any data tampering (owner-aware devices). Furthermore, it is important to ensure that all collected data is flawless and uncorrupted to ensure quality health care, as well as ensuring compliance with mandated HIPAA (The Health Insurance Portability and Accountability Act of 1996). Finally, it is also important to ensure that technology does not replace human care and will not result in older adults' isolation, or does not threaten trust in patient–physician relation.

VII. Conclusions and Future Research Path

Current AAL systems promise many opportunities for maintaining independence of older adults, as well as for monitoring and improving their health conditions. Several key emerging technologies have made it possible, such as the mobile and wearable sensors, assistive robots, smart homes, and smart fabrics. Meanwhile, advanced computational techniques have helped to unleash the full power of such technologies. But there are still many challenges that need to be addressed by the researchers in the future.

Sensor Technology: The new generation of mobile and wearable sensors should be more comfortable to wear and less obtrusive. To achieve this, such devices should take advantage of the future power harvesting and wireless power transmission technologies, as well as new human-tissue compatibles materials to achieve truly noninvasive solutions. Also, researchers need to address concerns regarding the absorption of electromagnetic energy by human tissue by employing devices with low transmission power and low duty cycles.

Assistive Robotics Technology: Currently assistive robots do not support a variety of daily tasks; rather, each robot is built to provide assistance with a very limited set of tasks [46]. In the future, more user studies should be performed regarding the acceptance of robots by the older adults, as well as the older adults' expectations of such assistive robots. The future robots not only should be capable of assisting the older adults in their day to day life, but also should be able to adapt to their gradual physical and cognitive decline, as well as to their sudden changes such as a hip fracture.

Security and Privacy: Deployment of AAL technologies will bring along new concerns about security, as a multitude of personal data is collected. The future AAL systems should employ a variety of noninvasive user authentication methods based on biometric and physiological features to safeguard user privacy. Different levels of security should be granted to different users in such complex systems, and the communication links should be made secure and more reliable.

Human Factors: In general, usability and user experience issues are of utmost importance when designing AAL systems. Besides the older adults, system developers and researchers should pay attention to other stakeholders such as the caregivers, physicians, and hospital teams. Also, it is important to provide users with sufficient training and information about AAL systems, as many older adults might shy away from using such systems due to their perceived system complexity.

Algorithms: Most current techniques such as activity recognition and indoor location detection still need to be improved to become more reliable and more accurate for use in real-world settings. Also, some simplifying assumptions should be relaxed, such as the assumptions regarding single resident homes and availability of labeled data. Besides, there is a need for standard benchmark datasets.

Legal and Ethical: There are currently no structured regulations regarding reimbursement of AAL tools, or regarding malpractice in complex tele-health systems. Also, to protect their rights as consumers, the older adults should be well-informed about the possible consequences of AAL solutions.

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