International Journal of Advanced Computer Research (ISSN (print): 2249-7277 ISSN (online): 2277-7970)
Volume-4 Number-1 Issue-14 March-2014

A Survey on Automatic Fall Detection in the Context of Ambient Assisted Living Systems

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Abstract

Ambient Assisted Living (AAL) systems are a relatively new and expanding area of research. Due to current demographic trends towards gentrification of the population AAL systems are bound to become more important in todays and near future's societies. Fall detection is an important component of AAL systems which could provide better safety and higher independency of the elderly. This paper presents a survey on automatic fall detection in the context of AAL systems.

Keywords

Ambient assisted living, fall detection, accelerometers, computer vision, comparative study.

1. Introduction

Demographic tendencies in today's societies lead to gentrification of the population both in developed and developing countries as well as in third world countries. According to a report by the UN published in 2009 [1] the number of people aged 60 or over worldwide is expected to surpass the number of children (people aged 15 or under) for the first time in 2045. By 2050 the population of people aged 60 or over will be around 30% of the global population [1].

These gentrification processes are already reality in developed countries such as EU countries, USA, Canada, Japan, Australia, etc. and will only worsen in the future [2]. The increase of the number and percentage of old people will put the social, pension and health systems at great pressure as the demand for health services, caring personnel and institutions will also increase [3]. Falls constitute a major risk for the elderly causing significant mortality, disability, loss of independence, and early admission to nursing homes [4]. In 2012, Robinovitch et al. [5] report that falls are the most frequent cause of unintentional injuries at the elderly (people aged 65 and over), accounting for 90% of hip and wrist fractures and 60% of head injuries in this age group. Also, unintentional injuries are the fifth leading cause of death in older adults [6].

Around 30% of community-dwelling citizens aged 65 and over fall at least once per year [4,5,7,8], and the percentage increases for elderly living in long-term care institutions [5,7]. A fall at the elderly, even without injury, often results in developing a post-fall anxiety syndrome, also known as fear of falling [6,7]. Fear of falling could lead to reduced physical activities and in general lesser physical fitness which in turns is a predisposition for subsequent falls.

Another problem associated with falls at the elderly is the long lie. Long lie means remaining on the ground or floor for more than an hour after the fall because one is unable to signalize for help [7]. The long lie could have serious implications to the health of the fallen person – hypothermia, dehydration, muscle damage, etc.

The focus of this paper is on fall detection systems in the context of Ambient Assisted Living systems. The rest of the paper is organized as follows: Section 2 presents an introduction to AAL systems, Section 3 concentrates on a survey of papers focusing on fall detection, Section 4 presents an overview of the current challenges to fall detection systems in particular and AAL systems in general. Finally Section 5 concludes the paper.

2. Ambient Assisted Living – an Innovative Approach to Personalized Healthcare

Ambient intelligence and ambient assisted living systems

A new direction of research since the beginning of the millennium is Ambient Intelligence (AmI). AmI systems consist of environments, digitally enriched with sensors, processing and communication technologies, in order to understand, analyze and respond to user's needs [9]. In 2009, Augusto [10] defines AmI as "A digital environment that supports

Manuscript received February 17, 2014.
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people in their daily lives by assisting them in a sensible way". By definition AmI systems are responsive, they react adequately to the user's behavior and/or input, they are able to extract the necessary information from a rich set of data provided by various sensors and, if possible, they should be able to anticipate and adapt to the user's needs [11]. AmI systems use automated reasoning and other artificial intelligence techniques in order to achieve their purpose [12].

AmI-enabled smart environments have potentially diverse applications, such as smart offices, smart classrooms, digital cities, etc. [13]. However, one of the most impactful areas given the ageing population is their application in personalized healthcare. A research area closely related and recently converging to AmI is Ambient Assisted Living (AAL). An AAL system could be defined as a system that could extend the time an old or disabled person can live at home by increasing the user independence and assisting him/her in carrying out activities of daily life [12, 14].

In general AAL systems use advances in Information and Communication Technologies in order to improve the quality of life of their users and to "maintain them as longer as possible independent, active and involved in the community" [15]. They achieve the above-mentioned by the pervasive use of sensors, processors, actuators and communications devices. AAL systems also often provide presence-awareness, location-awareness and context awareness features [12].

AAL sub-domains

Ambient Assisted Living is itself a broad research area which includes different aspects of the user's daily life. The AALIANCE roadmap on AAL [16] subdivides AAL into three main areas – AAL4persons (which is further subdivided into AAL@home and AAL@mobile), AAL@community and AAL@work. **AAL4persons** includes applications enabling the user to stay healthier for longer period of time and to benefit from a higher quality of daily life. The area is further subdivided into **AAL@home**, which provides assistance to the users in their homes, and **AAL@mobile** which provides services while they are on the move. **AAL@community** focuses in assisting the users in order to help them remain socially active and creative, as well as providing them with help when accessing public and commercial social services. **AAL@work** focuses on the concept of "active ageing at work", i.e. remaining active and productive for a longer time and benefiting from a better work-life balance.

There are growing numbers of research efforts concentrated in the area AAL@home, which is evident by the exponential growth of the number of research papers in recent years. After a review of the published papers in the recent 10 years, the following research directions in the area AAL@home have been identified:

- *Telemetric systems* – these systems monitor vital parameters of the user such as pulse, blood oxygen saturation, ECG, glucose levels, blood pressure, etc. and often transmit the gathered data to a remote server. An example is the web services based ECG telemetric system presented in [17].
- *Human Computer Interaction (HCI)* – these systems are focused on developing innovative and intuitive user interfaces to be used in home applications such as speech recognition, gesture recognition, etc. The target users are people who don't have much technological knowledge and are reluctant and/or incapable of using more sophisticated user interfaces. Examples are the systems presented in [18, 19].
- *Indoors localization* – a very important feature of an AAL system is the location-awareness of the system. This is especially valid for applications whose primary users are people with cognitive disabilities such as Alzheimer's disease and other forms of dementia. Examples of papers focusing on indoors localization are [20-23].
- *Social platforms* – these systems enable better social communication between the elderly and their relatives, friends and carers. Examples of such systems are the ones presented in [24, 25].
- *Emergency detection* – emergency detection systems are of vital importance for ensuring personal safety of users with deteriorating physical and cognitive abilities such as the elderly. Emergency situations could be related to the home environment, e.g. forgetting the stove on, forgetting the shower on, etc., or related to the user, e.g. loss of consciousness, sudden change in vital parameters, etc. Example of the latter is [26]. An important sub-domain of the emergency detection systems are fall detection systems which are also the focus of this paper.

AAL Platforms

A number of AAL platforms that have been developed in recent years are presented in this section. Some of them cover only one or two of the AAL research directions, whereas some of them aim for higher degree of versatility.

With the demographic changes that lead to gentrification of the population, many countries' governments are investing in funding schemes that benefit the development of AAL solutions. EU FP7 program also has dedicated some of its funding to AAL solutions. Some of the projects that have been funded under this scheme along with other platforms are presented in Table 1.

Table 1: AAL Platforms

Paper	Year of publication	Platform(s) name(s)	Short description
Amoretti et al. [27]	2013	PERSONA	A highly modular, non-invasive, highly responsive activity monitoring AAL system.
Antonino et al. [28]	2011	Alhambra, Hydra, OASIS, Open AAL, PERSONA, universAAL	The paper presents an evaluation of the platforms by non-functional parameters - security, safety, maintainability, reliability and efficiency. UniversAAL scores best.
Aquilano et al. [15]	2012	RITA	An AAL tele-health system in Pisa, Italy.
Bothorel et al. [24]	2011	Mazadoo	A Smart TV Facebook-based social platform for the elderly in a residency home.
Bourke et al. [29]	2012	eCAALYX	A tele-monitoring system that incorporates fall detection, activity classification and energy expenditure algorithms.
Chessa et al. [30]	2011	EvAAL	A competition to test different aspects of AAL systems through universal methodologies and benchmarks.
Drobics et al. [25]	2011	FoSIBLE	A multiple input modes (remote control, tablet, gesture recognition) smart TV social platform for the elderly.
Furfari et.al [31]	2011	universAAL	An open-source platform to facilitate the creation, deployment and configuration of AAL systems.
Schneider et al. [32]	2012	ALIAS	A project to create a robot that will be a social assistant of the elderly helping them preserve their social function as well as reminding them to take medicines, etc.
Tazari et al. [33]	2011	universAAL, AMIGO, GENESYS, MPOWER, OASIS, PERSONA, SOPRANO	The paper presents how universAAL consolidated the results of previous AAL projects.
Wagner et al. [34]	2009	OpenCare	Free, scalable, flexible and open source infrastructure architecture to be used in AAL systems.
Wille et al. [35]	2012	TinySEP	A compact and flexible platform for AAL solutions.

Requirements to AAL systems

Apart from the functional requirements to the AAL system, which are in direct relation to the purpose of the AAL system and the concrete problem it resolves, there are a number of non-functional requirements which are valid for all AAL systems regardless of their application domain [16, 36, 37].

In 2006, Nehmer et al. [36] present their detailed view on the requirements of assistive systems. They list robustness, availability, extensibility, safety, security, timeliness, resource efficiency, natural and anticipatory human-computer interaction and adaptivity (with its three directions – self-optimization, self-configuration and self-maintenance).In 2010, Broek et al. [16] list the following requirements to AAL systems: embedded (non invasive), distributed throughout the environment, personalized, adaptive and anticipatory. In 2010, O'Grady et al. [37] add open, scalable and intuitive to the set of requirements.From these papers it is evident that developers of AAL systems face very high number of requirements. This is not surprising as AAL systems interact directly with people who in many cases are more prone to accidents and health risks, and whose quality of life and health directly depend on the supporting technology.

The above mentioned requirements are specified for AAL systems but they are also valid for fall detection systems.

3. Fall Detection

As previously mentioned, falls are among the most potentially dangerous risks related to aging. As such, almost all AAL systems targeted at the elderly have a fall detection module. Fall detection could be the primary focus of the developed system as in [38], or falls could be detected as a side effect of an activity recognition system such as the one presented in [27]. In this overview both standalone fall detection systems and detection of falls in activity recognition systems are reviewed. Falls are complex processes whose causes and development could differ significantly on a case-by-case basis, but in general the fall is a temporally short event which starts with a sudden loss of balance and results in an impact with the ground or a piece of furniture. Very few papers (e.g. [39]) focus on automatically monitoring pre-fall user activity in order to investigate conditions that may lead to a fall and to issue fall prevention alarms.

Different researchers use different sensors in order to detect falls. In 2010, Kaluza et al. [40] separated fall detection approaches into accelerometer based and computer vision based. In 2011, Chen et al. [41] investigated activity recognition in pervasive healthcare and separated the approaches for activity recognition into the more general sensor based and computer vision based. In 2011, Khan [42] also focused on activity recognition and further subdivided the approaches into environmental sensor based, wearable sensor based and video based. This taxonomy seems to be the most widely accepted taxonomy for fall detection systems – Mubashir [43], Mubashir et al. [44] and Yu et al. [45] classify fall detection approaches into **wearable sensors based**, **ambient sensors based** and **computer vision based**. A variation of the above classification is given by Hijaz et al. [46] who classify algorithms into kinematic sensor based, acoustic and ambience sensor based and computer vision based. In 2013, El-Bendary et al. [47] presented a review of fall detection algorithms which could be classified as wearable sensor based, computer vision based, smartphone based and wireless networks based. Finally, in 2013, Igual et al. [48] published a very broad survey on fall detection algorithms in which they have classified the different approaches as context-aware and wearable sensors based. Context-aware approaches were further subdivided into computer vision based, pressure floors and acoustic; and wearable sensors based were further subdivided into accelerometers attached to the body and accelerometers integrated into smartphones. It could be seen from the taxonomies presented above that most generally the fall detection approaches could be classified into wearable sensors based, ambient sensors based and computer vision based. **Wearable sensors based** approaches use sensors that are worn by the user either directly attached to the user's body, or integrated into some form of smart clothing or accessory. The most widely used sensors are accelerometers but other types of inertial sensors such as gyroscopes could also be used. **Ambient sensor based** approaches make use of sensors embedded in the environment. Typical examples are pressure or vibration sensors (smart floors), arrays of infrared sensors or microphones. **Computer vision based approaches** use cameras in order to either capture single images or video sequences which are then fed into computer vision systems in order to detect the fall.

Recent papers tend to classify fall detection algorithms that use accelerometers embedded in smartphones in a separate class. In this paper smartphone based algorithms are reviewed under the class of wearable sensor based algorithms. Also, in this paper we define an additional class of algorithms - **multimodal** approaches. Multimodal approaches use two or more sensors form one or more of the above defined classes, for example an accelerometer and a camera. The taxonomy of fall detection algorithms used in the rest of this survey is presented at Figure 1.

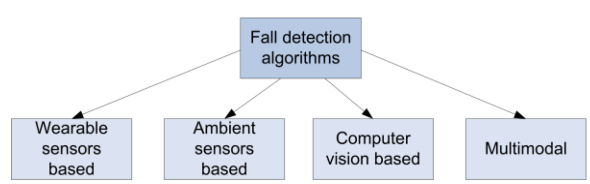

Figure 1: Taxonomy of Fall Detection Algorithms

Two important concepts should be defined when evaluating different fall detection algorithms –

sensitivity and **specificity** [49]. The so-called confusion matrix is used in order to define sensitivity and specificity. The confusion matrix is presented at Figure 2.

	Classified as A	Classified as not A
Is A	TP	FN
Is not A	FP	TN

TP – True Positive; FN – False Negative
FP – False Positive; TN – True Negative

Figure 2: The Confusion Matrix

Sensitivity is defined as the percentage of correctly detected events (in our case falls):

sensitivity = TP/(TP + FN). (1)

Specificity is defined as the percentage of correctly detected non-fall activities.

specificity = TN/(TN + FP), (2)

Accuracy is another metric which is used to characterize the correctness of an algorithm and is defined as the percentage of correctly detected events:

accuracy = (TP + TN)/(TP + FP + TN + FN).(3)

Wearable Sensors Based Fall Detection

Wearable sensors based approaches were among the first algorithms developed for fall detection. The main advantage of these approaches is the relative simplicity of the algorithms and their ease of implementation in real-time systems.

Most algorithms whose focus is only fall detection and the simpler activity recognition systems are threshold based. They require a “set of empirically derived thresholds for each classification subclass” [50]. More sophisticated fall detection and activity recognition algorithms use machine learning enabled methods such as Artificial Neural Networks (ANN) or statistical schemes for pattern recognition [51]. Pattern recognition approaches most often use supervised machine learning algorithms such as k Nearest Neighbor (kNN), Naïve Bayes, Support Vector Machines (SVM), Hidden Markov Models (HMM), Gaussian Mixture Models (GMM), etc. [51]. Accelerometers are used by the vast majority of published research papers and accelerometer based algorithms set the tendency in wearable sensor based approaches. As such only accelerometer based algorithms (with the exception of Lustrek et al. [52] who use radio tags) are reviewed in Table 2. Also all of the multimodal approaches reviewed later in this section use accelerometer(s) as one of their modalities.

Table 2: Wearable Sensors Based Fall Detection

Paper	Year of publication	Algorithm type	Sensor position	Sensitivity	Specificity	Notes
Abbatte et al. [53]	2011	Threshold-based	waist	100%	100%	The paper focuses especially on distinguishing false alarms using Average Acceleration Magnitude Variance index.
Attalah et al. [54]	2010	kNN (k Nearest Neighbors)	ear, chest, arm, waist, wrist, knee, ankle	NA	NA	The paper has a good research into which features from the raw acceleration data are best for action recognition.
Bourke et al. [55]	2010	Threshold-based	waist	100%	100%	The algorithm has less than 1 (0.6) false positive alarms per day of walking hours.
Cavka et al. [56]	2013	Threshold-based	waist	97.00%	95.00%	The fall detector has also an emergency button.
Iliev et al. [38]	2011	Threshold-based	wrist	NA	NA	The system is integrated in a watch-like device.
Kangas et al. [57]	2007	Threshold-based	wrist, waist, head	wrist = 75%, waist = 100%, head = 100%	wrist = 100%, waist = 100%, head = 100%	Only data, simulated by young volunteers were used.

Kangas et al. [58]	2008	Threshold-based	wrist, waist, head	wrist = 71%, waist = 97%, head = 98%	wrist = 100%, waist = 100%, head = 100%	Only data, simulated by middle-aged volunteers were used.
Kurdthongmee [59]	2012	SOM (Self Organizing Maps)	waist	up to 100%	NA	The algorithm runs on a smartphone.
Lai et al. [60]	2010	Threshold-based	neck, waist, both wrists, both thighs	NA	NA	Accuracy = 99.55%
Lustrek et al.* [52]	2009	SVM (Support Vector Machines)	sholders, elbows, wrists, hips, knees, ankles	NA	NA	Accuracy = 96.5%. The authors use radio tags.
Mannini et al. [61]	2010	HMM (Hidden Markov Models)	hip, thigh, wrist, arm, ankle	96.40%	93.70%	The authors use 5 sensors and train the classifier with data from all of them.
Narasimhan [62]	2012	Threshold-based	anywhere on the torso	99%	100%	The accelerometer is placed in a skin-contact adhesive sticker that could be placed anywhere on the user's torso.
Pereira et al. [63]	2012	Logistic regression	waist	NA	NA	Accuracy = 98.0%.
Soaz et al. [64]	2012	Threshold-based	waist	100%	reasonable (percentage unavailable)	The authors used simulated falls and real-world daily activities signals.
Stoimenov et al. [65]	2011	Threshold-based	wrist	NA	NA	The processing of the acceleration signals is done by Field Programmable Analogue Array.

**** Lustrek et al, 2009 use radio tags, all other papers use accelerometers.***

Although the use of wearable sensors in general and accelerometers in particular has many benefits, it also comes with a set of drawbacks and challenges. One of the more obvious problems is the scarcity of resources. Wearable devices should be battery powered, but they should also be connected to a home gateway or remote server, i.e. they should have some communication interfaces to transmit data. Communication is energy consuming and advances in battery manufacture are currently insufficient for prolonged device life, meaning that some compromise should be achieved between granting enough self-sustainability of the device and ensuring timely transmissions of alarms and status information.

Another drawback to wearable fall detectors is that the elderly could often forget to wear them which would turn them useless for the aims of fall detection.

Another less obvious problem is caused by the differences between real-world and simulated data. In 2011, Klenk et al. [66] and in 2012, Bagala et al. [67] have proven experimentally that there is substantial drop in the performance of fall detection algorithms when they run in real world as compared to runs with simulated (by young volunteers) data. All the algorithms presented in Table 2 suffer from this problem as they all use simulated data in order to test their implementations. Consequently, although at first glance the algorithms in Table 2 have good performance in terms of sensitivity and specificity (or accuracy), in real-world scenarios it is likely that there will be much more false alarms and their performance wouldn’t be that good. The problem of simulated vs. real-world data is mostly due to the lack of enough real-world fall data to be used during the development of fall detection algorithms. Much more tests with elderly in their natural habitat are needed in order to overcome this issue.

Ambient Sensors Based Fall Detection

Ambient sensors based algorithms are also considered relatively easy to develop. Their benefit is that the users aren’t required to wear or carry with themselves additional sensors or equipment. Examples of ambient based solutions are systems with pressure or vibration sensors (smart floors), arrays of infrared sensors or microphones. Most of them are in the lower to mid-price range, however, they could sometimes be difficult to install in users' homes, especially in the case of smart floors. Table 5 presents some of the research papers focusing on ambient sensor based approaches for fall detection and activity recognition.

It could be seen from Table 5 that some ambient sensors based approaches have very good performance metrics. An example is Alwan et al. [68] who use two vibration sensors in order to detect falls. The problem with this approach is that the sensors are heavy and bulky and it will be impractical to install such sensors in every room of the user's home. Most of the other approaches don't have convincing performance metrics or their metrics are unavailable.

Table 3: Ambient Sensors Based Fall Detection

Paper	Year of publication	Sensor	Algorithm type	Sensitivity	Specificity	Notes
Alwan et al. [68]	2006	smart floor (vibration)	Hardware implemented	100% with 95% CI of 94.87%-100%	100% with 95% CI of 93.28%-100%	CI = Confidence Interval
Fleury et al. [69]	2008	8 microphones	GMM (Gaussian Mixture Models), HMM	76.19%	NA	76.19% sensitivity for falls.
Huang et al. [70]	2012	array of ultrasonic transducers	Threshold-based	NA	NA	The system was tested for 3 months in a care community. It has fired false alarms several times.
Klack et al. [71]	2010	smart floor (pressure sensors)	SVM	NA	NA	The smart floor is integrated in a Living Lab in Aachen University.
Li et al. [72]	2012	microphone array	kNN	100%	97%	They use steered response power (SRP) in order to determine the location of the person.
Liu et al. [73]	2011	radar	kNN	NA	NA	They have area under curve of true positives = 0.96.
Tao et al. [74]	2012	infrared ceiling network	SVM	NA	NA	The algorithm achieved F1 score of 95.14%.

Computer Vision Based Fall Detection

The computer vision based approach for fall detection has gained popularity among researchers in recent years and the number of published papers has grown substantially. The decrease of the cost of cameras and the maturity of the computer vision domain have simplified the development and deployment of computer vision in different areas of everyday life.The benefits of computer vision based approaches are that images and videos are semantically rich, meaning that they bring potentially rich set of data features. The drawback of vision based algorithms is the complexity that comes with computer vision. Contrary to wearable and ambient sensors based approaches which choose from a limited set of possible signals for the classification of fall and non-fall activities, computer vision based algorithms have a much broader set of features to choose from. Also, the required processing time and computer resources for vision based algorithms are much more demanding.

In 2010, Poppe [75] defines vision based action recognition in its simplest form as the combination of feature extraction and image classification. Vision techniques are used to "extract discriminative features from video sequences", and machine learning tools "attempt to learn statistical models from these features and to classify new features based on the learnt models" [76].

There are a number of papers that present research related to human detection and pose estimation which is related to the task of fall detection. In 2005, Dalal et al. [77] published a fundamental paper introducing for the first time the concept of Histograms of Oriented Gradients (HOG) for human detection. In 2007, Thurau et al. [78] published an approach which builds up on the previous paper introducing the concept of Behavior Histograms for human detection. In 2008, Aghajan et al. [79] presented an algorithm for pose estimation while in 2009, Brulin et al. [80] focused on determining the position of the human in the image frame in the context of fall detection. In 2008, Chung et al. [81] published a good implementation of background subtraction, once again in the context of fall detection.

In 2011, Cardinaux et al. [82] published a very good overview paper on video technologies for AAL applications. They present a taxonomy of vision-based action recognition as well as a good insight into the challenges to vision technologies in the personal healthcare domain. According to them visual based action recognition could be divided into recognition using postural features (which is further subdivided into static postural and dynamic movement based approaches) and ambulatory features (motion tracking). The main challenges identified in [82] are the technical, acceptability (related to privacy and data protection) and integration challenges.

One of the decisions to be taken when implementing vision based fall detection or action recognition is where to process data – locally on a smart camera or to a remote server. In 2011, Pinto [83] presented a good discussion and research into this topic with the conclusions that local processing is better in terms of latency and energy consumption. Local processing could also have an impact on ensuring better privacy for the user.

Table 4 presents an overview of computer vision based research papers on fall detection or action recognition. As can be seen from the table most of the computer vision approaches which have reported performance metrics show high sensitivity (above 90%). However, as with wearable sensors based approaches, most experiments with vision based algorithms are conducted in controlled environments which differ significantly from real-world scenarios. Changes in background (e.g. displacements of furniture), light, occlusions, and multiple occupants are only some of the potential problems.

Table 4: Computer Vision Based Fall Detection

Paper	Year of publication	Camera type	Number of cameras	Algorithm type	Sensitivity	Specificity	Notes
Auvinet et al. [84]	2011	2D camera	4	Threshold-based	99.70%	99.80%	The presented results are for 4 or more cameras.
Belbachir et al. [85]	2011	stereo camera	1	ANN	NA	NA	Fall detection rate > 96%, false positives < 5%.
Doulamis et al. [86]	2010	2D camera	1	Threshold-based	NA	NA	False positives = 11.60%, false negatives = 23.54%. The algorithm is real-time.
Doulamis et al. [87]	2011	2D camera	1	Threshold-based	NA	NA	False positives = 22% - 26%, false negatives = 3% - 13%.
Edgcomb et al. [88]	2012	2D camera	1	Times series analysis	91%	92%	The algorithm covers the user in the frames by graphical oval in order to enhance privacy.
Hung et al. [89]	2012	2D camera	2	Time series analysis	95.80%	100%	The 2 cameras are placed in such a way so that their fields of view are orthogonal.
Jansen et al. [90]	2007	3D ToF camera	1	Threshold-based	100%	NA	The setup in a nursing home consists of one camera per room.
Machajdik et al. [91]	2010	2D camera	4	Fuzzy logic	85%	96%	The number of cameras can be increased.
Makantasis et al. [92]	2012	2D camera	1	Threshold-based	92% - 96%	NA	The proposed algorithm extract 3D human features from a single 2D camera.
Mirmahboub et al. [93]	2012	2D camera	1	SVM	100%	98.55%	Accuracy = 99.23%, error rate = 0.77%

Rougier et al. [94]	2008	2D camera	1	Procrustes shape analysis	95.50%	96.40%	The dataset is designed for maximum diversity of volunteers and background.
Rougier et al. [95]	2011	2D camera	1 or many	GMM	NA	NA	More than 98% accuracy when multiple cameras are used.
Tang et al. [96]	2013	omni-camera	1	Threshold-based	94.04%	97.16%	The authors use Motion History or Energy Images (MHoEI) to extract the relevant classification features.
Thome et al. [97]	2008	2D camera	many	Layered HMM, Fuzzy logic	82 - 98%	NA	The authors use LHMM for motion classification and fuzzy logic for data fusion.
Yogameena et al. [98]	2012	2D camera	1	GMM, RVM (Relevance Vector Machine)	95.83%	97.50%	Accuracy = 96.67%.
Yu et al. [99]	2013	2D camera	1	One Class SVM	NA	NA	True positive rate = 100%, false negative rate = 3%.
Zhang et al. [100]	2012	Kinnect	1	SVM	NA	NA	Accuracy = 94% - 98%.

Another conclusion that could be drawn from the approaches summarized in Table 4 regards the high number of algorithms' types used in computer vision based fall detection. As could be seen from the table, there are various classification algorithms, most of which are in the area of machine learning. As computer vision algorithms are very specific and complex to implement, it is difficult to recreate several algorithms to be used in comparisons and evaluations.One of the main drawbacks in using computer vision for fall detection is that the algorithms are often computationally intensive and it is not always easy or even possible to implement them as real-time systems, especially if they are supposed to run locally on smart cameras.

Another challenge mentioned in [101] is the choice of a dataset on which to train and test the developed algorithm(s). Although there are a number of universally available and used datasets for action recognition, none of them have image sequences representing falls. Thus researchers have to gather and label their own falls datasets which makes it very difficult to benchmark and compare different algorithms.

Multimodal Approaches

One interesting sub-domain of fall detection algorithms are multimodal algorithms. As it could be seen from the above subsections, all single modality algorithms have issues and none of the presented algorithms could offer 100% sensitivity and 100% specificity, especially in the real world scenario and on real world data.

Multimodal approaches could offer a solution to these problems. Multimodal algorithms use two or more sensors in order to combine data from them and to achieve more precise and reliable results. An almost omnipresent modality in multimodal fall detection systems is accelerometry. It is often combined with other wearable or ambient sensors and in some papers with camera(s). The main task in front of multimodal detectors is data fusion, i.e. how to combine and correlate data coming from different sources.

Table 5 presents an overview of papers focusing on multimodal fall detection systems. It could be seen from the table that the majority of the presented multimodal approaches achieve sensitivity or accuracy of 94% or above, coming also with high specificity. This is still insufficient performance for the real-world scenario but it could serve as a starting point for further research.

Another conclusion that could be drawn from the table is that in almost all of the papers included in Table 5 one of the used modalities is accelerometry. This is expected as the benefits of accelerometer based fall detectors are substantial and their drawbacks could be compensated with the addition of other modalities.

Another interesting observation is that unlike single mode accelerometer fall detectors which are most often threshold based, the tendency in multimodal approaches seems to be oriented towards more sophisticated algorithms.

Table 5: Multimodal Fall Detection

Paper	Year of publication	Sensors	Algorithm type	Sensitivity	Specificity	Notes
Bianchi et al. [102]	2009	barometer, accelerometer	Threshold-based	97.80%	96.70%	Accuracy = 97.1%.
Crispim et al. [103]	2012	accelerometer, gyroscope, camera	Ontologies	93.51%	NA	Presision = 63.61.
Dai et al. [104]	2010	magnetic field sensor, accelerometer	Threshold-based	97.87%	92.30%	The algorithm is implemented on a mobile phone.
Fleury et al. [105]	2010	camera, accelerometer, microphone, door contact, infrared presence sensor	SVM	NA	NA	True positives ranging between 64.3% - 97.8%.
Gjoreski et al. [106]	2012	gyroscope, accelerometer, radio tag	Context-based approach	NA	NA	F-score = 96.6% - 98.5%.
Grassi et al. [107]	2010	ToF camera, accelerometer, microphone	HMM, Threshold-based	81.3% - 98.0%	59.1% - 99.2%	More work on sensor fusion will improve the sensitivity and specificity values.
Khawandi et al. [108]	2012	hearth rate, camera	ANN (Artificial Neural Network)	100%	97.58%	Accuracy = 99.15%.
Li et al. [109]	2009	gyroscope, accelerometer	Threshold-based	91%	92%	Accelerometer is used to detect static postures, while gyroscope - the transition between postrures.
Ojetola [110]	2011	gyroscope, accelerometer	Decision trees	NA	NA	Precision = 81%, recall = 92%.

4. Challenges and barriers to AAL and fall detection systems

Ambient Assisted Living systems have the potential to benefit their users by improving the quality of their daily life and prolonging the time they live independent in their homes. Regardless of the many benefits that these systems could offer, they are not without their challenges and barriers. The main barrier towards the mass adoption of AAL solutions in general and of particular solutions such as fall detection systems is the users' acceptance of these systems.

The main users of AAL systems are the elderly. Age comes with a change in motor, audio, visual and cognitive abilities which often leads to older adults getting more technology wary and less willing to accept new technological concepts, devices and solutions [111]. Other factors that may influence acceptance of new technologies include gender, nationality, cultural background, religion, etc. [112]. Another barrier to the acceptance of assistive technologies is the lack of suitable legislative framework and regulations that would address the AAL domain [113].

Challenges to AAL systems

Ambient Assisted Living has set high goals and as a consequence it should meet serious requirements. Developers of AAL solutions face a number of challenges when designing their products. AAL applications inherit the challenges of their enabling technologies but they also have a set of unique challenges due to their nature to directly interact with the users.

Challenges to AAL solutions could be classified as:

- ***Technological challenges*** - there still are numerous purely technological issues in the way of AAL systems. E.g. battery life of wireless nodes, unobtrusiveness of the sensors, security of data and communications, quality of service under restricted resources, lack of compatibility between different platforms, etc.
- ***Ethical challenges*** – there are no clear definitions who could access what information and under what circumstances.
- ***Legal challenges*** – for the moment there isn't a legislative framework defining the responsibilities, obligations, rights and relationships between different parties in AAL solutions (such as users, carers, equipment manufacturers, etc.).
- ***Psychological challenges*** – for example limited acceptance by the users caused by fear, reluctance or inability to use Ambient Assisted Living solutions.

Fall detection systems as a particular type of AAL systems inherit all of the aforementioned challenges but they also have challenges, specific to their own application domain. Examples of these are the choice of approach (wearable sensors based, ambient sensors based, computer vision based or multimodal) and concrete algorithm (simple threshold based or more sophisticated machine learning based), the compromise between sensitivity and specificity, the price and ease of installation of the system, the problem of real-world data gathering and testing, etc. It is evident that there are a lot of open research questions regarding fall detection in particular and AAL systems in general.

5. Conclusion

Ambient Assisted Living is a relatively new research area which is bound to receive more attention over next years due to the current and future demographic trends. The gentrification of developed and developing countries will put the social, pension and health systems of afore mentioned countries at great pressure. Enabling the elderly and people with slight disabilities to live independently for longer periods of time is one direction for dealing with this problem. AAL systems build the technological foundations for such prolonged independent living of older adults.

Falls are among the greatest risks to the elderly leading to injuries and decreased physical activities, and as a consequence fall detection is a very important component of AAL systems. However, even though there is a great amount of research on fall detection, there still isn't a fall detection algorithm that is both reliable and trustworthy to the degree required for real-world applications. Wearable and ambient sensors based fall detection algorithms are often threshold based and simple for implementation but in order to obtain higher sensitivity they often make compromise with specificity, thus decreasing the usefulness and trustworthiness of the system. In addition to that, ambient sensors based approaches are difficult to install and maintain. Computer vision approaches for fall detection are complex and they are often computationally and memory expensive which makes them unsuitable for real-time applications. Multimodal approaches seem a promising research direction as they combine several modalities in order to detect falls and have the potential to achieve higher accuracy even in real-time. The choice of modalities to use and data fusion techniques are of great importance in multimodal algorithms but are still open research problems.Another issue is that the performance of fall detection algorithms is almost without exception evaluated on simulated data. There is very little research on the performance of fall detection algorithms under real-world data. In the few cases where such evaluation has been done, the results indicate that simulated data is different than real-world data and the performance of the developed algorithms under real-world data is lower than under simulated data. This is indicative that more tests with users in their daily habitat should be conducted.

Finally, protection of privacy is a major concern for the users of an AAL system and is a major barrier to the acceptance of these systems. AAL systems should be designed with privacy in mind and it should be explained to their users how exactly privacy is protected and if and how they can control the level of privacy protection.

Acknowledgment

This study is supported by the Bulgarian National Scientific and Research Fund, project ДДВУ02/18.

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