Systematic review of indoor fall detection systems for the elderly using Kinect

Amina Ben Haj Khaled*, Ali Khalfallah
and Med Salim Bouhlel

Sciences and Technologies of Image and Telecommunications,
Higher Institute of Biotechnology,
University of Sfax, Sfax, Tunisia
Email: aminabenhajkhaled@isbs.usf.tn
Email: ali.khalfallah@enetcom.rnu.tn
Email: medsalim.bouhlel@enis.rnu.tn
*Corresponding author

Abstract: The fall of the elderly presents a major health problem as it may cause fatal injuries. To improve the life quality of the elderly, researchers have developed several fall detection systems. Several sensors have been used to overcome this problem. So far, Microsoft Kinect has been the most used camera-based sensor for fall detection. This motion detector can interact with computers through gestures and voice commands. In this article, we presented a comprehensive survey of the latest fall detection research using the Kinect sensor. We provide an overview of the main features of the two Kinect versions V1 and V2 and compare their performances. Then, we detailed the method used for the articles selection. We provided a classification of the fall detection techniques to highlight the main differences between them. Finally, we concluded that it is not enough to evaluate a system performance under simulated conditions. It is important to test these approaches on old people who are likely to fall.

Keywords: depth sensor; elderly healthcare; fall detection; Kinect V1; Kinect V2; PRISMA; machine learning.

Reference to this paper should be made as follows: Khaled, A.B.H., Khalfallah, A. and Bouhlel, M.S. (2022) 'Systematic review of indoor fall detection systems for the elderly using Kinect', *Int. J. Telemedicine and Clinical Practices*, Vol. 3, No. 4, pp.276–301.

Biographical notes: Amina Ben Haj Khaled holds a PhD in Electronics from the National Engineering School of Sfax – Tunisia (ENIS). She has been teaching practical work of medical image processing, digital signal processing and audio and image coding at the National School of Electronics and Telecommunications of Sfax – Tunisia (ENETCOM). She obtained her research Master in Information and Communication Sciences and Technology (ENETCOM). Currently, she is a researcher working in the unit related to the Science and Technology of Image and Telecommunications Sfax – Tunisia (SETIT). The focus in her research is on image processing, motion detection, motion recognition, monitoring, and serious games.

Ali Khalfallah is an Assistant Professor in the National School of Electronics and Telecommunication of Sfax, Tunisia (ENETCOM). He holds a PhD in Electronics from the National Engineering School of Sfax, Tunisia (ENIS). He obtained his diploma as an electrical engineer from the National Engineering

School of Sfax, Tunisia (ENIS) in 2003 and acquired a Master in Electronics from the same school in 2004. He has attended several national and international scientific conferences and published several review articles, research papers as author and co-author. He is a member in the research unit of Sciences and Technologies of Image and Telecommunications (SETIT). He is the organisation chairman of the international conference: Sciences of Electronic, Technologies of Information and Telecommunication SETIT'07, SETIT'09 and SETIT'12. His fields of interest include image fusion, image segmentation, image processing, serious games, and pattern recognition.

Med Salim Bouhlel is a Professor at Sfax University, Tunisia. He is the president and founder of the Tunisian association on HMI since 2013. At present, he is the Head of the Research Group in Science and Technology of Image and Telecommunications Sfax – Tunisia since 2003. He is the Editor-in-Chief of the international journals *HMI*, *MLHC* and a dozen of special issues. In addition, he is the chairman of many international research conferences interested in: image processing, telecom and HMI in which he has obtained more than 20 patents so far. More than 500 articles were published in IJ, IC and books.

1 Introduction

A fall has serious consequences on health and especially for the elderly. Its gravity increases exponentially with age and frailty. Indeed, the elderly falls are very common. According to the World Health Organization (WHO), the percentage of falls among people aged 65 is between 28 and 35% and it is between 32 and 42% for those who are over 70 years (WHO, 2008). Being the third cause of admission to acute medicine and the first cause of fatal accidents among seniors, a fall is a real scourge resulting from various personal, behavioural or environmental factors (Coogler, 1992).

Although this is a real public health problem, the elderly fall was neglected for too long. In Tunisia, statistics on fall are very scarce and even non-existent. The last cross-sectional descriptive survey of the INSP (National Institute of Public Health) was carried out in 1995 covering a representative sample of the Tunisian population consisting of 2,229 people aged 65 and over living at home (Hdiji et al., 2017).

The survey consist of a social and medical questionnaire to assess the overall health status and functional abilities of the subjects. The subjects were asked to answer the following question: 'Have you ever fallen to the ground in the past years?'

More than 25% of those surveyed confirmed that they had dropped at least once in the last 12 months with a predominance of falls among women. Bivariate and multivariate analyses have shown that many other parameters increase the risk of falling, and the most important one is a low mobility (16.9%). The experience of fall weakens the elderly, even in the absence of a traumatic consequence, hence comes the need for a powerful fall detector.

Indeed, several researches based on the surveillance and follow-up of movements were carried out on the fall detection. Most of the fall detection systems are equipped with traditional equipment such as the wearable systems (accelerometer-based, gyroscopes or tilt sensors), environmental systems (based on vibration sensors or sound sensors) and camera-based systems. Most of these systems have several disadvantages in their usage like the lack of autonomy and confidentiality, complexity, intrusiveness and high cost.

No universal solution has been discovered to detect a fall so far. Despite the technological development, and the big number of researches on the fall detection, the number of investigations related to the progress and trends of fall detectors is very low and was conducted several years ago. For that reason, we decided to carry out a global study on the new approaches of fall detection using only the camera sensor and more precisely the Kinect RGB-D camera sensor considering its various advantages, which will be mentioned next. To explore the development in this field since 2017 we performed a search, using the keywords 'fall detection Kinect' on Google scholar and found 2,930 results. The number of searches has increased significantly in recent years. Using the same keywords on the same search engine for the period from 2010 to 2014, 4,150 results were found whereas from 2014 to 2018 the number of results was 11,100, hence showing the importance of the fall magnitude.

Previous fall detection surveys provided a general overview of the different approaches that exist in the literature by explaining the type of the used sensor, the methodology of using it and its performance. However, trends have changed since these publications. In this study, we present a detailed analysis of the most reputed approaches used in the detection of falls with Kinect, as well as a comparison between them. This work will be organised as follows: A related work is provided in Section 2. Section 3 explains the reason for using the Kinect. The methodology of using this system is detailed in Section 4. Section 5 outlined the obtained results. Finally, the paper ends with a discussion and a conclusion.

2 Related work

This section briefly reviews the existing surveys in the literature on fall detection systems during the last ten years. We especially look for revues that focus on the camera-based fall detectors. Considering the magnitude of the fall, research has grown significantly over the past few years, hence the importance of a review to evaluate the previous research work on fall detection.

The first fall detection synthesis study appeared in 2007and was proposed by Noury et al. (2007). It is an analysis of algorithms, systems, and sensors that detect automatically and early the elderly fall. These authors explained the difficulty of comparing between the performances of the different existing systems. In addition, they suggested an effective evaluation procedure.

A year later in 2008, a survey, by Yu (2008), identified the different approaches and principles of fall detection methods for the elderly. Depending on how the fall detector is used, methods are classified into three approaches: worn systems, environmental systems, and camera-based systems. Each approach was divided into two or three categories according to the principle of use. Then each category is analysed to determine its advantages and disadvantages.

In 2010, Abbate et al. defined the fall, its causes, its consequences and its different scenarios. In fact, the most relevant approaches over the last thirty years were underlined to allow the design of a new fall detection system to solve the problem of the elderly' falls. This contribution collects the most relevant parameters, data filtering techniques and test methods from the accomplished studies. This survey provides a standard procedure and structure for constructing a database by taking into account the problems and challenges of a fall detection system. Finally, it highlights the importance of a fall prediction, hence the importance of detection.

In 2013, Igual et al. presented a literature review of fall detection systems to conduct a comparative study. They identified the different problems and trends in the fall detection. This study serves as a reference for clinicians and engineers.

The same year, El-Bandary et al. (2013) listed the causes and consequences of the fall and introduced a new review of the trends and technologies of academic and commercial fall detection and prevention systems that help seniors overcome this problem.

In 2014, Chaudhuri et al. studied the new fall detection approaches. They are tested in the real world and accepted by the elderly. The different existing devices are divided into two categories according to their evaluation: devices evaluated by precision, sensitivity and specificity and devices evaluated by other methods.

Pannurat et al. also proposed in 2014 a review of an automatic fall monitoring. Platforms are classified into two categories: worn systems or non-worn systems. Thus, classification and evaluation methods are divided into different parts: threshold-based approaches, rule-based approaches, and machine-learning approaches.

In 2015, Zhang et al. reviewed the fall detection algorithms and grouped them into two categories, namely the camera-based approaches and sensor-based ones. This review focused on the camera-based methods. For the sensor-based fall detector category, five public databases are introduced. Three of them are based on the Kinect camera. The second category includes fall detectors using a single camera, fall detectors using multiple RGB camera for a 3D scene reconstruction and 3D method using depth cameras. The authors proposed the association of a speech recognition system to carry out a dialogue with the subject to confirm or deny the fall and trigger the alarm.

In 2016, Koshmak et al. described a review of approaches using a fusion of several sensors to detect the elderly fall. They also highlighted the difference between the techniques based on a single sensor and those based on several sensors.

In 2017, Khan and Hoey introduced a new taxonomy for the detection of falls in relation with the availability of fall data. This taxonomy is not related to the type of sensor used, the methods of extraction, and specific selection. Different categories of classification methods for the fall detection studies are identified and analysed in detail. Approaches treating the fall as an abnormal activity represent a more effective direction of research. Several problems and proposals for improving future research are developed.

In 2018, Lapierre et al. aimed to examine the extent and diversity of the current fall detection technologies for the elderly. The authors reviewed the literature since 2006 in three languages: English, French and Spanish. 118 articles are analysed to provide a rigorous and comprehensive study. Their analysis deduced the difficulty of comparing the results since the level of the technological maturity is low and the evaluation is rarely linked to ecologically valid conditions.

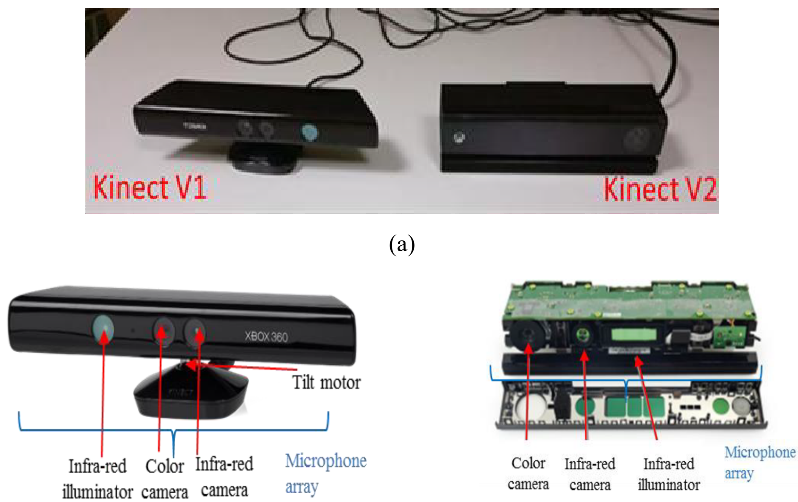
Several journals on the fall detection have appeared in recent years. They dealt with this problem from a different point of view. Although some journals are recent, they present an ancient bibliography (the articles date from 2017). Indeed, there is no updated survey to deal with advanced technologies and new trends.

Most journals inferred the effectiveness of depth camera-based approaches for fall detection. However, they also indicated that it is difficult to compare between different approaches because of the diversity of sensors, technologies, and evaluation methods. To overcome this problem, we decided to carry out a review of the algorithms and approaches of fall detection by using the advantages of Kinect to detect the fall. This enables us to effectively evaluate the different existing systems. This study of the latest camera-based technologies using the Kinect sensor will serve as a review for engineers, doctors and researchers to help discover the performance and the weak points of this sensor for the elderly monitoring.

3 Why using the Kinect

In this research, we focus on articles that use the Kinect technology to detect the fall. For this, it is essential to explain the reasons why we chose this sensor and determine its performance and benefits.

Figure 1 Representation of the two existing versions of Kinect, (a) Kinect V1 and V2 (b) the components of Kinect V1 (c) the components of Kinect V2 (see online version for colours)



(b) (c)

Kinect is a game console. It was introduced by Microsoft in November 2010. It has been used in many areas besides the game like education, biometrics, smart home, robotics, artificial intelligence, and recently in medicine. Microsoft introduced two versions of Kinect: version 1 and version 2 as seen in Figure 1. In the following subsection, we specify the characteristics and specifications of these two versions.

3.1 Kinect hardware

From a hardware point of view, Kinect is composed of different sensors: (RGB camera, depth camera and four microphones) that are able to provide the image colour, depth map, 3D full body movements, facial recognition, hand recognition, and voice recognition. Kinect has also a motorised tilt feature that allows for a better scene capture, and a more effective person and object tracking (Zhang, 2012). Kinect V1 and V2 use two different principles to provide a picture depth. The image depth acquisition of

Kinect V1 uses the principle of a structured light. The infrared projector projects, into the space, a known pattern of light beams in the field of view of the camera. The recorded deformation of these patterns gives information on the structure of the scene, whereas the depth acquisition of Kinect V2 is based on the principle of flight time (TOF) (Fankhauser et al., 2015). Here, we do not calculate the deformation of the light pattern, but rather the delay between the bursts of the infrared light emitted and received. This technique provides a 3D reconstruction of the scene. Table 1 summarises the differences between both devices, such as RGB image resolution, depth sensor range, field of view, system latency, and audio sensor sampling rate.

Table 1 Comparative table of the hardware of Kinect V1 and V2

Characteristics	*Kinect version 1*	*Kinect version 2*
Colour camera RGB	640 × 480 (30 fps)	1920 × 1080 (30 fps)
Depth camera	320 × 240	512 × 424
Infra-red image	No IR	512 × 424
Depth distance (min~max)	(40 cm to ~ 4 m)	(50 cm to ~ 4.5 m)
Techniques	Structured light	Time to flight
Horizontal field of view	57°	70°
Vertical field of view	43°	60°
Tilt motor	Yes	No
Audio stream	16 khz, 16 bits	48 khz, 16 bits
Minimum latency	102 Ms	20–60 Ms
USB standard	2.0	3.0
Price	\$99.95	\$199

3.2 Kinect software

A Kinect software refers to the library development as well as the various algorithmic components that are included. Different software are available allowing the development of several applications. OpenKinect (2012), OpenNI (2019), robot operating system (ROS) (Quigley et al., 2009), and CL NUI (Laboratories, 2010) are the four main free projects that are available and can be used for data acquisition and processing of this sensor.

Two projects for data acquisition and processing from a sensor were created by a developer bearing the nickname of AlexP and Hector Martin, who took on the challenge of Adafruit industry competition, before the launch of Kinect.

OpenKinect (LibFreeNect) is the result of the competitive achievement of the software realised by Hector Martin who is a recognised winner of the Adafruit industry competition. This software offers Kinect drivers, and wrappers in different languages and for different projects. It is a free and open source library maintained by a community interested in using Kinect. It is available under Apache 2.0 licenses and optional under GPL2.

Microsoft used the second project designed by AlexP to develop a NUI Driver / SDK platform available only for Windows. This is a free software. The last version used until today 29 March 2019 is 26.1.1.

OpenNI or Open Natural Interaction is an open source software project. It is created by a group of companies, including PrimeSense. It still works with a compliant middleware called NITE. Its most recent version is 2.2. OpenNI and SDK have almost comparable functions. Before the release of OpenNI (2.0), it was not possible to use both OpenNI and SDK packages, but now it is possible to install and enjoy the benefits of these two libraries in the same computer.

Table 2 Comparative study of different Kinect drivers

Characteristics	*Openkinect*	*SDK*	*OpenNI*	*ROS*
Languages	C, Python, actionscript, C#, C++, Java JNI and JNA, Javascript, CommonLISP	C, C# ,C++	C, C++	Python, C++
Platforms	Linux, Windows, Mac OS X	Windows	Windows, Linux, Ubuntu	UNIX
Accelerometer data	YES	YES	YES	NO
Motor and led control	YES	YES	YES	YES
Colour and depth images	YES	YES	YES	YES
Audio data	YES	YES	YES	YES
Automatic body calibration	NO	YES	NO	NO
Standing skeleton tracking	NO	YES (20 joint points Kinect V1/25 joint points V2)	YES (15 joint points)	NO
Seated skeleton tracking	NO	YES	NO	NO
Full skeleton tracking	NO	YES (2 skeletons for Kinect V1/6 skeletons for Kinect V2)	YES (2 skeleton)	NO

The American company Willow developed an open source computer tool named ROS for its Robot PR2. The ROS makes it possible to develop software in the robotics field. The latest version of the ROS is called Melodic Morenia (published in May 2018). Table 2 presents a comparative study of the different Kinect drivers defined above.

Kinect is evaluated from a hardware and software point of view. This assessment helps us understand both the advantages and disadvantages of the Kinect sensor and determine the best performing fall detectors in the literature. This study also allows us to design an effective low cost fall detector.

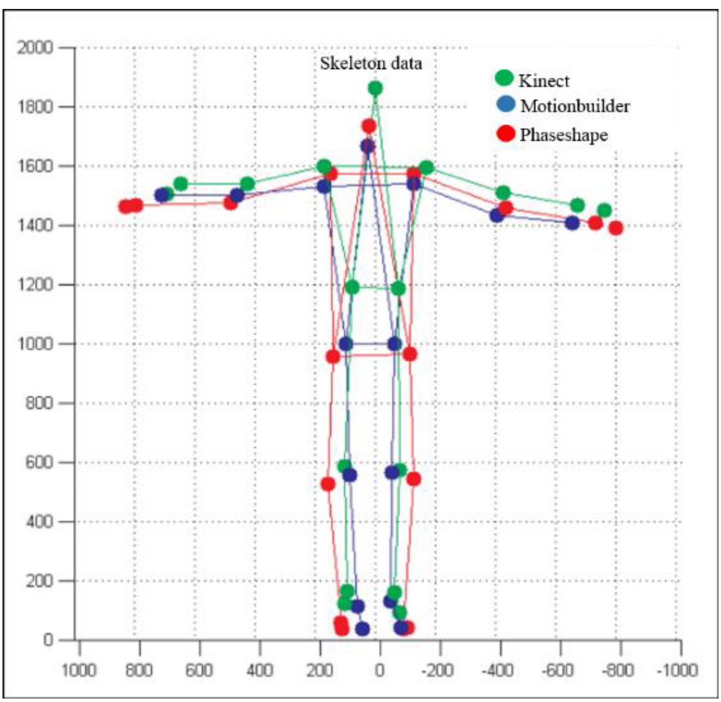
3.3 Evaluation of the Kinect performance

To justify the choice of the Kinect sensor, it is not enough to study only its technical characteristics but it is also necessary to evaluate its performance compared to other depth cameras in order to analyse both its advantages and disadvantages.

Several studies were developed in this context. The studies were classified into two categories. The first class deals with the performance of Kinect cameras and the second one evaluates the performance of the skeletal tracking.

Since the appearance of the Kinect in 2011, Smisek et al. carried out an experimental study, comparing quantitatively the 3D capacity of the three different cameras (Kinect, stereo camera, and TOF camera). Smisek et al.'s (2013) experiment demonstrated that the Kinect accuracy level is comparable to that of the stereo camera, and it is higher than the accuracy level of the TOF camera. In the same year, Stoyanov et al. (2011) repeated the same experiment by comparing the Kinect camera with other TOF ones. The results showed that the Kinect camera performance is better than that of the other two TOF cameras but it is comparable to that of the short-range laser camera (distance < 3.5 metres). They concluded that employing a Kinect camera is better than using the TOF cameras because of its low cost and good performance. In 2012, Khoshelham and Elberink abandoned the idea of comparing the Kinect sensor with other cameras, and analysed the resolution and accuracy of the depth data. Khoshelham and Elberink's (2012) experiment showed that the distance and the random error of the depth measurements are proportional.

Figure 2 Representation of pose estimation using three different systems (see online version for colours)



Source: Obdržálek et al. (2012)

Diverse studies focused on Kinect's skeleton tracking software capabilities. Dutta compared the Kinect motion capture with the existing motion sensors based on markers (Dutta, 2012). In an appropriate field of view and a distance of 1 to 3 metres to the Kinect, the results obtained are similar, with a minor error of less than 1 cm. In other words, Obdržálek et al. (2012) decided to observe the robustness of the Kinect's pose estimation in the context of the elderly training. For this, they simulated six types of exercises in which the subject is sitting or standing next to a chair. The difficulty of pose recognition is the occlusion and change over time of the angle of view. Then the acquired data is compared to that generated by other marker-based motion capture systems, such as Phasespace and Motionbuilder as seen in Figure 2.

They finally concluded from the results that the Kinect sensor has a good potential in the robustness of the pose estimation and motion capture and real-time body tracking in healthcare applications. However, in general, the typical error of the Kinect skeletal tracking is about 10 cm.

4 Methodology

To carry out our bibliographic database, we explored the following search engines: Google scholar, IEEE, JURN and PubMed. The used keywords are a combination of words such as fall detection Kinect, fall monitoring Kinect, falling Kinect, fall detection using depth camera.

A first pre-selection is made from the most relevant titles. A second selection is carried out by minutely studying the abstracts. Then, all selected articles are considered relevant. They are numbered and saved in a file. The bibliographic search ended on 20 March 2019.

4.1 Inclusion conditions

We have integrated all the articles of conferences and scientific papers written in English using the following key words: fall detection Kinect, fall monitoring Kinect and elderly fall Kinect. Studies treating the elderly fall using the Kinect fall detection directly or indirectly were included in the research for the elderly rehabilitation and the improvement of posture and walking; more specifically, those who use Kinect as a harmful interface for the prevention of falling through exergame.

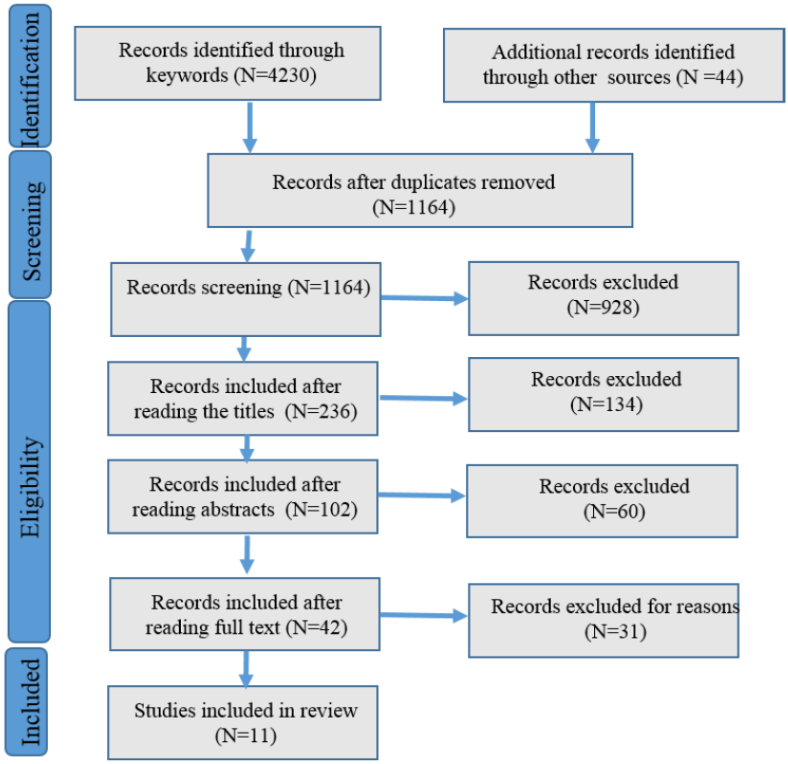
4.2 Exclusion conditions

Several elimination criteria are taken into consideration. Only the articles that are evaluated by a scientific committee and written in English were selected. The publication date of the article is a very important criterion to get an updated review. For this, we are recommended to study the published articles since 2017. Finally, we selected the most quoted papers during this period.

5 Results

Following a selection process carried out according to the inclusion and exclusion criteria previously explained, the number of included studies is 11. Figure 3 summarises the steps followed in the search of articles.

Figure 3 Results of preferred reporting items for systematic reviews and meta-analyses (PRISMA) process (see online version for colours)



Through an automatic search method on the scientific search engines listed in the method part, 4,230 records were made. Forty-four studies are taken from additional manual searches and completed in research lab archive websites and universities such as *Open Directory Access Open Journals* (*DOAJ*), and FreeFullPDF. Several studies were eliminated (72.5%) for different reasons. The first reason is redundancy. An article can exist in several versions ranging from 12 (maximum) to one (minimum). There is also an intersection between the different search engines. The second reason for eliminating certain studies is that many of the keywords used are generalised. A search for 'Kinect detection' can lead to different results such as the detection of Parkinson's disease, emotion detection, and motion detection. As a result, 1,164 articles were eliminated. Of these, 928 articles were excluded just after reading the titles and 132 articles after reading the abstracts. Only the relevant titles and abstracts were included. Therefore, only 42 articles met all the inclusion criteria. Then, a final selection was made to sort out the most interesting studies that fit this review. Indeed, only the most cited articles in the years 2017/2018 and the articles judged interesting in 2019 were chosen. At the end, the final number of the articles selected for study is 11. These 11 selected studies met all the inclusion criteria. Tables 3, 4, 5 and 6 provide an overview of the literature research and minutely explain the methodology and the progress of the experiments.

Table 3 Overview of selected study methodologies using a depth frame

	Cited	*Hard ware*	*Soft ware*	*Techniques*	*Methods*
Akagündüz et al. (2017)	15	• Kinect v1 • A quad-core Intel i5 3.3GHz processor	• MAT-LAB	• Silhouette orientation volume (SOV) • Bag-of-words SOV • Naïve Bayes classifier (NBC)	1 Proceed by a pre-processing (composed of segmentation, noise removal, and edge detection for video frame) 2 Extraction of the SOV features. 3 Use of BoSOV model (K-medoids clustering: every cluster centre is transformed in a code word, BoSOV is formed by a histogram of occurrence number of words). 4 Classification: each action represented by BoSOV is introduced to NBC for fall classification
Abobakr et al. (2018)	8	• Kinect v1	• MoCap MapReduce component of Hadoop	• Random decision • Forest (RDF) classifier • Depth comparison • feature (DCF) • VM classifier	1 Segmentation of the foreground. 2 Identification of the current articulated posture by the use of RDF. 3 Training and evaluation of RDF using synthetic datasets to get over the limitation of finding different fall detection datasets. 4 Analyse the modification of the of the lying posture through SVM classification 5 Indicate the occurrence of fall events 6 Triggering the alarm
Dubois and Charpill (2017)	6	• Microsoft Kinect sensor	• Unspecified	• Hidden Markov models • Baum-Welch (BW)	1 Measure of the gait parameters • Selection of indicators by analysing spatio-temporal parameters to evaluate the general state of a person. • Extraction of the indicators including step length, pace, and speed of the gait. 2 Real time human activity and fall recognition by depth images analysis • Matching each HMM, from the eight HMM of the model, to one activity. • Arranging the eight HMM on three observations: a The position of the centre of mass on the vertical axis. b The vertical velocity of the centre of mass. c The vertical dispersion of the silhouette (standard deviation) on the vertical axis. • Estimation parameters using Baum-Welch algorithm to learn the parameters of each model from the built database.

Table 3 Overview of selected study methodologies using a depth frame (continued)

	Cited	*Hard ware*	*Soft ware*	*Techniques*	*Methods*
Kong et al. (2017)	5	• Microsoft Kinect V2	• C++ • Open CV 2.4.9 • Microsoft Kinect SDK 2.0	• Median filter • Canny filter	1 Pre-processing • Detection of the human • Getting the binary image of the human. • Removing the undesirable noise by a median filter. • Computation of the outline using a canny filter 2 Proposed algorithm • Calculation of the tangent vector angle of the outline image 3 Fall detection • Getting all the white pixels in the outline image • Calculation of the tangent vector angle of each white pixel • Repartition of the calculated tangent into 15° groups • Computing how many angles are between 0°–15°, 15°–30°, 30°–45°, 45°–60°, 60°–75°, 75°–90°. • Calculation of the percentage of each group
Mazurek et al. (2018)	5	• IRMT v1:two Kinect apparatuses (model V1) • TST v2: Microsoft Kinect V2 and an inertial measurement unit	• Unspecified	• Median filter • Means of the region growth algorithm MRG) • Discrete cosine transform (DCT) • SVM • Artificial neural network (ANN) • NBC	1 Data acquisition • IRMTv1 fall detection dataset measuring data using two Kinect model V1 • TST fall detection dataset v2 using Microsoft Kinect V2 and an inertial measurement unit 2 Data pre-processing • Preliminary subtraction of static background • Filtering using a median filter and a closing operator • Extraction of the person's silhouette performed by means of the region growth algorithm • Removing all the obtained segments representative of the monitored person 3 Transformation of coordinate system 4 Generation of features and classification • Kinematic features: Description of the person's movements in terms of his/her position. a Total distance from the centre of the absolute coordinate system: horizontal component (h-distance) and vertical component (v-distance) b Total velocity: the horizontal plane (h-velocity) and vertical plane (v-velocity) c Total acceleration: in the horizontal plane(h-acceleration) and in the vertical plane (v-acceleration) • Mel-cepstrum-related features 5 Classification by means of (SVM), (ANN), and (NBC)classifiers

Table 4 Overview of experimental results using a depth frame in some selected studies

	Location	*Type of falls*	*Candidates*	*Experience*	*Evaluation*
Akagündüz et al. (2017)	Kinect camera is installed at a height of 1.5 m	• First group: walking, bending, squatting sitting, laying, and falling • Second group: walking, running, jumping, galloping sideways, bending, one-hand waving, two-hands waving, jumping in place, jumping jack and skipping	• First groups: ten young male and female subjects • Second groups: nine subjects	First group: • Realising the experiments on the SDU-fall dataset. • Applying different variations, as carrying or not carrying a large object, and varying the room arrangement, to make the dataset realistic. Second group: • Applying one sequence for each subject. • Selection of action of certain subjects as training set and the rest as a test set. • Selection of different subjects, for different experiments, as the training set for the purpose of cross-validation.	More than 91.89% fall detection accuracy for SDU-fall dataset
Abobakr et al. (2018)	One Kinect is installed on ceiling	URFD dataset: • Fall from standing and from sitting on a chair, • 30 typical daily life activities (ADL) • Fall-like activities as lying on a wooden sofa and lying on the floor.	URFD dataset: five persons of different anthropometric measures	1 Test dataset: • Evaluation of the system performance using three test datasets: synthetic, real, and URFD dataset. • Use of URFD dataset to train and evaluate the performance of the SVM classifier. 2 Examining the effect of various parameters, to recognise posture, such as forest size, number of tree levels, and size of the training dataset on the generalisation capabilities 3 Evaluation of the performance of the overall system on the challenging URFD Dataset 4 Comparing the results to other approaches.	• Sensitivity rate of 99%on synthetic and live datasets • Specificity rate of 99% on synthetic datasets • Specificity 96% on popular live datasets without invasive accelerometer support.
Dubois and Charpillet (2017)	Kinect camera is installed on corner of the apartment	Squatting, bending, sitting, walking, falling, lying on the ground, going up on an obstacle, and lying on a couch	28 subjects aged from 20 to 53 including eight women and 20 men	1 Experiment on gait analysis • Testing the accuracy of gait parameters • Comparing the results on the three gait parameters the length of the steps, the pace, and the speed of the gait. 2 Experiment on activity recognition • Realisation of the experiment of activity recognition in a laboratory apartment • Obtaining seven situations carried out by the subjects and filmed by a RGB-D camera • Corresponding the defined activity during the construction of the HMMs to a situation • Building a HMM for each activities using 80% of the subject's sequences. • Tested in real situation.	Unspecified

Table 4 Overview of experimental results using a depth frame in some selected studies (continued)

	Location	*Type of falls*	*Candidates*	*Experience*	*Evaluation*
Kong et al. (2017)	Kinect camera is installed in 2 m height on the cupboard	Standing, falling (horizontal), and falling (declining)	Three subjects aged 24–40 years and their heights, are 170cm–185cm. Subject A is a male of 1.8 m and 68 kg. Subject B is a male of 1.85 m and 90 kg. Subject C is a male of 1.7 m and 60 kg	• Subject A: Tangent line from 0°–45° is less than 25% while standing and more than 50% while falling. • Subject B: Tangent line from 0°–45° is less than 20% while standing and more than 60% while falling. • Subject C: Tangent line from 0°–45° is less than 25% while standing, and more than 60% while falling. • Detected fall if tangent line from 0°–45° is more than 40%	Accuracy is improved to 97.1%
Mazurek et al. (2018)	• IRMT v1: Both Kinect cameras are installed in two opposite corners of the scene with a 58° tilt. The room is 3 m wide and 4 m long. • TST v2: not specified	• IRMTv1: Forward backward and lateral fall • TST v2: four types of daily-living actions and four types of fall actions	• IRMTv1: two PhD students, males in their mid-twenties, without any physical disabilities or other health problems • TST v2: 11 volunteers aged between 22 and 39, their height varied between 1.62 and 1.97 m	1 IRMTv1 fall detection dataset • Location of the subjects at a distance of cameras 1.5–4 m from each of them. • Realisation of the sequences of a length of 75 images each (the window of analysis has a duration of 2.5 s which covers the movement of fall or not of the subject, specific to each type of scenario) • Conception of a set of 20 fall scenarios and 20 scenarios corresponding to other actions 2 TSTv2 fall detection dataset • Repeating each activity three times. • Building a whole set compose of 264 recordings representative of 132 falls and 132 other human behaviours. • Realisation of the sequences of a length of 75 images each (the window of analysis has a duration of 2.5 s which covers the movement of fall or not of the subject, specific to each type of scenario)	• IRMTv1 98.6–100% sensitivity • TSTv2 93.9–97.7% sensitivity

Table 5 Overview of selected study methodologies using a skeleton frame

	Cited	*Hard ware*	*Software*	*Techniques*	*Methods*
Alazrai et al. (2017)	13	Kinect sensor for XBOX 360	Kinect SDK v1.0 beta 2 (Microsoft, Redmond,WA, USA)	• Motion-pose geometric descriptor (MPGD) • Histogram based representation (HBR) • Multi-class SVM classifier	1 Dataset • Manual annotation of input data into multiple temporal segments performing as a sub-activity 2 Human activity representation • Modification of MPGD to describe the activities of a single human. • Development of movement profiles by introducing a set of geometrical relation-based features to had better typify the events related to the fall. a Motion profile • building a body-attached coordinate system • Recalculation of 3D skeletal joint positions respecting the body attached origin. • Construction of the three anatomical planes. • Description of the movement of a specific body part in terms of the position of the displacement vector. b Pose profile describing the different human postures using the distance-based features and angle-based features • Construction of the modified MPGD of the frame at index by merging both the motion and pose profiles to form a descriptor vector.
Tran et al. (2017)	10	Microsoft Kinect Intel Core i7-2600 3.40 GHz processor, 16 GB of RAM).	Microsoft Kinect SDK	• Gray scale motion map (GMM) • SVM	Depending on the availability of skeletal data. 1 Fall detection using a single camera a Skeleton-based fall detection • Computation of the average distance and the average velocity of the available joints. • Detection of fall when the average distance and the average velocity values are less than pre-defined thresholds. b RGB-based fall detection • Representation of motion using a grayscale motion map • Computation of kernel descriptor from GMM 2 Fall detection using multiple Kinect sensors in a large environment.

Table 5 Overview of selected study methodologies using a skeleton frame (continued)

	Cited	*Hard ware*	*Software*	*Techniques*	*Methods*
Patsadu et al. (2018)	2	• Kinect • Intel core i5 Central Processing Unit (CPU) @1.7 GHz and 4 GB RAM processing platform	• User Generator method of OpenNI • C#	• K-means clustering model • MLP (multilayer perceptron) • SVM	1 Data progressing • Selection of body joint positions: the torso position provides higher accuracy and a faster run time. • Data normalisation • Data transformation: the normalised body-joint positions are mapped into a time series of Euclidean distance between two consecutive Kinect video frames. 2 Segmentation of a body transition in real time • Decomposing a fall event into three sequential phases: pre fall, body transition phase and post fall phase. • Applying configured K-means clustering model with 3 clusters to detect the boundaries of the transition phase. 3 Fall motion detection based on a machine learning approach 4 Fall severity level estimation • Analysing factors related to the fall severity (the velocity) • Scaling the severity:(proposing an anatomical-based coding system (SIS) as a framework to classify the severity level of falls)
Li et al. (2018)	2	• Kinect sensor 2.0 • Intel ® Core ™ i7-6700 CPU @3.4 GHz	Unspecified	• Dynamic supporting area (DSA) • ZMP (zero moment point) • SVM classifier	• Acquisition of Kinect skeleton stream • Reduction of noise with a median filter • Detection of skeleton(25joint-points) • Obtaining of the three-dimensional position information of 25 joints of the human • Dividing the human body into 15 segments to get the multi rigid model • Combining somatosensory information from the Kinect sensor and the mass proportions of body parts to obtain the dynamic multi rigid model • Computation of ZMP of the human body • Verification if ZMP is within the dynamic supporting • Decision making if human is on a balance state or not.

Table 5 Overview of selected study methodologies using a skeleton frame (continued)

	Cited	*Hard ware*	*Software*	*Techniques*	*Methods*
Nizam et al. (2018)	1	Kinect sensor	Unspecified	Threshold	1 Process 1 • Acquisition of skeleton data from the sensor. 2 Process 2 • Computation of the required fall detection parameters (fall risk factor and velocity). • Storage of data in a buffer. • Obtaining fall detection parameters • Use of the required fall detection parameters to decide the next processes to be executed. • Proceeding to the process 3, if the fall risk factor is flagged as high. 3 Process 3 • Detection fall risk factors. • Starting process 4 or process 5, if the fall risk factors are normal or low. 4 Process 4 • Detection of a normal fall using the computed velocity from Process 2 5 Process 5 • Confirmation of fall detection if the velocity from Process 2 or Process 3 is flagged as high and no activity or high acceleration is flagged from Process 4
Peng et al. (2019)	0	Kinect sensor	userMap of Simple-OpenNI	Point cloud (PC)	1 Extraction of acceleration feature values 2 Judge of point cloud height 3 Judge of recovery time

Table 6 Overview of selected study experimental results using a skeleton frame

Article	*Location*	*Type of falls*	*Candidates*	*Experience*	*Evaluation*
Alazrai et al. (2017)	Unspecified	four fall-related activities of elderly people, including: walking, sitting, falling form standing and falling from sitting	Six healthy subjects (one female and five males) aged 33 (±8.7) years.	• Simulation of four activities related to the fall event for each subject • Performing the activities with different speeds and style several times to capture inter and intra-personal variations between different subjects. • Execution of the experiment in a laboratory environment • Placement of a mattress on the ground to protect the subjects during falling. • Development of three evaluation scenarios based on the number of unobserved video sub-sequences in the testing videos.	An average recognition accuracy of 93.6%, 77.6% and 65.1%, in recognising the activities during the first, second and third evaluation scenario.
Tran et al. (2017)	• Dataset-A: URFD1: Not specified • Dataset-B: Not specified • Dataset-C: MICAFALL-13: four Kinect sensors are installed at places to observe full space	• Dataset-A: URFD1: 30 falls and 40 daily living activities • Dataset-B: Not specified • Dataset-C: MICAFALL-13: 40 falls (20 falls during walking and 20 falls from bed) and 200 daily activities • Dataset-D: 95 free falls and 206 daily activities	• Dataset-A: URFD1:five persons • Dataset-B: Not specified • Dataset-C: MICAFALL-13: 20 subjects aging from 25 to 35 years old • Dataset-D: four subjects aging from 30 to 40 years old.	• Evaluation of the method on some available datasets for fall detection • Dataset-A: dataset URFD1 does not provide skeleton data. • Dataset-B: dataset LE2I2: Used to validate the robustness of methods to location changes. • Dataset-C: MICAFALL-13: Used to observe space with the least number of sensors. • Dataset-D: Used to evaluate the roles of combining RGB and Skeleton and the role of using multiple Kinects for fall detection in a large-scale space.	Accuracy of 91.5% at average frame-rate of 10 fps.
Patsadu et at. (2018)	Kinect sensor is installed about 1 metre above the floor. The size of the room is about 5 × 7 m	Falls (11 types) ADLs (18 types)	Ten adult subjects (equal number of males and females) aged 30 ± 8 years, with body mass 75 ± 35 kg, and height 165 ± 15 cm equal number of males and females).	1 Fall motion detection • Use of 4,350 (10x29x15) video clips. 2 Fsis • Evaluation of FSIS performance using 330 video clips of various fall motions at different speeds and on a variety of seat types.	Accuracy of 99.97% with zero false negative

Table 6 Overview of selected study experimental results using a skeleton frame (continued)

Article	*Location*	*Type of falls*	*Candidates*	*Experience*	*Evaluation*
Li et al. (2018)	• Kinect sensor is installed at the distance of 1.0 m (height). • The distance between the Kinect sensor and the human body is 1.5–4.5 m.	Normal stand, squat, and rise, from stand to topple and fall, normal walk, from walk to stumble over a barrier but does not fall, and from walk to stumble over a barrier and fall	healthy male adult aged 25 year-old	• Balancing back and forth to achieve by the subject until the production of the fall during the trials from stand to topple and fall. • Adding a barrier and walking to cause a fall event during the trials from walk to stumble over a barrier and fall • Adding a barrier and walking and avoiding the fall event by adjusting the posture during the trials from walk to stumble over a barrier and fall • Using 36 trials as the test set	Sensitivity of 100%, a specificity of 81.3%, and an accuracy of 91.7% using the modified zero moment point criterion.
Nizam et al. (2018)	Unspecified	Daily life activities such as walking in different directions, lying on the floor, picking objects from the floor, sitting on the floor or chair and fall events	• Two healthy adults	• Test in simulated activities in the laboratory	Accuracy 88.57%
Peng et al. (2019)	Unspecified	Falls in different directions	• Four adults	• Performing movements on a mat three centimetres thick. • Collection of 360 samples • Fall production in different directions • Lengthening on the carpet, after the fall, for ten seconds • Repetition of the fall 60 times by each subject • Repetition of LDAs six times for each action	Accuracy 98.8%

To extend the utility of these tables to the reader, all the studies are classified in two categories: studies that use the depth stream of the Kinect (Table 3 and Table 4) and those that use the skeletal flow (Table 5 and Table 6). Concerning the methodology, various parameters are specified such as the number of citations of the article, the hardware and software part, the techniques used and the steps of the fall detection. Then the experimental conditions are detailed including the installation of the equipment, the type of fall detected, the subjects chosen to carry out the experiment, the realisation stage and the experiment as well as the evaluation results.

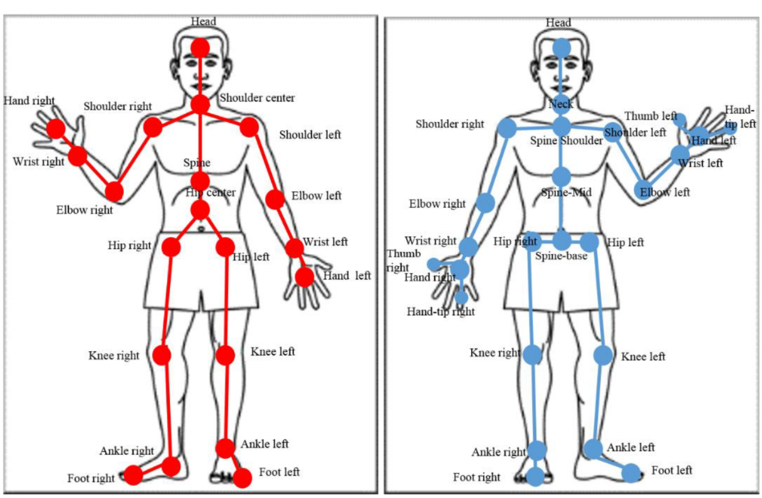
5.1 Methods of research using depth frame of the Kinect

Most of the fall detection cameras based approaches are not effective at night because of the darkness. It is possible to install a dim light, but it can affect the sleep of the elderly. To resolve this problem the use of a depth camera is recommended. It can provide images in the dark and preserve the privacy of monitoring people.

5.2 Methods of research using skeleton frame of the Kinect

Approaches using a skeletal tracking for a fall detection as a special case of recognising human activities have the principle of defining the human body in the form of joints. Thus, the body is represented as a 3D skeleton in space. The use of a skeletal frame is used to improve robustness and achieve a better performance. Different libraries studied previously (Table 2) can provide a skeleton tracking like OpenNI (unofficial version) and the different versions of Kinect SDK official for both versions of Kinect V1 and V2. Each of these two libraries has some advantages and disadvantages. OpenNI can recognise six people and follow only two people. Each person is represented by a 3D skeleton with 15 joints. Kinect SDK 1.5, 1.6, 1.7 and 1.8 have the same features but detect 20 joints per person. While Kinect SDK V2 can recognise and track six people and detect 25 joints as seen in Figure 4.

Figure 4 SDK skeleton joint points (in red SDK 1.5, 1.6, 1.7, 1.8, and in blue SDK 2.0) (see online version for colours)



Using the official Kinect Software Development Kit for fall detection is recommended for a skeleton tracking for multiple reasons:

- SDK does not require a calibration or a specific action pose for a skeleton tracking.
- SDK allows a full body tracking from the head to the foot; the tracking is possible even in the seated position.
- Unlike RGB images, the skeletal frame of SDK preserves the privacy of the monitored person.
- The collected images have an acceptable quality and do not require complex pre-processing steps.

6 Discussion

Fall detection alternatives are multiple. The fall detection systems were classified in three parts. Wearable fall detection devices, environmental fall detection devices, and camera-based fall detection devices. These systems are effective but they have certain use limitations.

Certain old people may forget to wear the accelerometer-based fall detector. This can present a great danger and may increase the severity of the fall. Others may refuse to wear it because they do not want to admit their dependence and their lack of autonomy.

Environmental fall detectors systems are installed in the environment or life of the elderly. They can be installed in the floor and detect the fall as a vibration or installed in the doors and detect the presence or absence of the person. These detectors have a big number of false positives, which is a huge problem.

Camera-based fall detectors have become highly widespread because of their good performance and low cost. Their major problem is that they are intrusive because they are harmful to privacy and they are not functional in the dark.

Since 2014, the use of the Kinect sensor as a fall detector has become more popular than stereo cameras. This sensor has overcome the weaknesses of the traditional cameras. To detect the fall, the Kinect sensor can be used separately or in association with other devices such as an accelerometer or a mobile phone.

In this study, we chose approaches that use only Kinect. The selected studies were divided into two categories. The first category is interested in the fall detection by means of depth stream whereas the second category is devoted to studies using a skeletal tracking or skeletal flow in association with the RGB flow.

Machine learning was adopted as a Kinect-based fall detection algorithm. First, SVM is the most widely employed algorithm, followed by NBC and RDF. HMM is rarely used as seen in Table 3 and Table 5.

In order to allow a comparison between different fall detection systems, it is obvious to use the same evaluation criteria. To detect the fall four cases are possible (as explain on Table 7): True positive (TP), false positive (FN), true negative (TN), false negative (FN).

Table 7 Possible cases for fall detection

	TP	*FP*	*TN*	*FN*
Fall	Yes	No	No	Yes
Fall detection	Yes	Yes	No	No

To evaluate the performance of the fall detector systems these four cases are used in three criteria as (Broadley et al., 2018):

- *Sensitivity* is the capacity to detect fall:

$$Sensitivity = \frac{TP}{TP + TN} \tag{1}$$

- *Specificity* is the capacity to detect just a fall:

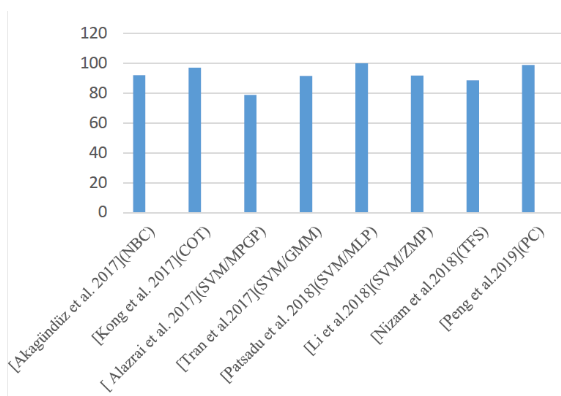
$$Specificity = \frac{TN}{TN + FP} \tag{2}$$

- *Accuracy* is the proportion of alarms, which are true falls:

$$Accuracy = \frac{TP + FN}{TP + FN + FP + FN} \tag{3}$$

The most significant indicator for evaluating the performance of fall detection systems is accuracy. Some articles did not test a single database to assert a better evaluation. For example, Alazrai et al. (2017) used the three scenarios, to graphically represent the accuracy; we calculated the average of the obtained accuracy from these three scenarios. In addition, some articles did not use accuracy but rather sensitivity and specificity as given by Abobakr et al. (2018) and Mazurek et al. (2018).

Figure 5 Accuracy percentage of the most cited papers since 2017 (see online version for colours)



The percentage of accuracy of the selected items is generally greater than 90% as seen in Figure 5. The accuracy of Patsadu et al. (2018) is 99.97% almost 100%. It means that all the simulated falls were detected. Alazrai et al. (2017) has the lowest accuracy in the curve 78.76%, it is the average accuracy of three scenarios (93.6%, 77.6% and 65.1%) that depend on the number of video sub-sequences not observed in the videos test.

In the selected articles, both versions of Kinect were used. We could not decide about the most adequate version because the experiments were not tested using the same database and under the same conditions. Based on the precision results, it can be seen that Kinect V1 reaches an accuracy of 99.97%, while Kinect V2 has an accuracy of 97.1% (Kong et al., 2017) and 91.7% (Li et al., 2018).

In the realised experiments, the Kinect sensor was placed differently. We notice that it was generally installed at a height of 1 to 2 meters, and the subject must perform the requested actions at a distance of 1 to 4 meters from the Kinect sensor.

All the fall detection databases used to evaluate the performance of the selected items were not tested by the elderly subjects. Volunteers are often healthy adults who have simulated different falls. Some studies divided the fall into several sub-categories: falls forward, backward and sideways. Daily living Activities (ADL) such as sitting, walking, sleeping, crouching were also simulated. A fall is an accidental event so it is difficult to simulate it. This is the cause behind the difficulty of creating a database of real falls. Here lies the difficulty of this research. Therefore, fall detection algorithms with a high accuracy level in the laboratory are unsatisfactory in practice.

7 Conclusions

The elderly fall causes very serious health problems. Given the importance of this phenomenon, research has grown in the area of seniors monitoring and home assistance. Fall detection systems have evolved in recent years. Kinect is one of the most used sensors for designing a low-cost, highly efficient and easy to install detector. In this paper, we reviewed 4230 articles that deal with the detection of falls in older Kinect-based patients. We chose the most recent, relevant and cited studies. We divided the included studies into two categories: depth-based fall detection and 3D skeletal based detection. The methodology of each study was specified (specifying the hardware, the software, the techniques used and the operating principle). The progress of the experiment was described (location of the sensor, type of fall, subjects, and steps of experiment and results of the evaluation). Most of these articles have used machine-learning techniques that are predominantly SVM. The selected items have a high accuracy greater than 90%. However, several technical limitations still exist such as the detection margin of the Kinect sensor, the occlusion problems and especially the lack of standardisation of evaluation method under real conditions. We conducted this systematic review to resolve existing limitations in this area. In a future work, we will offer a fall detection system for older people based on Kinect's skeletal flow. We will build our own database to test the effectiveness of this system. We will also test it on real conditions with a real fall.

It is important to detect a fall to reduce its consequences. However, it is also important to prevent it to reduce the probability of falling. For this reason, we have proposed a Kinect-based fall prevention system. This is an exergame using the techniques of occupational therapy (Khaled et al., 2018).

Acknowledgements

This research was developed at the SETIT research unit, University of Sfax. The authors like to express their deepest appreciation to all the scientists of the clinic of Ibn Annafis Sfax. Also, they are grateful to Dr. Bouattour, med geriatrician, and Taktak, a physiotherapist for their precious help.

References

Abbate, S., Avvenuti, M., Corsini, P., Vecchio, A. and Light, J. (2010) 'Monitoring of human movements for fall detection and activities recognition in elderly care using', *Wireless Sensor Network: A Survey*, in *Application-Centric Design Book*, 1st ed., Rijeka, Croatia, InTech, Chapter 9, pp.147–166.

Abobakr, A., Hossny, M. and Nahavandi, S. (2018) 'A skeleton-free fall detection system from depth images using random decision forest', *IEEE Systems Journal*, Vol. 12, No 3, pp.2994–3005.

Akagündüz, E., Aslan, M., Şengür, A., Wang, H. and İnce, M.C. (2017) 'Silhouette orientation volumes for efficient fall detection in depth videos', *IEEE Journal of Biomedical and Health Informatics*, Vol. 21, No. 3, pp.756–763.

Alazrai, R., Momani, M. and Daoud, M. (2017) 'Fall detection for elderly from partially observed depth-map video sequences based on view-invariant human activity representation', *Applied Sciences*, Vol. 7, No. 4, p.316.

Broadley, R., Klenk, J., Thies, S., Kenney, L. and Granat, M. (2018) 'Methods for the real-world evaluation of fall detection technology: a scoping review', *Sensors*, Vol. 18, No 7, p.2060.

Chaudhuri, S., Thompson, H. and Demiris, G. (2014) 'Fall detection devices and their use with older adults: a systematic review', *Journal of Geriatric Physical Therapy*, Vol. 37, No. 4, p.178.

Coogler, C.E. (1992) 'Falls and imbalance', *Rehab Management*, Vol. 5, pp.53–117.

Dubois, A. and Charpillet, F. (2017) 'Measuring frailty and detecting falls for elderly home care using depth camera', *Journal of Ambient Intelligence and Smart Environments*, Vol. 9, No. 4, pp.469–481.

Dutta, T. (2012) 'Evaluation of the Kinect™ sensor for 3-D kinematic measurement in the workplace', *Applied Ergonomics*, Vol. 43, No. 4, pp.645–649.

El-Bendary, N., Tan, Q., Pivot, F.C. and Lam, A. (2013) 'Fall detection and prevention for the elderly: a review of trends and challenges', *International Journal on Smart Sensing and Intelligent Systems*, Vol. 6, No. 3, pp.1230–1266.

Fankhauser, P., Bloesch, M., Rodriguez, D., Kaestner, R., Hutter, M. and Siegwart, R. (2015) 'Kinect v2 for mobile robot navigation: evaluation and modeling', in *2015 International Conference on Advanced Robotics (ICAR)*, IEEE, July, pp.388–394.

Hdiji, O., Damak, M., Bouzidi, N. and Mhiri, C. (2017) 'Risk of neurological falls in an elderly Tunisian population', *NPG Neurologie-Psychiatrie-Gériatrie*, Vol. 17, No. 97, pp.20–27.

Igual, R., Medrano, C. and Plaza, I. (2013) 'Challenges, issues and trends in fall detection systems', *Biomedical Engineering Online*, Vol. 12, No. 1, p.66.

Khaled, A.B.H., Khalfallah, A. and Bouhlel, M.S. (2018) 'Fall prevention exergame using occupational therapy based on Kinect', *International Conference on the Sciences of Electronics, Technologies of Information and Telecommunications*, Springer, Cham, December, pp.479–493.

Khan, S. and Hoey, J. (2017) 'Review of fall detection techniques: a data availability perspective', *Medical Engineering and Physics*, Vol. 39, pp.12–22, doi:10.1016/j.medengphy.2016.10.014.

Khoshelham, K. and Elberink, S.O. (2012) 'Accuracy and resolution of Kinect depth data for indoor mapping applications', *Sensors*, Vol. 12, No. 2, pp.1437–1454.

Kong, X., Meng, L. and Tomiyama, H. (2017) 'Fall detection for elderly persons using a depth camera', in *2017 International Conference on Advanced Mechatronic Systems (ICAMechS)*, IEEE, December, pp.269–273.

Koshmak, G., Loutfi, A. and Linden, M. (2016) 'Challenges and issues in multi-sensor fusion approach for fall detection', *Journal of Sensors*, Vol. 2016, pp.684–695.

Laboratories, C. (2010) *About: CL NUI Platform. Code Laboratories* [online] http://codelaboratories.com/kb/nui (accessed 2015).

Lapierre, N., Neubauer, N., Miguel-Cruz, A., Rincon, A.R., Liu, L. and Rousseau, J. (2018) 'The state of knowledge on technologies and their use for fall detection: a scoping review', *International Journal of Medical Informatics*, Vol. 111, pp.58–71, doi:10.1016/j.ijmedinf.2017.12.015.

Li, M., Xu, G., He, B., Ma, X. and Xie, J. (2018) 'Pre-impact fall detection based on a modified zero moment point criterion using data from Kinect sensors', *IEEE Sensors Journal*, Vol. 18, No. 13, pp.5522–5531.

Mazurek, P., Wagner, J. and Morawski, R.Z. (2018) 'Use of kinematic and mel-cepstrum-related features for fall detection based on data from infrared depth sensors', *Biomedical Signal Processing and Control*, Vol. 40, pp.102–110, doi:10.1016/j.bspc.2017.09.006.

Nizam, Y., Mohd, M. and Jamil, M. (2018) 'Development of a user-adaptable human fall detection based on fall risk levels using depth sensor', *Sensors*, Vol. 18, No. 7, p.2260.

Noury, N., Fleury, A., Rumeau, P., Bourke, A.K., Laighin, G.O., Rialle, V. and Lundy, J.E. (2007) 'Fall detection-principles and methods', in *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE*, August, pp.1663–1666.

Obdržálek, Š., Kurillo, G., Ofli, F., Bajcsy, R., Seto, E., Jimison, H. and Pavel, M. (2012) 'Accuracy and robustness of Kinect pose estimation in the context of coaching of elderly population', in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, August, pp.1188–1193.

OpenKinect (2012) *OpenKinect Main Page 2012* [online] http://openkinect.org/ (accessed October 2014).

OpenNI (2019) *OpenNI 2019* [online] https://structure.io/openni (accessed April 2019).

Pannurat, N., Thiemjarus, S. and Nantajeewarawat, E. (2014) 'Automatic fall monitoring: a review', *Sensors*, Vol. 14, No. 7, pp.12900–12936.

Patsadu, O., Watanapa, B., Dajpratham, P. and Nukoolkit, C. (2018) 'Fall motion detection with fall severity level estimation by mining Kinect 3D data stream', *Int. Arab J. Inf. Technol.*, Vol. 15, No. 3, pp.378–388.

Peng, Y., Peng, J., Li, J., Yan, P. and Hu, B. (2019) 'Design and development of the fall detection system based on point cloud', *Procedia Computer Science*, Vol. 147, pp.271–275, doi:10.1016/j.procs.2019.01.253.

Quigley, M., Conley, K., Gerkey, B., Faust, J., Foote, T., Leibs, J. and Ng, A.Y. (2009) 'ROS: an open-source robot operating system', in *ICRA Workshop on Open Source Software*, May, Vol. 3, No. 3.2, p.5.

Smisek, J., Jancosek, M. and Pajdla, T. (2013) '3D with Kinect', in *Consumer Depth Cameras for Computer Vision*, pp.3–25, Springer, London.

Stoyanov, T., Louloudi, A., Andreasson, H. and Lilienthal, A.J. (2011) 'Comparative evaluation of range sensor accuracy in indoor environments', *5th European Conference on Mobile Robots, ECMR 2011*, pp.19–24, Örebro, Sweden, 7–9 September.

Tran, T.H., Le, T.L., Hoang, V.N. and Vu, H. (2017) 'Continuous detection of human fall using multimodal features from Kinect sensors in scalable environment', *Computer Methods and Programs in Biomedicine*, Vol. 146, pp.151–165, doi:10.1016/j.cmpb.2017.05.007.

World Health Organization (2008) *Ageing, & Life Course Unit 'WHO global Report on Falls Prevention in Older Age*, World Health Organization.

Yu, X. (2008) 'Approaches and principles of fall detection for elderly and patient', in *HealthCom 2008-10th International Conference on e-health Networking, Applications and Services*, IEEE, July, pp.42–47.

Zhang, Z. (2012) 'Microsoft Kinect sensor and its effect', *IEEE Multimedia*, Vol. 19, No. 2, pp.4–10.

Zhang, Z., Conly, C. and Athitsos, V. (2015) 'A survey on vision-based fall detection', in *Proceedings of the 8th ACM International Conference on Pervasive Technologies Related to Assistive Environments*, ACM, July, p.46.