Comparison of Some Methods for the Elderly Patient Telemonitoring System

Hendra Setiawan*[1], Elvira Sukma Wahyuni[2]
[1,2]Universitas Islam Indonesia/Electrical Engineering Department
hendra.setiawan@uii.ac.id*[1], elvira.wahyuni@uii.ac.id[2]

Abstract

This paper analyzes some research results related to patient telemonitoring system. The main objective is to collect many useful information for telemonitoring implementation and its development in the future. Telemonitoring system is focused on fall detection that generally occur prior to critical condition. There are 14 research results that discussed in this paper which have been published from 2013 to 2017. Those researches are grouped into three types i.e. intrusive, non-intrusive and mixed. Analysis is done on aspects of the comfort, complexity, cost, accuracy, and coverage. Furthermore, based on those information, a study of application feasibility is done for elderly patients in Indonesia. The result shows that the non-intrusive method using the camera or access point are the most appropriate system for the elderly fall detection.

Keywords: *Patient Telemonitoring, Elderly Patient, Fall Detection, Critical Condition*

1. Introduction

Based on the report [1], life expectancy in Indonesia is 69.4 in 2015. This figure is estimated to increase to 73.5 in 2045. From the same source [1], the population in Indonesia in 2017 is 263 million with 47% of them aged 25-59 years. From the data, it is estimated in 2045, Indonesia will have an enormous population of elderly. The same indication will also occur in the most countries in Asia.

Based on these data, it will arise some problems related to the characteristics of the elderly one of which is a health problem. One of the biggest problems is elderly degenerative diseases that occur damage or prostitution of tissues or organs of the body. According to [2], degenerative diseases are classified into three main groups i.e. cardiovascular, neoplastic, and nervous system. The most common cardiovascular diseases are hypertension, coronary disease and myocardial infarction. Neoplastic disease includes tumors and cancer. Diseases that affect the nervous system include Parkinson's and Alzheimer's.

With the limited ability of the elderly and the potential for existing health problems, an appropriate procedure is needed for treatment and early detection of elderly health problem when they are at home. The procedure becomes more important when the elderly is not accompanied by other family members. While at any time there is a possibility of elderly conditions can change rapidly from normal to critical conditions. Therefore, we need an early detection procedure when elderly condition changes from normal to critical and hence medical treatment can be done as early as possible.

A telemonitoring system is one solution for those problems. It can be used to monitor or detect the condition of the patient that could be fatal if there is no an intensive care immediately. In practice, telemonitoring can be applied in two models: (1) real time (synchronous) and (2) store and forward (asynchronous). Telemonitoring in real time is done by monitoring and sending the patient's clinical information continuously without any significant delay. While in telemonitoring with store and forward, patient’s clinical data is collected, processed and accessed in the next time.

Telemonitoring as part of telemedicine system plays an important role for improving the continuity of health services from hospital wards to the home [3]. Telemonitoring services has been tested by some researchers reported that tele-homecare has benefits in the management of patients with chronic diseases, such as diabetes mellitus, heart failure, hypertension, spinal cord injury, chronic obstructive pulmonary disease (COPD), chronic wounds, and has been applied for some cases of cancer and stroke [4].

Setiawan, H., & Wahyuni, E. (2018). Comparison of Some Methods for the Elderly Patient Telemonitoring System.Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, 3(3). doi:http://dx.doi.org/10.22219/kinetik.v3i3.627
Receive March 12, 2018; Revise April 21, 2018; Accepted April 27, 2018

2. Research Method

This paper describes several methods of telemonitoring systems for elderly patients at home. However, it is not only limited for the elderly, but also can be applied to outpatients with chronic diseases such as heart, nerves and stroke. The critical condition of the elderly or the patient in general begins with a fall event. Therefore, the critical condition can be detected when he/she falls. When the elderly or the supervised patient falls, the detection system will work and send messages or notifications to both the family and the hospital as well as turn on the warning alarms in the telemonitoring area. Thus, the elderly or patients can be immediately handled by medical personnel. The system model is illustrated in Figure 1. Hence, the discussion is focused in fall detection methods from recent research within the last five years.

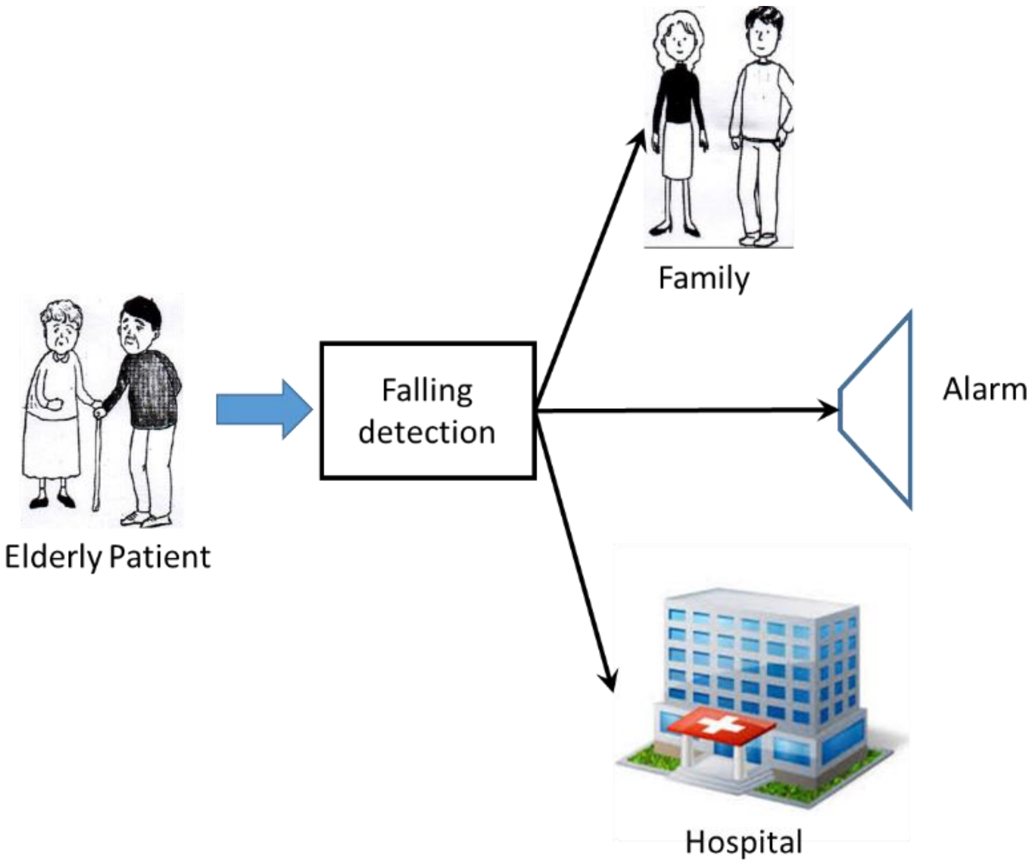

Figure 1. Elderly Monitoring System Model

Based on the initial state before the fall, Mubashir et al. [5] classifies falling event into four types: (1) falling from walk or standing conditions; (2) falling from standing with assisted (e.g. stairs); (3) falling from a bed; and (4) falling from sitting position. In this paper, the initial state prior to fall is neglected, thus the discussion covers all types of falls with any initial conditions. So that, all types of falls are still considered in this study.

In general, there are 3 methods of fall detection described in this paper. i.e. (1) using sensors attached to the body of the subject (intrusive), (2) using a device that is not in direct contact with the body (non-intrusive), and (3) a combination of the first and second methods by using sensors attached to the body and simultaneously using a device that is not in direct contact with the body of subject. In this paper, we summarize 14 methods proposed by the research results as shown in Table 1.

From Table 1, we see that 8 of 14 (57%) methods are non-intrusive, while the research with intrusive method is 29%, and the remaining 14% is the combination of intrusive and non-intrusive methods. In the next section, more detail information regarding each detection method are presented.

Table 1. List of Research Related to Fall Detection Methods

Code	Researcher(s)	Type of detection			Main device(s)
		intrusive	Non-intrusive	compound	
ROU	Rougier et.al. [6]		√		Camera
DUB	Dubois and Charpillet [7]		√		Kinect
CAS	Castillo et.al. [8]			√	Camera, accelerometer, GPS
BEV	Bevilacqua et.al. [9]		√		Kinect
YE	Ye et.al. [10]	√			Accelerometer, microprosessor, Zigbee-3G network
BIA	Bian et.al. [11]		√		Kinect
AMI	Amin et.al. [12]		√		Single radar
DIA	Dias et.al. [13]			√	Accelerometer, zigbee
WAN	Wang et.al. [14]		√		Access point, monitoring point
SAN	Santiago et.al. [15]	√			Wearable device, cellular phone
SAA	Saadeh et.al. [16]	√			accelerometer in smartphone, FPGA
HWA	Hwang et.al. [17]		√		Camera
OZC	Ozcan et.al. [18]	√			Wearable camera
ERO	Erol et.al. [19]		√		Multi radar

2.1 Intrusive

Some intrusive methods are proposed by YE, SAN, SAA, and OZC. YE, SAN and SAA use almost the same method by using accelerometer sensor to detect the state of the subject fell. YE attatchs sensors on the waist, SAN put sensors in necklaces, while SAA utilizes accelerometer available in the smartphone that generally are in the pocket. Some methods using accelerometer have similarity that detecting the existence of a big instantaneous signal from the sensor. This signal appears along the fall event where there is a change of acceleration value, speed and position quickly when the subject hit the floor. The delivery of information to the family or the person in charge is done through wireless devices such as zigbee, short message (SMS), or telephone. The weakness of this system is that the signal generated by the sensor is strongly influenced by the position of the sensor. It is also important to note that the comfort aspects of the subject become less noticeable. In addition, the position in which the subject falls is also not detected properly. Special for SAN method adds a verification process for the falling state using gyroscope and then check the position which cause a slower notification received by the subject supervisor. In terms of accuracy, the YE method gives an accuracy of 90% -100%, while the SAN has an accuracy of 83% -92%.

Unlike the three studies above, OZC does not use an accelerometer but a small camera mounted on the waist of the subject. The object captured by the camera is the image of environment around the subject. Fall detection process is done through image processing captured by the camera. However, the comfort of subject is sacrificed when he or she utilizes this method. Moreover, low light condition around the subject as well as the camera blocked by the subject's clothes are the others problem that may appear in this method. Anyway, the accuracy claimed in this method is 93,78% for indoor and 89,8% for outdoor.

2.2 Non-intrusive

Non-intrusive method can be implemented using camera, radar and access point. The camera might be closed-circuit television (CCTV), ordinary RGB camera or Kinect. The basic detection is based on image signal processing captured by the camera. The falling state of the subject can be detected in several ways. First is proposed by ROU, detecting the head vertical speed and head position. When the head speed in the vertical direction is negative and the position is close to the floor then the ROU method states that the subject is falling. The problem of this method is when the number of people in the room more than one that makes the system will face difficulties. In addition, hairstyle of the subject affect to the accuracy of the detection. Hence for the subjects with different hairstyles, re-setting of the system is required. The other fall detection using camera is proposed by HWA. The algorithm is combining 3D convolutional neural network (3D-CNN) and data augmentation to analyze continuous motion obtained from the camera. Accuracy obtained by HWA's method is 96.9%.

Furthermore, fall state is also detected using one or more Kinect cameras. Not only for fall detection, Kinect can also be used for distance estimation between the subject to the Kinect position. Kinect has been involved by some researchers to detect the falling state. Based on image from Kinect, DUB proposes a fall detection through a center of mass calculation, a speed and contour of the image using a hidden Markov model. DUB's algorithm gives accuracy up to 100%. Other scheme proposed by BEV, where the detection is done by calculating the vertical velocity as well as the composition of the image width and distance of the subject from the camera. The accuracy of BEV's scheme can reach only 76% - 87%. Both schemes, DUB and BEV, utilize the Kinect mounted on the wall. Unlike DUB and BEV, BIA employs a Kinect camera hanged on the ceiling of the room and therefore easy to detect the head position. In BIA, the pose-invariant randomized decision tree (RDT) algorithm is used for extracting the joint from the captured image. The Support Vector Machine (SVM) classifier is employed to specify the falling event. Furthermore, test results on BIA obtained 97.9% accuracy.

Problem that may be faced in BIA is the limited coverage of Kinect. For a wider area, BIA requires either higher position of Kinect that impact on image accuracy, or an additional Kinect that increase the complexity of the system. In addition, a marker is required to distinguish the subject from the other persons in that room. Another problem come up when the view of the camera is blocked by other objects such as spider web and great-tall furniture in the room.

Another device used for non-intrusive methods is a radar as performed in AMI and ERO. The main concept is detecting the shifting frequency characteristics of the radar signal reflection when the subject falls. The difference between AMI and ERO is that on AMI only single transmitter is used, whereas in ERO two transmitters are involved with an angle 90°. AMI does not specify its accuracy, while the ERO claims that the accuracy is up to 91.63%.

Other non-intrusive detection techniques are performed using access point as done on the WAN. In this method, the state of the indoor subject is known from the value of the channel status information (CSI). CSI is obtained from the wireless signal characteristics sent by the access point and received by the monitoring point. The accuracy obtained by WAN varies between 83%-96% depending on the room layout and the fall position.

2.3 Compound

Compound method is a combination of intrusive and non-intrusive methods, so it has both sensors attached to the subject and other sensors that are placed outside of the subject. Some researches proposed this method are CAS and HER. CAS combines accelerometer sensors attached on the chest, as well as cameras and GPS to get the subject location. Despite using two even more sensors, the CAS only provides 79.57% accuracy. The other compound method is proposed by DIA that incorporates an accelerometer in the hip and indoor system localization using a ZigBee system. Each room is equipped by an Xbee transceiver that will detect the presence of the subject. The strongest signal received by Xbee indicates the existence of the subject. DIA system provides an accuracy level above 90%. The integration of intrusive and non-intrusive methods will have an impact on complexity and cost that must be considered.

2.4 Scoring Criteria

This research pay attention on determining the most appropriate fall detection method to be implemented in Indonesia especially in middle Java. We use five aspects to decide the most appropriate system. Those are comfort of the subject, complexity, cost estimation, accuracy, and coverage. Then, we make a rubric as standard for scoring of those criteria as presented in Table 2. The scoring system is 1 up to 4, where 1 means the worst condition and 4 represent the best situation.

Table 2. Criterion Component Rubric

Aspect	Score	Description
Comfort	4	The subject is very comfortable with the monitoring system and can do any activity as usual
	3	The subject is less comfortable with the monitoring system but still can do any activity as usual
	2	The subject is not comfortable but still can move as usual
	1	The subject is completely unable to move due to the use of monitoring system
Complexity	4	Requires less than 3 types of devices with energy consumption that can still be supplied from batteries
	3	Requires more than 3 types of devices with energy consumption that can be supplied from batteries
	2	Requires less than 3 types of devices with energy consumption that can not be supplied from batteries
	1	Requires more than 3 types of devices with energy consumption that can not be supplied from batteries
Cost	4	Requires implementation costs below 2 million rupiah and operational below 100 thousand rupiah per month
	3	Requires implementation cost below 2 million rupiah but operational cost above 100 thousand rupiah per month
	2	Requires implementation cost above 2 million rupiah but operational cost below 100 thousand per month
	1	Requires implementation costs above 2 million rupiah and operational above 100 thousand per month
Accuracy	4	Accuracy 91-100%
	3	Accuracy 81-90%
	2	Accuracy 71-80%
	1	Accuracy less than 71%
Coverage	4	The indoor and outdoor with radius at least 100m
	3	Covering indoor and outdoor around a house with radius less than 100m
	2	It covers some rooms in a house
	1	For one room only

3. Results and Discussion

This chapter summarizes the results of several research investigations related to fall detection that has been discussed in Chapter 2.

From the information presented in chapter 2, the 14 methods discussed are summarized in Table 4 below. The information presented in Table 2 consists of a brief description of detection method, the accuracy that provided and the detection coverage. Especially for coverage, they are grouped into two categories i.e. indoor and outdoor. Indoor means that it is difficult or almost impossible to apply the proposed system for outdoors environment, while the outdoor means it is possible to apply the proposed system for outdoors environment.

By using the rubric in Table 2 into the 14 proposed methods (Table 2) produces the scoring table as presented in Table 3. The aspects are considered from the fall detection process until at the notification message to the family or the person in charge. In case of the aspects that cannot be determined from published papers, its score is set to the lowest value.

From the results of the scoring that presented in Table 3, it is found that the best scheme for fall detection is SAN with total score 16. This scheme involves accelerometer and mobile phone. The accelerometer sensor detects a falling state, while the mobile phone role is for sending emergency information to the family and the third party. In terms of comfort, it is ideal where the subject feel undisturbed by the sensor and mobile phone. Complexity is also low because it only needs a sensor device attached to the subject and mobile phone, and therefore the cost can be reduced. Since it uses a mobile phone, the coverage area is anywhere as long as the mobile phone signal still exist.

However, there is a big question related to the SAN scheme i.e. how the sensors in the necklace gives notification to mobile phone. There should be additional devices that be able to communicate from the sensors in the patient's body with the mobile phone. The system should have a battery as a source of energy. The existence of additional devices and battery cause the necklace attached to the subject becomes greater and heavy resulting in the inconvenience of the subject. For that reason, the SAN becomes a wrong choice.

Table 3. Summary of Falling Detection Methods

Code	Detection method	Accuracy	Coverage
ROU	Detects the head vertical speed and its position. The head is modeled as an ellipse. The vertical velocity threshold when falling is -1m / s, while the vertical position is 50cm from the floor.	N/A	Indoor
DUB	Calculates the center of mass, velocity and shape / contour edges of the image of the subject. The model is obtained with a hidden markov model. Proposed the vertical velocity to differentiate with other movements	100%	Indoor
CAS	An accelerometer is placed in the chest of subject. It uses for falling detection, while camera and GPS for location detection.	79,57%	indoor and outdoor
BEV	The falling is recognized from the vertical velocity and the size of length and width of the image of the subject	76% - 87%	Indoor
YE	This method calculates the acceleration, velocity, displacement of the subject in all axes. Fall event is recognized by calculating the change of energy due to movement. The energy change is related to the integral of the quadratic acceleration.	90%-100%	Indoor
BIA	A kinect camera with infrared is mounted on the ceiling of the room. A pose-invariant randomized decision tree (RDT) algorithm is used to extract the joints. Then a Support Vector Machine (SVM) classifier specifies the fall event based on the head position to the floor.	97,9%	Indoor
AMI	Analyze doppler frequency using wavelet transform. The falling condition is recognized by a special feature of the Doppler frequency shift	-	indoor and outdoor
DIA	Accelerometer is tied on the hip. In case of falling condition, it will send notification through zigbee. The location of the subject is known by detecting the strongest signal value. An Xbee transceiver is installed in every room	>90%	Indoor
WAN	The state of the subject in the room is recognized from the channel state information (CSI). CSI is obtained from the wireless signal characteristics sent by the access point and received by the monitoring point.	83%-96%	Indoor
SAN	The accelerometer is embedded in the pendant. The fall condition is recognized from the accelerometer and gyroscope. After 3 seconds from the trigger of accelerometer and gyroscope, the subject position is checked. If there is no change on the subject position within particular time interval, the system sends emergency notification.	83%-92%	indoor and outdoor
SAA	The proposed system calculates the acceleration of accelerometer. If exceed the threshold during three time interval, it means it is a fall event. The threshold is evaluated and determined using Matlab in every 1 second time interval.	98,1%	Indoor
HWA	Using 3D convolutional neural network (3D-CNN) and augmentation data to analyze continuous movement obtained from the camera.	96,9%	Indoor
OZC	Capture images around the subject with a small camera attached on the waist by facing forward. The method uses edge orientations histograms along with local binary patterns gradient techniques. Then automatically calculates the most optimal threshold for fall detection.	89,8%-93,78%	indoor and outdoor
ERO	Obtain a characteristic of a falling event by using two radars mounted in a 90 degree angle position.	91,63%	indoor

Since SAN has been eliminated, the alternative solutions are DUB, DIA, WAN, and HWA. DUB and HWA methods are superior in the comfort and accuracy, while WAN stands out in the comfort and coverage area, and DIA is good in accuracy only. Since the subject being supervised is the elderly, the preferred aspect is the convenience, so that DIA can be eliminated from the candidate list. Finally, there are three best candidates DUB, WAN and HWA. DUB and HWA have similarities in the detection of fall events by using the camera, while the WAN uses access point. Their methods have the same weakness that the accuracy is very affected by the room settings and condition. In addition to performing computational loads, the three schemes require a computer device because they involve the computation on both image signal and wireless signals.

Table 4. Scoring Results

Code	Comfort	Complexity	Cost	Accuracy	Coverage	Total Score
ROU	4	1	2	1	3	11
DUB	4	2	2	4	3	15
CAS	3	1	2	2	4	12
BEV	4	2	2	3	3	14
YE	3	1	3	4	3	14
BIA	4	2	2	4	2	14
AMI	4	2	2	1	4	13
DIA	3	2	3	4	3	15
WAN	4	2	2	3	4	15
SAN	3	3	3	3	4	16
SAA	3	1	2	4	3	13
HWA	4	2	2	4	3	15
OZC	2	2	2	3	4	13
ERO	4	2	2	4	2	14

4. Conclusion

In this research, we have conducted 14 studies related to fall detection schemes. In general, detection scheme can be done intrusively, non-intrusively or combined both of them. A review of the possible implementation of the 14 methods is also discussed in this paper. Selection of the most appropriate method is done by considering five aspects i.e. comfort, complexity, cost, accuracy and coverage. Based on the assessment, five candidates are nominated as the best implementation scheme for elderly, they are SAN, DUB, DIA, WAN, and HWA. SAN and DIA use intrusive methods with accelerometer sensor. For implementation purposes in the elderly, the comfort aspect is the highest aspect to be considered so that both methods are ignored. Moreover, there is no clear information on SAN regarding how the sensor communicates to mobile phone that makes SAN is eliminated from the candidate. Thus, the most appropriate telemonitoring method from the 14 methods for the elderly is DUB, WAN and HWA. All of them are non-intrusive methods (by using a camera, Kinect and access point) that do not interfere the comfort and elderly activities as the subject of supervision. However, the three recommended methods have the same weakness that is the accuracy is strongly influenced by the room settings and situation. In addition, all of them require a computer device to perform computation of both image and wireless signals.

Acknowledgment

The authors would like to thank to directorate research, technology and general high education (RISTEKDIKTI) Indonesia for supporting this project.

References

[1] United Nations, *"Department of Economic and Social Affairs, Population Division",* World Population Prospects: The 2017 Revision, Key Findings and Advance Tables. Working Paper No. ESA/P/WP/248, 2017.

[2] Söhretoglu, D., & Arroo, R. R. J. *"Dietary Flavonoids and The Prevention of Degenerative Diseases".* Studium Press LLC, USA, 2015.

[3] Dallolio, et. al. 2008. *"Functional and clinical outcomes of telemedicine in patients with spinal cord injury",* Archives of Physical Medicine and Rehabilitation, Vol. 89, Issue: 12, Pp. 2332–2341, 2008.

[4] K.H. Bowles, dan A.C. Baugh. *"Applying research evidence to optimize telehomecare,"* J. Cardiovasc Nurs, 22(1), Pp. 5–15, 2007.

[5] Mubashir, M., Shao, L., & Seed, L. *"A survey on fall detection: Principles and approaches,"* Neurocomputing, 100, Pp.144-152, 2013.

[6] Rougier, C., Meunier, J., St-Arnaud, A., & Rousseau, J. *"3D head tracking for fall detection using a single calibrated camera,"* Image and Vision Computing, 31(3), Pp.246-254, 2013.

[7] Dubois, A., & Charpillet, F. *"Automatic fall detection system with a RGB-D camera using a hidden Markov model,"* In International Conference on Smart Homes and Health Telematics, Pp. 259-266. Springer, Berlin, Heidelberg, 2013.

[8] Castillo, J. C., Carneiro, D., Serrano-Cuerda, J., Novais, P., Fernández-Caballero, A., & Neves, J. *"A multi-modal approach for activity classification and fall detection,"* International Journal of Systems Science, 45(4), pp.810-824, 2014.

[9] Bevilacqua, V., Nuzzolese, N., Barone, D., Pantaleo, M., Suma, M., D'Ambruoso, D., Volpe, A., Loconsole, C. and Stroppa, F. *"Fall detection in indoor environment with kinect sensor,"* In Innovations in Intelligent Systems and Applications (INISTA) Proceedings, 2014 IEEE International Symposium on, Pp. 319-324, 2014.

[10] Ye, Z., Li, Y., Zhao, Q., & Liu, X. *"A falling detection system with wireless sensor for the elderly people based on ergonomics,"* International Journal of Smart Home, 8(1), pp.187-196, 2014.

[11] Bian, Z. P., Hou, J., Chau, L. P., & Magnenat-Thalmann, N. *"Fall detection based on body part tracking using a depth camera,"* IEEE journal of biomedical and health informatics, 19(2), Pp. 430-439, 2015.

[12] M.G. Amin, M. G., Zhang, Y. D., Ahmad, F., & Ho, K. D. *"Radar signal processing for elderly fall detection: The future for in-home monitoring,"* IEEE Signal Processing Magazine, 33(2), Pp.71-80, 2016.

[13] Dias, P. V. G., Costa, E. D. M., Tcheou, M. P., & Lovisolo, L. (2016). *"Fall detection monitoring system with position detection for elderly at indoor environments under supervision,"* In Communications (LATINCOM), 8th IEEE Latin-American Conference on, Pp. 1-6, 2016.

[14] Wang, Y., Wu, K., & Ni, L. M. *"Wifall: Device-free fall detection by wireless networks,"* IEEE Transactions on Mobile Computing, 16(2), Pp.581-594, 2017.

[15] Santiago, J., Cotto, E., Jaimes, L. G., & Vergara-Laurens, I. *"Fall detection system for the elderly,"* In Computing and Communication Workshop and Conference (CCWC), *2017 IEEE 7th Annual*, Pp. 1-4, 2017.

[16] Saadeh, W., Altaf, M. A. B., & Altaf, M. S. B. *"A high accuracy and low latency patient-specific wearable fall detection system,"* In Biomedical & Health Informatics (BHI), 2017 IEEE EMBS International Conference on, Pp. 441-444, 2017.

[17] Hwang, S., Ahn, D., Park, H., & Park, T. (2017). *"Maximizing Accuracy of Fall Detection and Alert Systems Based on 3D Convolutional Neural Network,"* In Proceedings of the Second International Conference on Internet-of-Things Design and Implementation, Pp. 343-344, ACM, 2017.

[18] Ozcan, K., Velipasalar, S., & Varshney, P. K. *"Autonomous Fall Detection With Wearable Cameras by Using Relative Entropy Distance Measure,"* IEEE Transactions on Human-Machine Systems, 47(1), Pp.31-39, 2017.

[19] Erol, B., Amin, M. G., & Boashash, B. *"Range-Doppler radar sensor fusion for fall detection,"* In Radar Conference (RadarConf), 2017 IEEE, Pp. 0819-0824, 2017.