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Session IIA: Artificial Intelligence and Machine Learning (3:00 pm – 4:30 pm)				
Session Chair: Dr. Krishan Kumar, HoD CSE NIT Uttarakhand, Srinagar Rapporteur: Dr. Neelam Chaplot				
Sr.No	**ID**	**Time**	**Authors**	**Paper**
8.	**1570692375**	3.00 pm-3.15 pm	**BhawanaMaurya** (Government Women Engineering College, India); **SarojHiranwal** (RIET, India)	A Review on Liver Cancer Detection Techniques
9.	**1570694211**	3.15 pm-3.30 pm	**Anil Singh Parihar,ShivamSinghal, , SrishtiNanduri and YashRaghav**, Dept. of Computer Science and Engineering, Delhi Technological University New Delhi, India	A comparative analysis of Deep Learning based approaches for Low-light Image Enhancement
10.	**1570693295**	3.30 pm-3.45 pm	**Pushpendra Singh Sisodia** (Poornima College of Engineering, India)	An Elderly Fall Detection Techniques Using Depth Images
11.	**1570693476**	3.45 pm-4.00 pm	**SowmyaSanagavarapu** (Anna University, India), **Sashank Sridhar** (Anna University, India)	Dynamic Routing Framework Proposal for SDWAN Using Topology-Based Multitask Learning
12.	**Invited 1**	4.00 pm-4.15 pm	**CostinBadica, Amelia Badica**(University of Craiova Craiova, Romania); **Maria Ganzha** (Warsaw University of Technology Warsaw, Poland); M**arcin Paprzycki** (Systems Research Institute Polish Academy of Sciences Warsaw, Poland); **MirjanaIvanovic** (University of Novi Sad Novi Sad, Serbia)	Multi-Agent Simulation of Core Spatial SIR Models for Epidemics Spread in a Population
Session IIIA: Networks, Security and Biometrics (4:30 pm-6:00 pm)				
Session Chair: Dr. PriyankaDahiya, SOC, DIT Dehradun Rapporteur: Dr. Neelam Chaplot				
Sr.No	**ID**	**Time**	**Authors**	**Paper**
13.	**1570688080**	4.30 pm-4.45 pm	**Belen Septian** (Osmania University, India)	IoT Based Power Monitoring System for Diesel Generator
14.	**1570691093**	4.45 pm-5.00 pm	**PriyaMukundDeshmukh** (PRMIT&R, Amravati, Maharashtra, India)	Biometric Jammer: A Security Enhancement Using SVM Classifier
15.	**1570693893**	5.00 pm-5.15 pm	**GarimaMathur** (Poornima College of Engineering, Jaipur, India); **SanjeevYadav** (Govt. Women Engineering College Ajmer, India)	Monitoring and Detection of Blood Flow Based on Internet of Things
16.	**1570692213**	5.15 pm-5.30 pm	**DanialMubariq Mohamed Azzahar** (UniversitiTeknologi MARA Cawangan Kedah, Malaysia); **Siti Rafidah Muhamat Dawam** (UniversitiTeknologi MARA Cawangan Kedah & Faculty of Computer & Mathematical Sciences, Malaysia)	A Review: Standard Requirements for Internet of Vehicles (IoV) Safety Applications
17.	**1570687975**	5.30 pm-5.45 pm	**ShaifizatMansor** (UniversitiTeknologi Mara & Kedah Branch, Malaysia)	Blockchain-Based Internet of Vehicles (BIoV): An Approach Towards Smart Cities Development

5th IEEE International Conference on Recent Advances and Innovations in Engineering- ICRAIE 2020 (IEEE Record#51050)

An Elderly Fall Detection System Using Depth Images

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***Abstract*— In this proposed conceptual technique, we have collected the Microsoft Kinect depth images of elderly fall event. After collecting the necessary depth images the background subtraction algorithm has been used to subtract the background and retain the subject. Segmentation and feature selection process have been applied on various daily activity to train the fall detection model. The model has been train using decision tree. To ensure the fall confidence, ground truthing technique has been used.**

***Keywords*— Elderly Fall Detection, Decision Tree, Computer Vision, Kinect**

I. Introduction

As per World Health Organization (WHO), the aging is the major issue in among the old age people. It is estimated that one out of every three old age adult fall every year especially, those who have the age of 60 and above [**1**]. The number of elderly people above the age of 60 years is rapidly increasing especially in India. India is the second most populous country in the world that has approx. 1.36 billion people estimated in 2020. Whereas, 109 million people are over the age of 60 that is approx. 8% of total population and it is estimated that it will increase up to 20% till the year 2050 [**2**].

The major area of concern is the physical health of the elderly people. Recurrent fall is one of the major problem of the elderly people as they have inability to get up early and lying of prolonged period of time on floor due to sudden fall can lead serious health issues [**3**]. Elderly people especially who are living alone are in more risk as compared to others.

Recurrent fall of elderly people required medical assistance every time that can impact directly on their financial condition. There is immediately requirement of low cost automatic elderly fall detection system that could help to get assistance on time after fall. Many extensive methods have been applied for automatic fall detection among the elderly people [**4-5**].

Some of them are wearable devices that are worked on sensors like accelerometer and some of them allow elderly people to manually operate the wearable devices when any incident of fall happened **[6-9]**. Wearable devices are insensitive to the environment and required periodic maintenance like batteries replacement or recharge which is some time forgotten by elderly people. The other disadvantage is to cause inconvenience in daily activity. Research studies indicate that elderly people are not prefer wearable devices instead they prefer non-wearable devices **[10].**

Number of researchers has also suggested the environmentally mounted sensors for elderly fall detection. They have used ambient devices such as vibration sensors, sound sensors, infrared motion sensors, pressure sensors, video based sensors, including traditional cameras and depth cameras in multiple place of room to record daily activity of elderly people. Recorded activity further processed to detect elderly fall and significant alarm provided without delay **[11-14].**

Using multiple devices significantly increase the cost of solution and putting many sensors in a room could bring health issues for elderly people. Another major issues with tradition video sensor is the breach in the privacy of the elderly people. However, researchers have been suggested that vision based environmentally mounted sensors are helpful by using appropriate privacy preserving techniques **[15].**

In this paper, we have proposed an automatic elderly fall detection technique for an individual home using depth camera. We have proposed the environmentally mounted Microsoft Kinect sensor for the elderly homes for automatic fall detection. We have collected the depth images of elderly fall events. After collecting the necessary depth images, the background subtraction algorithm has been used to subtract the background. Segmentation and feature selection have been done for various daily activities and fall to train the model. The model has been train using decision tree and to ensure the fall confidence, ground truthing is also used. Finally, we have processed the result for analysis.

The paper has been organized as follows First, related work, Second, discussion on Microsoft Kinect sensor depth images, Third, methodology used for fall detection, Forth, results analysis, Fifth future work.

II. Related Work

There is an extensive study has been done on elderly fall detection system. Our study have found various elderly fall detection systems that have used different tools and techniques. We have categorized these studies in three parts First, sensor based, Second, radio signal based and Third, video based or vision based technology. Since, our work is based on vision based techniques so we will discuss it in more detail.

Sensor based fall detection systems are used the sensors such as accelerometer, and gyroscopes. These sensors are sensitive to sudden acceleration and can detect rapid motion changes like human fall [6-9]. These sensors are mostly human wearable but major disadvantage is that they require periodic maintenance like battery recharge or replace. This periodic maintenance are sometime ignored or forgotten by the elderly people. Therefor fall has not detected by these sensors.

Radio signal based fall detection system are used the Radio signals and built in accelerometer of smartphone. Whenever, elderly fall has been detect it tracked the elderly fall location and sent a short message service (SMS) and e-mail to set contact number on mobile [16-17]. The major disadvantage of these techniques is that elderly people have to carry their mobile phone every time with them to used accelerometer sensor which is some time impossible. This technique is used radio signal and it could be possible to delay the SMS.

Video based or vision based technique is used the standard imaging sensors for elderly fall detection. This technique has used different setup of the cameras such as single camera mounted on the wall. Some cameras are mounted on the ceiling and some are mounted on all four walls and ceiling to record three dimensional (3D) reconstruction of foreground objects [18-21]. However, Video based or vision based technique are having many limitations. Such as foreground extraction is difficult in color image due to variable lightening conditions and shadows [22].

Recording the video in low light or no light is impossible and we have required addition Infrared sensor that increase the setup cost [23]. In the case of single camera, modeling of 3D movement of the object is difficult and hence, it compromises the accuracy in the fall detection [18]. If we use multi-camera setup to capture 3D movement of object then it will increase the difficulty of calibration of the camera and it also increase the overall setup cost of fall detection system.

Due to these many issues, researchers have looked for an alternative of traditional camera setup that is cost effective as well as robust in term of fall detection. Recently, researchers have been focused on Microsoft Kinect depth imaging sensor to detect elderly falls.

Literature review indicate that Kinect sensor have been replaced the traditional cameras and became the most popular visual sensor for elderly fall detection. Kinect camera overcome the weakness of the traditional camera and can capture the 3D motion by using an infrared sensor and specialized microchip that make it less affected by the low lightning or no lightning conditions. Mastorakis et al. [24] have been used Kinect sensor to capture real time fall detection.

Gasparrini et al. [25] mounted Kinect sensor on-ceiling and set the camera face downwards to detect elderly fall based depth images. This kind of setup of Kinect sensor provides the privacy preserving fall detection in the indoor condition. Although extensive work has been done but previous work have some limitation such as poor data collection in laboratory mode or limited fall pose. Other limitations are as poor feature selection and background separation. We have proposed a robust technique that can detect the fall accurately.

III. Methodology

In methodology section, we will describe fall detection technique that we have used in the study. Our methodology have been divided in seven sections- (a) Depth Image Acquisition (b) Background Subtraction (c) Ground Segmentation (d) Feature Selection (e) Fall confidence (f) Ground Truthing (g) Fall Detection as shown in figure-(1).

A. (a) Depth Image Acquisition

Depth images are acquire through continuous video of Microsoft Kinect sensor that are mounted on a wall in a laboratory.

Figure 1 Depth Image from Kinect Camera

B. (b) Background Subtraction

Background subtraction is a commonly used method for generating a foreground mask using static cameras. A dynamic background subtraction algorithm is used to subtract the background to get the object (Human). Object is further processed to get its maximum height, height from object center and height up to the object knees. These three parameters we have used in our study to get fall detection.

Figure 2 Background subtraction

C. (c) Ground Segmentation

Ground fall motion segmentation is necessary for elderly fall detection. Ground fall motion segmentation has been done to get feature extraction of different pose of fall. We have consider some fall motion as standing fall in backward, sideway, and forward fall. Sitting fall has considered as left side fall, right side fall, and falling from bed.

D. (d) Feature Selection

Feature has been selected from fall motion segmentation to accurately detecting the elderly fall. These features are the maximum, minimum and average vertical motion velocity. These features helped us to accurately identify the elderly fall.

E. (f) Fall Confidence

The features we selected in feature selection step is used as an input to the decision tree algorithm to check the fall accurately. A decision tree algorithm has been used for fall confidence.

F. (g) Ground Truthing

A manual ground truthing has been done to check actual fall with detected fall in the system. For this process, we have selected random events where we have doubt about actual fall.

G. (h) Fall Detection

After collecting data from ground truthing we have detected fall for every pose mention in the ground segmentation step using decision tree. The binary has been used and trained to classify the fall event. Cross validation technique has been used to validate the result. For cross validation sitting, lying and walking activities have been used.

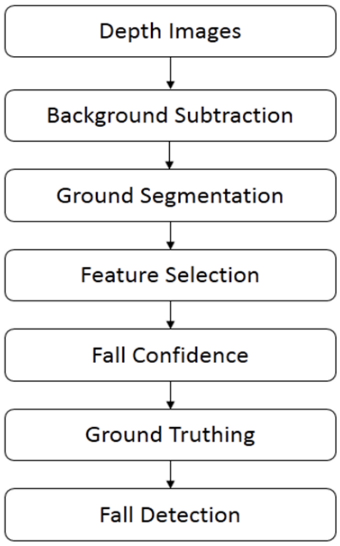

Figure 3 Flow Chart of Methodology

IV. Results And Discussion

In this section, we have discussed the expected results that we have achieved during the laboratory experiments of fall detection system. We have used volunteer to collect the fall data. The fall data have been collected as mention in the methodology section. The obtained results have been cross validated. Cross validation has been included the standing, sitting, lying positions and far distance (<4 meter) from camera. Result also cross validating with volunteer reported fall with fall detected by system. This ground truth is used to improve the performance of the technique. To calculate the accuracy of methodology, we have used accuracy, precision, specificity, and sensitivity as mentioned in eq. 1, 2, 3, and 4.

$$A_c = (T_p + T_n) / T_e \quad \text{-----------------------------------} \quad (1)$$

$$P_r = (T_{po}) / (T_p + F_n) \quad \text{---------------------------------} (2)$$

$$S_p = T_n / T_{ne} \quad \text{-----------------------------------} (3)$$

$$S_n = T_p / T_{po} \quad \text{--} (4)$$

A_c = Accuracy
T_p =True positives
T_n = True negatives
T_e = Total number of events
P_r = Precision
T_{po} = Total positives
F_n = False negatives
S_p = Specificity
S_n = Sensitivity

TABLE 1 FALL DETECTION RESULTS

Events	Falling	Sitting	Lying	Standing	Total
No. of Event	82	12	8	10	112
Tp	78	0	0	0	78
Fp	4	2	0	0	6
Tn	0	10	8	10	28

TABLE 2 PERFORMANCE OF PROPOSED TECHNIQUE

Metrics	Performance
A_c	94.64 %
P_r	97.5 %
S_p	93.33 %
S_n	95.12 %

We have presented a conceptual method of automatic fall detection system for elderly people using Microsoft Kinect camera. Results have been discussed in Table 1 and Table 2. The major issues with Microsoft Kinect are as the distance increased the resolution of depth image is decreased. Due to decrease resolution it is hard to calculate the background subtraction and segmentation of depth images.

V. FUTURE WORK

In the future work, we will include more realistic data and try to get actual data of elderly fall. Results will further improve against the realistic data. We will also compare our technique with state of art techniques having high accuracy.

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REFERENCES

[1]. Center for Disease Control and Prevention (CDC), “Falls among older adults: An overview,” Retrieved Sept. 9, 2013 from http://www.cdc.gov/homeandrecreationalsafety/Falls/adultfalls.html

[2]. https://www.who.int/ageing/projects/SEARO.pdf

[3]. M.E Tinetti, W.L. Liu, and E.B. Claus, "Predictors and prognosis of inability to get up after falls among elderly persons," JAMA: the journal of the American Medical Association, 269(1): 65-70, 1993

[4]. M.Mubashir, L. Shao, and L. Seed, “A survey on fall detection: Principles and approaches,” Neurocomputing, vol. 100, pp. 144–152, 2013, pp. 1.

[5]. M. Skubic, G. Alexander, M. Popescu, M. Rantz, and J. Keller, “A smart home application to eldercare: Current status and lessons learned,” Technol. Health Care, vol. 17, no. 3, pp. 183–201, 2009.

[6]. N. Noury et al., "Fall detection-principles and methods," 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 1663-1666, 2007.

[7]. A.K. Bourke, P.W. van de Ven, A.E. Chaya, G.M. OLaighin, and J. Nelson, “Testing of a long-term fall detection system incorporated into a custom vest for the elderly,” 30th Annual Int. IEEE Eng. Med. Biol. Soc. Conf. , pp. 2844–2847, 2008.

[8]. G. Wu and S. Xue, “Portable preimpact fall detector with inertial sensors,” IEEE Trans. Neural Syst. Rehabil. Eng., 16(2):178–183, 2008.

[9]. Prado-Velasco, Manuel, Maria Gloria del Rio-Cidoncha, and Rafael Ortiz-Marin. "The inescapable smart impact detection system (ISIS): An ubiquitous and personalized fall detector based on a distributed “divide and conquer strategy”." In 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 3332-3335. IEEE, 2008.

[10]. G. Demiris et al., “Older Adults' Attitudes Towards and Perceptions of Smart Home Technologies: A Pilot Study,” Informatics for Health and Social Care, 29(2):87-94, 2004

[11]. A. Ariani, S. Redmond, D. Chang, and N. Lovell, “Simulated unobtrusive falls detection with multiple persons,” IEEE Trans. Biomed. Eng., vol. 59, no. 11, pp. 3185–3196, Nov. 2012

[12]. C. Doukas and I. Maglogiannis, “Emergency fall incidents detection in assisted living environments utilizing motion, sound, and visual perceptual components,” IEEE Trans. Inf. Technol. Biomed., vol. 15, no. 2, pp. 277– 289, Mar. 2011.

[13]. Y. Li, K. Ho, and M. Popescu, “A microphone array system for automatic fall detection,” IEEE Trans. Biomed. Eng., vol. 59, no. 5, pp. 1291–1301, May 2012.

[14]. Y. Zigel, D. Litvak, and I. Gannot, “A method for automatic fall detection of elderly people using floor vibrations and sound-proof of concept on human mimicking doll falls,” IEEE Trans. Biomed. Eng., vol. 56, no. 12, pp. 2858–2867, Dec. 2009.

[15]. G. Demiris, O.D. Parker, J. Giger, M. Skubic, and M. Rantz, “Older adults' privacy considerations for vision based recognition methods of eldercare applications,” Technology and Health Care, 17:41- 48, 2009.

[16]. Aguiar, B.; Rocha, T.; Silva, J.; Sousa, I. Accelerometer-based fall detection for smartphones. In Proceedings of the 2014 IEEE International Symposium on Medical Measurements and Applications (MeMeA), Lisboa, Portugal, 11–12 June 2014; pp. 1–6.

[17]. Kau, L.J.; Chen, C.S. A Smart Phone-Based Pocket Fall Accident Detection, Positioning, and Rescue System. IEEE J. Biomed. Health Inform. 2015, 19, 44–56.

[18]. S.G. Miaou, P.H. Sung, and C.Y. Huang, “A customized human fall detection system using omni-camera images and personal information,” Transdisciplinary Conf. on Distributed Diagnosis and Home Healthcare, pp. 39 – 42, 2006.

[19]. T. Lee and A. Mihailidis, “An intelligent emergency response system: preliminary development and testing of automated fall detection,” Journal of Telemedicine and Telecare, 11(4):194 – 198, 2005.

[20]. D. Anderson, R.H. Luke, J. Keller, M. Skubic, M. Rantz, and M. Aud, “Linguistic summarization of activities from video for fall detection using voxel person and fuzzy logic,” Computer Vision and Image Understanding, 113(1):80–89, 2009.

[21]. E. Auvinet et al., "Fall detection with multiple cameras: An occlusionresistant method based on 3-d silhouette vertical distribution," IEEE Trans. on Info. Tech. in Biomedicine, 15(2):290-300, 2011

[22]. M. Piccardi, “Background subtraction techniques: a review,” in Proc. IEEE Int. Conf. Systems, Man, Cybernetics, 2004, pp. 3099–3104

[23]. Z. Zhou, E. Stone, M. Skubic, JM. Keller, and Z. He, "Nighttime In Home Activity Monitoring For Elder-care," Int. Conf. of the IEEE Engineering in Medicine and Biology Society, pp. 5299-5302, 2011.

[24]. Mastorakis, G.; Makris, D. Fall detection system using Kinect’s infrared sensor. J. Real Time Image Process. 2014, 9, 635–646.

[25]. Mastorakis, G.; Makris, D. Fall detection system using Kinect’s infrared sensor. J. Real Time Image Process. 2014, 9, 635–646.