[UCI]I804:48009-200000334304

Doctor of Philosophy

Fall Detection System for Elderly People using Vision-Based Analysis

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Fall Detection System for Elderly People using Vision-Based Analysis

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A Dissertation

Submitted to

The Graduate School of the University of Ulsan

In partial fulfillment of the requirements

for the degree of

Doctoral of Philosophy in the School of Electrical Engineering

by

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June 2020

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Dedication

This thesis work is dedicated to in loving memory of my mother in law Surajambika. You are not with us anymore, but your belief in me has made this journey possible.

ABSTRACT

The number of elderly people topped 14 percent of the total population in South Korea as per the reports from Statistics Korea. The ageing population in Korea is projected to be the most rapid among Organization for Economic Co-operation and Development (OECD) countries between 2000 and 2050. Due to the physical weakness associated with ageing, injury is a major global health concern. In a study by the burden of disease in South Korea, injuries such as falls, motor vehicle collisions (MVCs) and suicides were included in the top cause of disability. MVCs and suicides are decreasing compared to falls in the recent years. In this paper we are proposing a method to detect falls based on vision analysis.

Fall is one of the major causes of death in elderly aged people. Timely and accurate detection of falls is an essential factor to protect elderly people from reduced risk, especially those who live independently. Detecting the fall plays a major role in saving lives. Three different types of fall detection systems are commonly used, such as wearable, ambient sensor and vision-based methods. Various existing methods are analyzed and compared in the literature review. Even though, wearable sensors are giving better results, the main drawback associated is the inconvenience to elderly people since they must wear sensors all the time for efficient tracking and detection. There are drawbacks associated with ambient sensor-based systems as well such as acoustic sensors and floor vibration sensors are easily affected by noises such as TV sounds and other noises from the environment. In this research, focus on vision-based approaches to detect falls since cameras provide very rich information about the object and the environment. Nowadays cameras are installed in most of the places such as airports, train and bus stations, malls and even in the streets. Due to security reasons, even old age homes and the elderly care centers are installed with cameras. Proper utilization of the existing cameras would help us implement the system effectively and efficiently to monitor the elderly and detect a fall. The proposed algorithm is cost effective, easy to implement and useful for real-time applications. This system will provide an immediate attention and care to the aged group of people. Vision based system are better than other methods and this is explained in the literature section.

This research presents a real-time vision- based fall detection system to support the elderly people through analyzing the rate of change of motion with respect to the ground point. The aim of our work is to provide an efficient method to detect fall, without wearing any physical devices. Image processing technique is used for detection the human from a video captured by the camera. After human detection the detected object is tracked by using Kalman Filter.

One of the main advantages of this work is that, we are using 2D images and not the (3D) depth images.

The proposed method is a combination of ground point estimation based on texture segmentation using Gabor filter and a person's movement tracked by using a Kalman filter. This calculates the angle between the tracked points with respect to a ground point and calculates the rate of change of angle for detecting the fall detection.

For experimental analysis, we used two publically available datasets such as URFD and FDD. Along with this, we have created some data sets in our lab environment to test the suitability of the algorithm for real-time applications and analyzed different parameters such as sensitivity, accuracy and specificity. Test results shows that our system was able to achieve accuracy of 90.53% with a sensitivity of 91.17% and specificity of 96%. We believe that the proposed system will provide a better and efficient support system for elderly people who live independently.

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CHAPTER 1

INTRODUCTION

The human fall detection system is very important in today's ageing population. Especially in South Korea, as the number of elderly people topped 14 percent of the total population according to the 2017 census by Statistics Korea. Statistics shows that, by 2030 the aged population will be 24.5% of the total population.

Injury is one of the major cause of deaths in South Korea. The high incidence of injury on elderly people increases the risk of public health in South Korea. Hence it is necessary to develop an injury prevention program that targets the elderly people. The leading causes of the injury burden are due to road injuries, falls, and self-harm. The burden of road injury and self-harm have recently had shown a gradual decreasing tendency. On the other hand, injuries due to fall tends to increase among the people in the age group of over 50 years [1].

The number of falls in South Korea was 250,600 per year in 2012, placing it at 28th among 188 nations who joined the World Health Organization [2]. A fall is a sudden, unintentional change in position that causes a person to move quickly downwards onto or towards the ground. The frequency of fall increases with increasing age. About one third of the elderly population aged 65 years or older and about half of those aged 80 years or older experience at least a fall in a year.

The risk of falling and sustaining injuries is higher in elderly compared to younger individuals. Among the elderly, fractures of the hip, waist, wrist, and femur are caused by falls. As per statistics, about 80%–90% of hip fractures are known to be triggered by falls [3]. In addition to physical impairment, falls affect emotions, leading to functional limitations and impairment. In the elderly, falls are an important risk factor associated with quality of life. Korea has entered an ageing society with an elderly population exceeding 14% of the total population in 2017. The statistics are shown in Fig.1.1 and Fig.1.2 below.

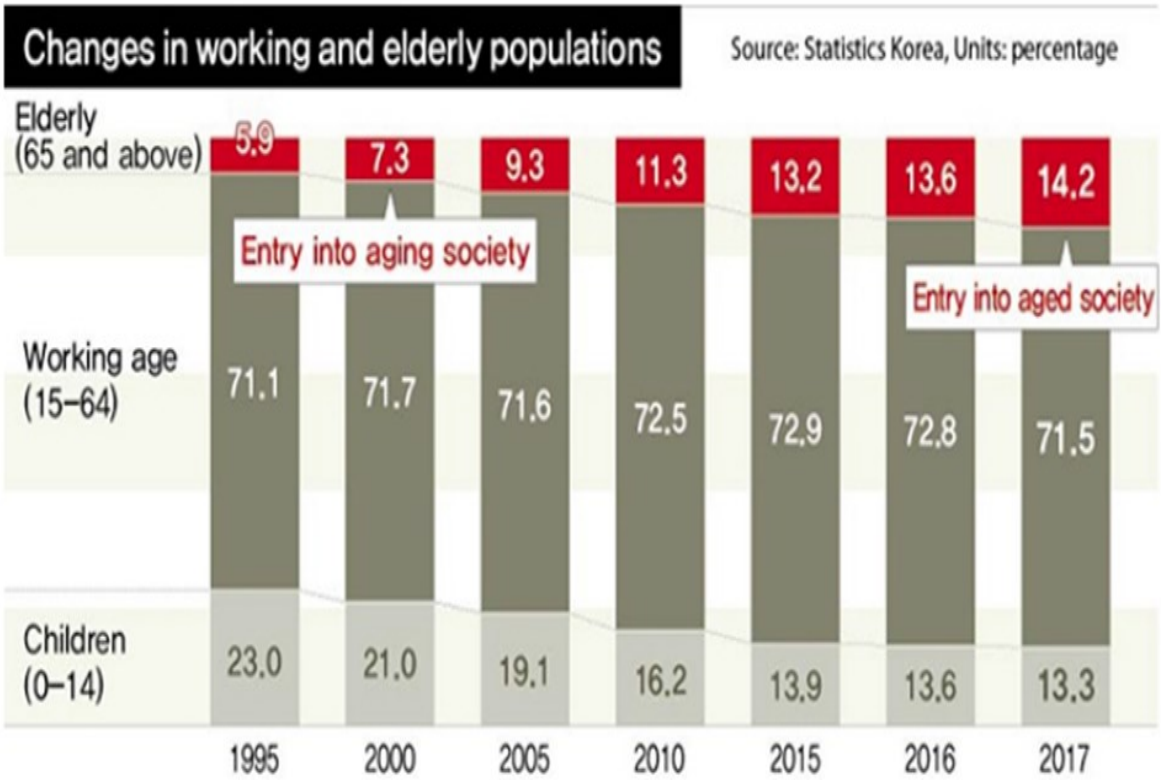


Fig.1.1. Elderly population based on Statistics Korea

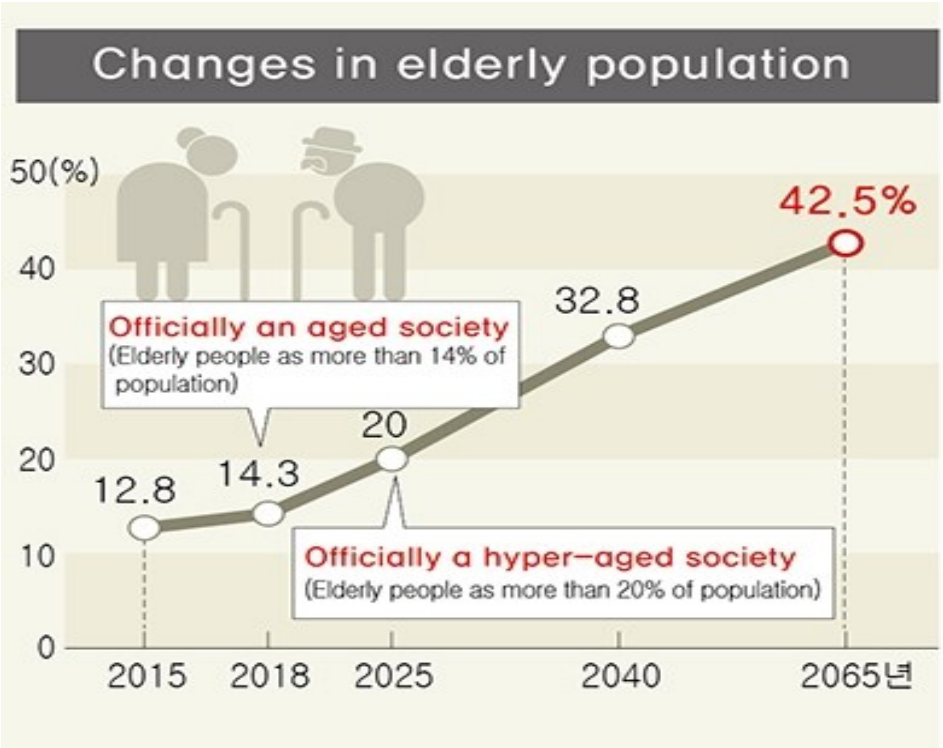


Fig.1.2. Changes in elderly population

Statistics Korea reported these findings in its "Future Population Estimates, 2015-2016" report released on Dec. 8. This report is published once every five years. The estimates are the indicating factors which influence the forecast of the future population in the light of the factors which directly affects it. These factors include births, deaths and migration. The productive population according to the estimates, is aged from 15 to 64 is set to the peak value of 37.63 million in 2017 and this started declining from then. By 2020, the generations born between the 1955 and 1963 will turn senior citizens, the productive population is set to dip by a yearly average of 340,000 in numbers. In another 10 years' time in 2030, the decline is expected to dip further and is predicted to be 440,000 per year. As the senior population is climbing up the ladder quickly, South Korea is expected to become an elderly aged society (14% or more of the population aged 65 and older in 2018) and a hyper-aged society (20% or more) by 2025 - a year ahead of schedule from an estimate made five years ago. [Population projections for 2015-2065. Data: Statistics Korea report]. The survey of population and further projections for Korea until 2050 is shown in Table1.1 below.

People at their final stage of old age (85 and above) gradually drift away from the Elderly community centres since they need more help to get around and get things done.

Table1.1. Population indicators and projections for Korea

Year	Population (in milions)	Growth rate (%)[a]	Fertility rate[b]	Life expectancy (in years)	Medium age (in years)	Proportion of elderly population (%)[c]
1960	25.0	2.3	6.0	55.3	19.9	2.9
1970	31.5	1.8	4.5	63.2	19.0	3.1
1980	37.4	1.5	2.7	65.8	22.2	3.8
1990	43.4	0.6	1.6	71.3	27.0	5.1
2000	46.1	0.6	1.5	75.9	31.8	7.3
2010	49.2	0.1	1.2	79.1	37.9	10.9
2020	50.0	-0.1	1.2	81.0	43.7	15.7
2030	49.3	-0.5	1.3	81.9	49.0	24.1
2040	46.7	-1.0	1.3	82.6	53.1	32.0
2050	42.3	_	1.3	83.3	56.2	37.3

Note: Korea National Statistical Office projections for the period 2005 to 2050.

[a]The annual average growth rate for the decade. In the row for 1960, for example, the figure shows the rate for the decade 1960–1970.

[b]The average number of children that a woman can expect to bear during her lifetime.

[c]The number of persons aged 65 and older as a percentage of the total population [4].

With the ageing population increases, the risks of falling and fall-related injuries increase rapidly [2]. To ensure safety of the elderly and improving the quality of their life, the technology should have an important part, especially for detecting falls and provide proper aid to the people. The consequences of a fall are highly dependent on the response and the time taken to rescue the victim. A well designed fall detection system may able to improve the response time and hence decrease the nasty consequences of fall, especially in elderly aged and those who are staying alone. To improve the response time and safety of life by providing quick and emergency medical support, recently many researches focus on areas of fall detection among the elderly people. In this paper, we propose a novel method to detect falls based on video analysis.

A fall detection system is a device which assist elderly people and the main objective is to detect and alert when a fall even is occurred. A fall detection system can directly reduce the fear of fall in human beings and this in turn help them to improve their quality and way of life. Individuals who fall often develop a fear which will increase the anxiety, depression and reduce the level of physical activities. A fall detection system can be broadly classified into three and they are wearable devices, context aware based system and the vision-based system. The general block diagram which shows the various classification of human fall detection system is shown in Fig.1.3. Wearable fall detection devices are devices made up in electronic platform that are worn by a person either under or over their clothes or it can even be in the form of a wrist band. Various sensors such as gyroscopes, accelerometers etc. are embedded within the device to be worn by the subject. The various parameters such as variability of heart rate, electrocardiogram, pulse oximetry etc. are measured by the sensors. The data measured and collected by the sensors are either fed to a system based on threshold or to a machine learning system in the form of feature sets to accurately detect the fall. The main advantage of these devices is less expensive, low power consumption, and the chances of the sensors separated from the body is less. However, the major drawback is that the person needs to carry the device with them all the time. The context-aware fall detection systems include sensors which are installed in the environment around the humans to detect a fall. Systems designed based on this type of technology include ambience and acoustic sensors such as pressure sensors, floor sensors, infrared sensors etc. The system consists of the above-

mentioned sensors to collect the data and a system to process the data to detect the fall. The vision-based fall detection techniques monitor real-time movement of an object through a normal video camera or depth video camera. This system does not monitor the parameter of any sensors, rather rely on the image processing techniques and tools to process the video or images captured by the vision-based sensors. A dedicated algorithm at the background is used to determine the posture of the object. More accurate fall detections are enabled by using machine learning algorithms over the image processing techniques. The major advantage of the vision-based system is the easy installation and maintenance, convenience of use and they do not have to be carried all the time by the object. However, some of the drawbacks are the inaccurate results due to ambient change in lighting, not able to maintain personal privacy, inaccurate results due to blind spots and obstructions. A much-detailed coverage of various fall detection techniques is explained in the literature section in chapter 2.

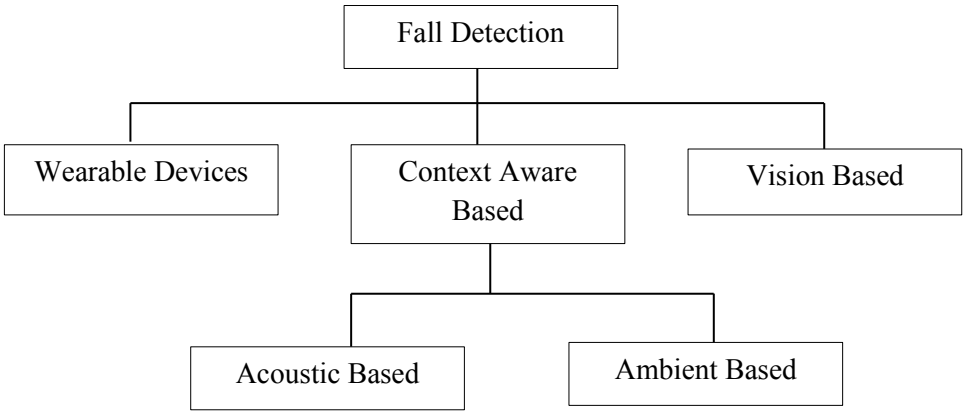


Fig.1.3. Classification of fall detection methods [5]

Compared to the wearable sensor and acoustic-based methods, vişion-based fall detection technique is more promising. The end user does not need to carry any type of sensors or other type of hardware, which is the major advantage. One of the other advantages is that, cameras can be placed everywhere such as airports, train stations, bus stations, malls, streets etc. Majority of the old aged care centers are even equipped with cameras. These cameras could possibly be used to collect more accurate information compared to multiple sensors. Computer vision method overcomes the limitations of both wearable based and context-aware based fall detection systems. Vision-based system provides health care system by assisting the elderly people in a better and accurate way [6-7].

Because of the rapid increase in technology development in the recent years, a lot of researchers focus on the fall detection mainly based on sensors like acceleration and vibration which can potentially overcome the limitations of the wearable and sensor-based methods. This may overcome some of the limitation of the sensor-based fall detection system. However, the major limitation of carrying the sensor-based fall detection equipment all the time remains unchanged. The major aim of this research work is to provide an efficient method for fall detection without wearing any physical device or sensors.

The advantages of this proposed method are:

- No need for additional sensors and no need to wear any physical device.
- Videos captured with a single camera from a real-time situation. (Cameras can be wall or ceiling mounted and the whole area can be monitored without any human intervention)
- This method is based on 2D images and not considering depth images. This will majorly reduce the cost of implementation.
- Easy to implement, cost effective and useful for real-time applications.

Whenever a fall is determined, immediate attention and urgent medical care can be given to the aged people. The cost and various performance properties of various fall detection systems are given in the table 1.2 below.

Table 1.2. Cost and Performance Properties

Approach	Cost	Recognition Rate	Setup	Reliability	Accuracy
Wearable	cheap	low	easy	no	low
Ambient	cheap	low to medium	easy	depends	medium
Vision based	medium	high	medium	high	high

Vision based fall detection systems differ from each other due to various factors. Some of them are the feature set provided to the machine learning system, placement of the sensors, the specific algorithms applied in the system, the data sets used, different parameters monitored to improve the accuracy of detection etc. Thanks to the advancement in technology that the usage of surveillance camera has now increased and has now become an integral part of human life. This surveillance camera can be utilized to detect the falls among elderly aged

group. The advantage of automatic human fall detection as one of the major components in the elderly monitoring system for those elderly individuals without a spouse or who live by themselves includes the increased physical activities among these group with less fear. With the help of these automatic fall detection systems, the quality of life among elderly aged group has improved and the risk factors are majorly reduced when they are alone.

In this research work a novel approach to vision-based method is proposed to detect the fall based on image processing algorithm by calculating the rate of change of angle with respect to ground plane. The proposed method includes different module such as detection of human as a foreground object, tracking the detected object and detect the falls from the normal activities. The proposed architecture and the detailed methodology are explained in chapter 3.

CHAPTER 2

LITERATURE SURVEY

2.1 Fall Detection

Fall detection for elderly has become an active research topic since the demand for products and technology in the healthcare industry has grown high. Many technical solutions have been studied and developed in the last decade for to detect/prevent falls. Fall detection taxonomy has been defined according to the used sensors [8].

Most of the current fall detection methods are based on the wearable sensors. However, this is practically difficult for the elderly people since they must wear the sensors all the time in order to efficiently detect a fall. The intelligent vision-based fall detection system overcomes the limitation of wearable sensors. The fall detection technique gives mental support to aged people to do their daily activities with much confidence. Falls are particularly dangerous for a person who lives alone, since a significant amount of time can pass before they receive any kind of assistance.

The literature survey of fall detection methods is mainly focused on sensors and vision-based approaches and a detail explanation is given below. However, in this research work, we are focusing on vision-based approaches.

Some of the advantages of vision-based systems are that they can run is any computers, and that there are many algorithms and libraries implemented in open-source. Although a variety of algorithms has been developed to detect falls, some of which are designed to analyze static images or treat each frame individually. A number of characteristic steps are frequently found in most fall detection systems, which are explained in the following subsections.

A universal architecture of a fall detection system is shown in Fig. 2.1. The sensing unit is responsible to sense and capture the various activities of human beings with the support of various sensors. This information is then passed on to the data processing unit which then detects the fall based on the algorithms. Once the fall is detected, an alert message will be sent to the emergency medical team or caregivers in order to provide with the adequate level of help within minimal time after the occurrence of the fall.

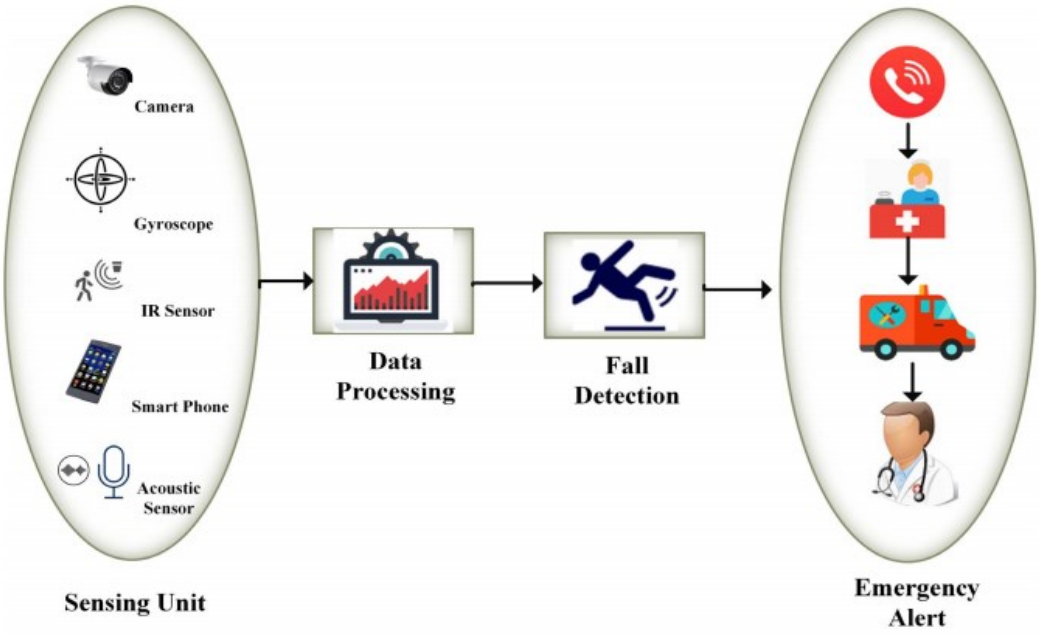


Fig.2.1. A universal architecture of a fall detection system [9]

2.2. Classification of Fall Detection Systems:

The fall detection systems are majorly classified into wearable sensor-based methods, ambient sensor-based methods, computer vision-based methods and multimodal methods [10]. A simplified block diagram of the available technologies to detect fall is as shown in Fig. 2.2.

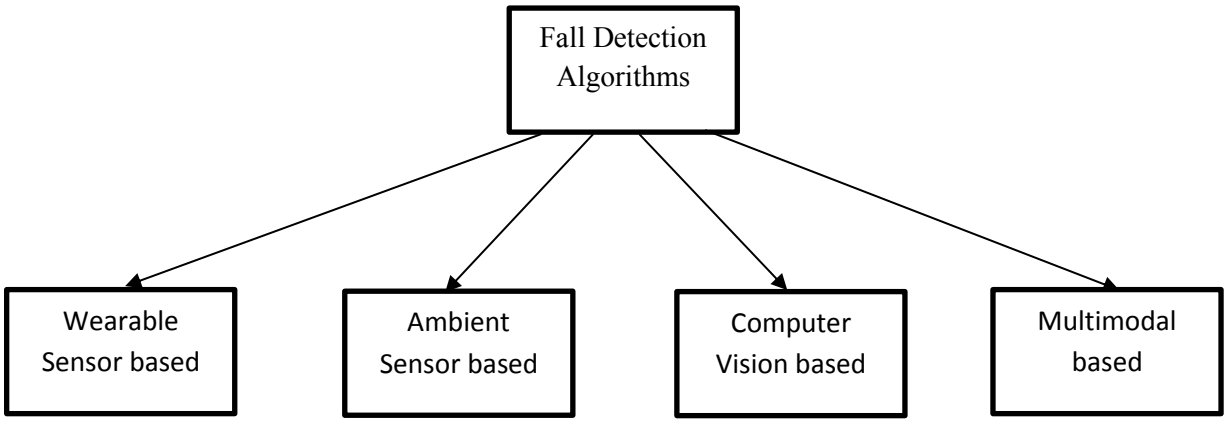


Fig.2.2. Classification of fall detection system [9]

2.2.1 Wearable Sensor-based Methods

Wearing devices with sensors embedded is used to detect the posture or movement of the person. Those sensors are either placed on garments or they are in the form of wearable belts or they can be even in the form of wrist bands. There are different types of sensors used to make such devices and hence there are plethora of methods to detect falls. Anita et.al [11] reviewed recent advances in wearable fall detection systems with focus on the application of machine learning.

There have been many research works carried out on elderly healthcare that are based on wearable sensors, since wearable sensors can provide more accurate information on elderly health status (e.g., heartbeat, respiration, muscle movements, and blood flow). For prolonged independent living, elderly people may not be inclined to use body-worn sensors [12-14].

The two major approaches used in the wearable sensors-based fall detection systems are threshold-based systems and machine learning based systems. Threshold based wearable fall detection systems have been a widely researched by researchers due to the simplicity and cost-effective implementation. The focus of such research has been on multiple aspects, such as ability to detect falls and classify falls from activities of daily life (ADLs) and near-fall conditions and sensors, fusion of readings from multiple sensor nodes [11]. While threshold-based systems have been popular because of the low computational complexities, it could be prone to more false positives and false negatives since the thresholds themselves maybe affected by various factors. The Machine Learning-Based wearable systems for fall detection have attracted researchers. Majd Saleh et.a [15] proposed a low-cost accurate machine learning based fall detection algorithm. The low computional cost of this algorithm not only enables to embed it in a werabale sensor but also makes the power requirements quite low and hence enahances the autonomy of the werabale devices considering the significance of low power in fall detection systems.

Some of the technologies used in the wearable sensor based fall detection system includes accelerometer based devices, posture sensor based devices etc. A brief overview of these techniques are given below.

2.2.1.1 Accelerometer Based Devices

Accelerometer is the cost effective and the most commonly used device to detect a fall. Measure of the acceleration of the body plays a major role in detecting a fall. Most research on fall detection using wearable sensors make use of accelerometers to determine the change in the magnitude of the acceleration of the body. A fall is detected when the rate of acceleration exceeds a critical threshold value. This system detects the fall of a person by attaching sensors to the body of the person who is at risk of falling. Generally, three-axis accelerometers are attached to the specific parts of the body, including the waist, wrist, or trunk, and data are collected for each axis. A critical point will be set and if the value collected from the acceleration sensors exceeds a that critical point, the situation is determined as a fall. The method that is used to combine, classify, and analyze the values for the x-, y-, and z-axes is different in each study and [16] suggests a real-time location tracking system for fall detection using a smartphone with sensors inside.

A demonstration of fall detection system using an accelerometer is shown in the Fig. 2.3. The analysis of accelerometer data allows the system to detect both voluntary and involuntary activities. Voluntary activities include walking, sitting, lying etc. and involuntary activities includes fall, sudden change of position etc.

Fig.2.3. Fall detection method using an accelerometer [16]

2.2.1.2 Posture Sensor-Based Devices

Falls can be detected by analyzing the posture of a person. Body orientation as posture is used in this method to detect fall using either posture sensors or multiple accelerometers. A sensor is attached to the body of the subject to detect the fall. However, this is practically difficult for some cases. This method produces more false alarms due to high level of obtrusiveness and there may be a chance to forget wearing such devices as well [17-19].

Falin Wu et.al [17] proposed a method to detect falls on elderly based on wearable devices. In this method, the wearable device is placed on the waist of the person. Acceleration analysis is used to detect fall in this method. This device collects information about a person's geographic position and send fall alarm short message to caregivers or to the health care representatives.

Guilherme Gerzson et.al [19] proposed a method using wearable sensor for ultra-low-power networks which are capable to interact with a smart system. The movement of the person wearing the system is monitored through a 3-axis accelerometer and gyroscope, which is attached to the chest. The real-time detection of falls using this system is based on threshold algorithm. However, in most of the literature reviews, there are no theoretical explanations for the analysis and determination of the threshold.

Faisal Hussain et.al [9] has proposed an efficient machine learning based method based on wearable sensor to continuous monitor the fall of a person. This research work uses the sensor data such as accelerometer and gyroscope to recognize the activities of a person and detect fall when it happens. This algorithm has reported an accuracy of 99.98% with the Support Vector Machine (SVM) classifier.

Some of the fall detections devices and its units based on wearable sensors and the placement of such devices are demonstrated in the Fig. 2.4.

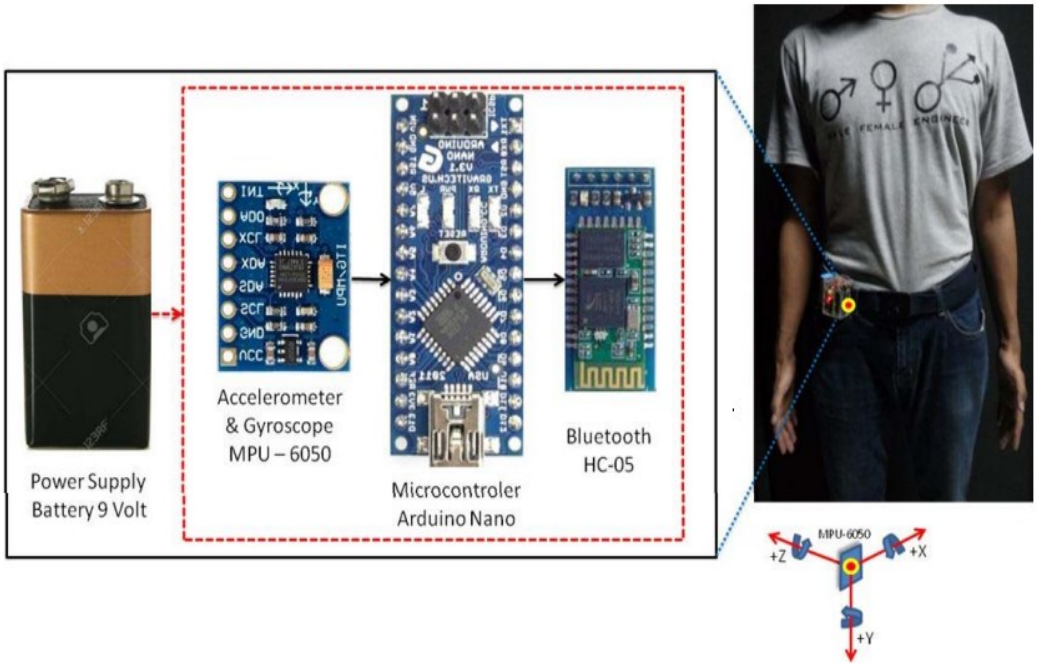


Fig.2.4. Fall detection device and device placement [20]

A battery is always an integral part to power the sensors and hence the low power techniques drags much attention in the research happened in the recent past. The power consumption of the system depends upon various factors such as how the device is configured, what kind of sensors are used, what kind of communication technologies are used etc.

Wearable technologies are not restricted within jackets or wrist bands. Asada et al [21] designed a ring sensor to measure the saturation level of blood oxygen and heart rate. This sensor is in the form of a ring and can be worn like a normal ring on the finger of the patient. A motion artifact reduction technique is integrated the improve the accuracy of the measurements. Another example is a system designed by Corbishley et al [22] to measure the respiratory rate using a wearable acoustic sensor such as microphone. The microphone placed around the neck regions can record the breathing pattern, which then passed through an appropriate filter to retrieve the modulation envelope of the signal. By carefully removing other noises and artifacts, the measurement of the rate of breathing can be accurately measured. When there is a fall occurs in such cases, the breathing pattern may be affected, and this method can be incorporated with an existing system to improve the accuracy of the detection of a fall.

Most of the literature on wearable sensor-based methods indicates that the performance of the algorithms varies with the position of the sensors. The threshold factor is dependent on the physical parameters and hence the performance of the threshold –based methods depends on the customizations set according to features of the experimentation environments [11].

2.2.2 Ambient Sensor-Based Methods

This method uses an array of sensors to identify the activities of the elderly to detect falls. Some of the sensors used are pressure sensors, vibration sensors, IR sensors, far-field microphones etc. This approach is completely unobtrusive and avoid the common problems such as misplacing and damaging the wearable sensors. Ambient sensors can monitor the regular activities of a human being such as the regular activity patters, the quality of sleep, bathroom visits etc. and alert the health professionals if there are something unusual incident happens. The major advantages of this method are:

a. Cost effective (Mostly cheap to medium cost)
b. The installation and set up of this method are relatively easy.
c. One of the major advantages is that the person's privacy is preserved.
d. The system is less intrusive for the surveillance system.

However, the advantages are accompanied with the cost of some disadvantages such as sensing the pressure of all the objects around the person, generation of too many false positive and false negative alarms and the biggest one is the detection accuracy which is relatively medium.

Some of the most commonly used ambient sensors are explained briefly in the following section of this report.

2.2.2.1 Pressure and Vibration Sensor-Based Methods

This method deploys sensors, externally within the vicinity of the subject. The most popular sensor is the pressure sensor since weight or vibrational data can be captured to detect and track the subject. But these methods have several practical and implementation issues that will increase the rate of false detections. These false detections will affect the performance of the system and the sensor installation is expensive. In real life applications where the subject is in a large area of ground, these methods may not be advisable [23-26] due to the expense and difficulty to install sensors over the large area.

Md.Zia Uddin et.al [27] did a survey about ambient sensors for elderly care. In this method various types of sensors are placed in the smart home such as passive Infrared (PIR) Motion sensors, pressure sensors, sound sensors, floor sensors, radar sensors etc. The setup of such a smart apartment for elderly care is as shown in Fig. 2.5.

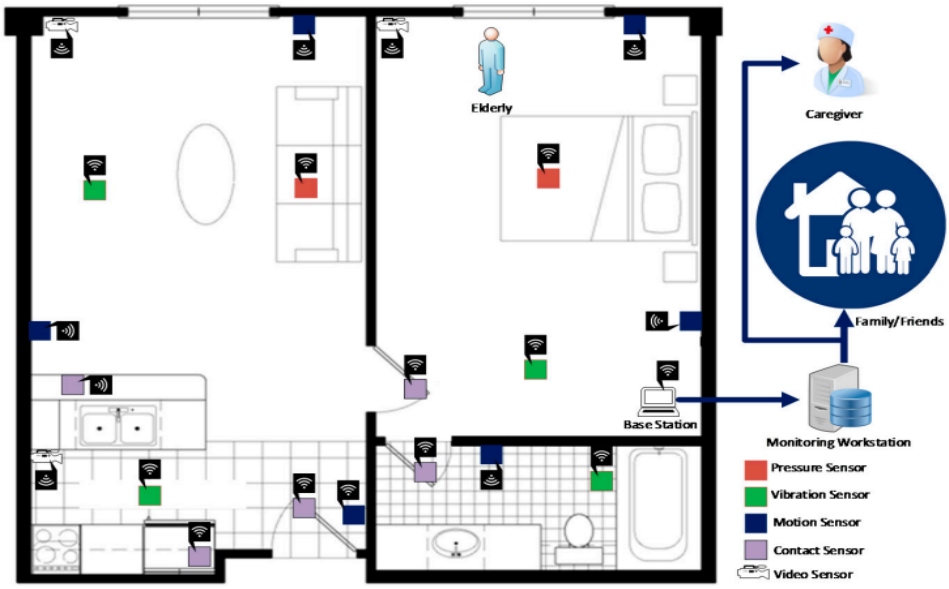


Fig.2.5. Sample schematic setup of a smart apartment for elderly care based on different ambient sensors [27]

As seen in the image, different types of ambient sensors are placed at the different areas of the apartment based on the practicability. The combined data of all the sensors will effectively utilized by the system to identify the activities done by the elderly people and detect if there are any falls occurred. The combination of wearable and ambient sensors has gained more interest among researchers in the past few years in the rehabilitation field. One such application in the rehabilitation field includes the identification of a person's normal pattern of activities and provide suggestions regarding specific or unusual behaviors or exercise life to maintain and manage the health condition. For instance, the data collected from the wearable sensors could be augmented by the other sensors installed in the apartment to determine the type and the intensity of activity which the person is undertaking. This can be effectively utilized to identify and detect possible falls as well. In the case of rehabilitation, the combined data could be fed into a system to identify the hazard and an appropriate feedback and the performance measures to maintain a satisfactory functional level can be given back to the end user or in case of fall detection, an alert can be given to the health care professionals. Even though rehabilitation is not within the scope of this research, a tiny emphasis is given in this section since rehabilitation is the process which helps an elderly after a fall, to come back to a normal life.

2.2.2.2 Passive Infrared (PIR) Motion Sensors

A Passive Infrared (PIR) sensor measures the infrared lights radiated from the objects which are in the field of view. Passive infrared motion sensors have always been used to detect the movement of individuals since early 1990s. Normally these sensors are installed on walls or ceilings of the home of the elderly people to continuously monitor and collect the data related to the movement of the individuals which are considered as the predefined activities. The structure of a commonly used PIR sensor is given in Fig. 2.6.

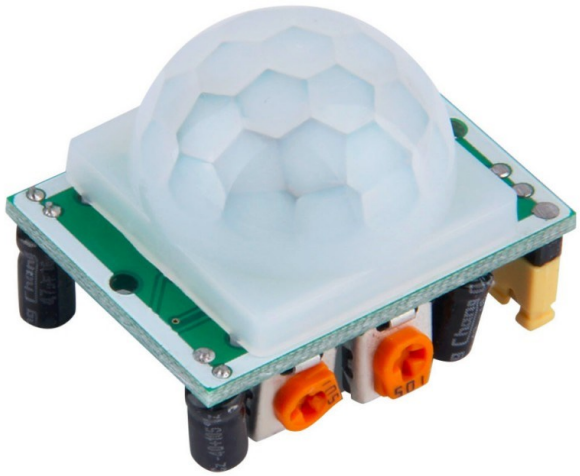


Fig.2.6. Structure of a PIR sensor [28]

PIR motion sensors are usually heat-sensitive which means, the IR radiation impinging depends in the temperature of the objects. The sensors detect the presence of users in rooms by utilizing the changes in the temperature. Motion data are collected and transmitted to the caregivers of an elderly, through a transmitting base station. Then, the collected data are interpreted and analysed to collect the trends and determine any changes in daily activities. They can also be analysed to identify potential changes in health status. However, the major drawback is that, PIR sensors is that it can provide the presence of human beings at a specific area, but not the typical activities they are doing. This implies that PIR sensor alone cannot detect a fall.

2.2.2.3 Pressure Sensors

Pressure sensors are applied to detect the presence of residents on chairs or on the bed. They can be used to detect the transfer of movement from sit-to-stand and stand-to-sit. Three articles are reported in this work that applied pressure sensors in smart homes [11]. Given

that all three articles focused on detecting transitions from sit-to-stand and from stand-to-sit, determining the transfer duration was the main outcome and again this sensor alone is not capable enough to detect a fall. This is one of the measures to analyse the quality of the life of an individual during the rehabilitation phase. A typical pressure sensor is given in Fig. 2.7.

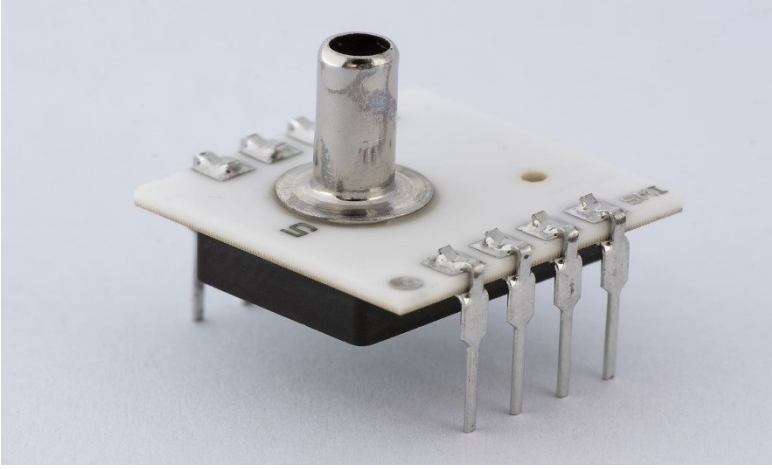


Fig.2.7. A typical pressure Sensor

2.2.2.4 Sound Sensors

Sound sensors such as microphones are utilized to detect different events such as daily activities of an elderly person. This type of sensors gives an opportunity for the caregiver or the health care assistant to listen to the generated sound and determine what kind of activity has happened. E.g. the sound generated while washing the dishes will be different while a fall occurred [29-34]. On the other side, if the elderly person is suffering of a fall, they can always seek for help though the microphone. The message passed on through the microphone would be delivered to the health care assistant or caregiver and appropriate actions can be taken. A most common structure of a microphone-based sound sensor is as shown in Fig. 2.8.

Fig.2.8. Sound Sensor

2.2.2.5 Floor Sensors

Sensing of floors plays an important role in the development of sensing environments with maintaining high levels of privacy. The sensing layer can be made invisible to the user since this can be laid under the normal floor carpet or insulation area which makes the floor area appears to be normal. These are relatively easy to implement and can be installed in various practical areas which includes private houses as well as public environments such as an auditorium. For instance, smart buildings can use floor sensors to detect the presence of people to automatically control the switches of the lighting and heating systems. In smart eldercare systems, floor sensors can be used to detect emergency situations such as falls [35]. One of the practical demonstrations of detecting a fall using floor sensor is shown in Fig. 2.9.

This has been an initiative from one of the German start-up company where they came up with a high-level monitoring system for elderly people using floor-based sensors. A conductive covering of sensors is installed in the floor which consistently detects the movements of the elderly and measures the area of the activity. If the activity is walking, the area will be much lower than if the activity is a fall and hence a fall can be easily identified. The whole floor will effectively become a touch sensor. This is demonstrated below. Continuing the opportunity, researchers had showed their interest in this area and some of the research outcomes are articulated here.

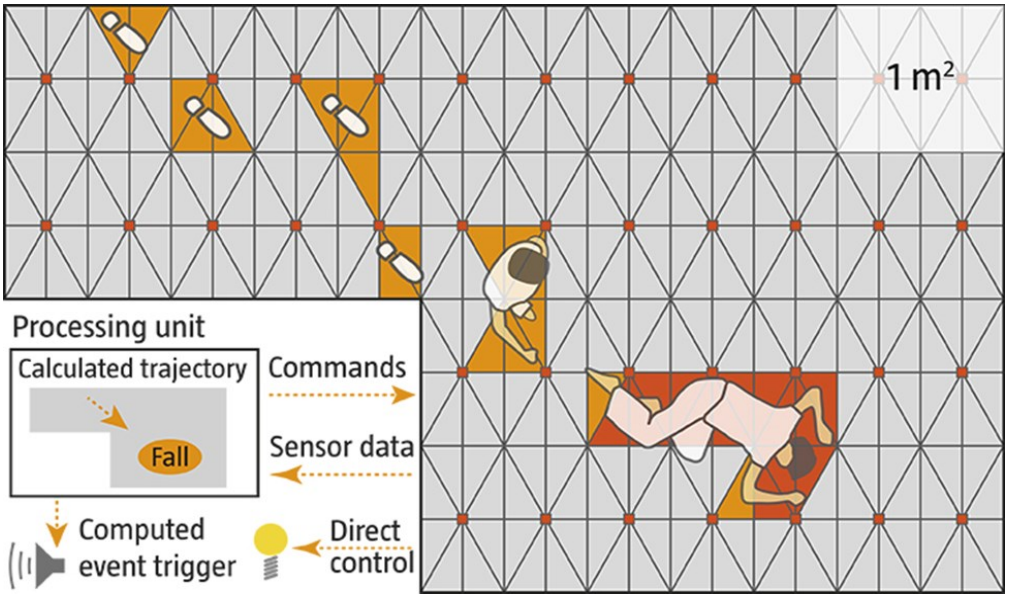


Fig.2.9. Pressure- sensitive floor and fall detection [36]

Ludovic Minvielle et.al [37] developed a fall detection monitoring system based on a sensitive floor sensor made of a piezoelectric material and a machine learning approach. Combination between a supervised Random Forest and an aggregation of its output over time is used to detect a fall. Even though the experimental results are better and promising, further improvements are required such as bringing more temporal information to increase the accuracy of a fall detection. Thus, to pursue this work, the researchers considered a general analysis to aim a systematic approach to resolve the trade-off between variable computation complexity and the most discriminant and less redundant features that has been considered to detect a fall. A classical floor sensor-based system installation is as shown in Fig. 2.10. Enter a floor are with floor sensors can be difficult for practical application like old age centres.

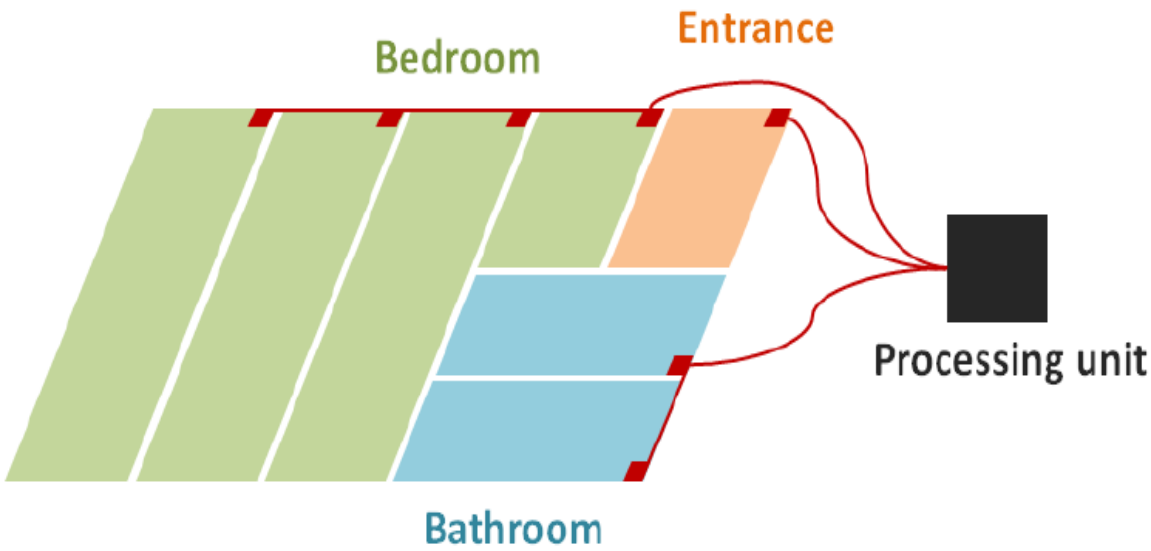


Fig.2.10. Classical system installation [37]

2.2.2.6 Video Sensors

The most popular commonly used ambient sensors for eldercare are video sensors. There has been an extensive number of research works carried out in ambient assistive technology using video cameras. This technique has been used in various applications, such as locating residents and recognizing their activities at their homes. The video sensors are installed on the walls or ceilings to detect the activities of the elderly. A sequence of operations is done to detect the activity which includes background subtraction, body shape extraction, feature analysis, and machine learning. Among many applications, video monitoring technology has mostly been used to detect activities of daily living and falls [38-41].

2.2.2.7 Combined Ambient Sensors

Every sensor is capable to perform certain tasks. However, from an overall system point of view, the combination of more than one sensor will improve the performance and accuracy of what the system is capable to do. As an example, it can be a combination of an accelerometers with video cameras and PIR sensors. Combinations of the multiple types of sensor technologies were very frequent and diverse in nature. The most popular combination was PIR motion sensors and video cameras. The next most frequent was a combination of pressure and PIR sensors. The combination of different types of ambient sensors, undoubtfully improves the quality of life within different target groups, such as residents and caregivers [42]

2.2.3 Computer Vision-Based Methods

In this era, cameras are increasingly included in the home assistive and care systems as they possess multiple advantages over the other sensor-based systems. On the positive side, cameras can capture and used to detect multiple events simultaneously with minimal or no disruptions [43].

In vision-based systems, cameras are the most important peripheral. The vision-based approaches are practical on a real time scenario by the execution of a real-time algorithm using standard computing platforms such as a desktop or a laptop computer and low-cost cameras. There are various methods in place to obtain the semantic information through the video analysis. Most of them use a 2D or 3D model of the captured images, while others are based on the extraction of some features after the video image is segmented.

A detailed explanation of these approaches could be found in where they are classified into the following categories: body and shape change, posture detection, inactivity, spatiotemporal and 3D head change. Two types of cameras are mainly used in fall detection such as 2D cameras (like the one used in this paper or in [44], and 3D cameras or time of flight (ToF) cameras which are used in the reference papers [8, 45]. The lateral resolution of a time-of-flight (ToF) cameras is generally low compared to a standard 2D video cameras and they are much more expensive [46].

Vision based system unlike other sensor-based methods do not perform any analysis or monitoring of the parameters of the subject. However, they rely applying the image processing techniques on the video frames of images captured by the video-sensors around the region of interest [11].

Vision based systems deals with intrusion in a better way, compared to other approaches. Recent research and advancements in computer vision on surveillance indeed provides a practical and complex framework. Most of the emphasis in the context of surveillance in computer vision is dedicated to methods with the ability of real time execution using standard computing platforms such as desktop or laptop computers and image processing tools along with low-cost cameras. These methods, with the promising capability of dealing with robustness, still leave a wide-open area for further research and development. The human behaviour analysis from the captured video has the high-level abstractions such as semantic description of the activities and the low-level abstractions such as the segmentation of the motion along with feature extraction.

The 3D techniques are not completely automated and usually requires manual attention and interventions. Current posture related methods are classified depending on the use of a model. Generally, a model dependent method obtains the postures relatively easily and are robust to occlusion to an extent after labelling the body parts. Most of the body modelling techniques are 2D models. Features are used to compute the postures in other non-model-based techniques. The models are learned through extended observation such as the interpretation of human activities in a specific scene, provides contextual representation of the activities carried out. These models provide recognition and summary of the possible events and activities. Several techniques have been developed to learn how these models can be automated so that the limitations of manual interventions can be reduced. The range involved in dealing with the complexity and abstraction of comprehensive activity and event analysis determine to what extend fall detection can be automated with these models. However, interpreting human behaviours and the further pattern analysis depends on the choice of level of abstraction [43]. A general framework of the existing wearable sensor and ambient based approaches are show in the Fig. 2.11. In this model, the data is acquired through the sensors which are then passed through the initial pre-processing unit to filter out unnecessary noises and other disturbances. The relevant data in then processed using the data processing unit into an appropriate format and the processed data is then compared with the existing machine learning technique or similar methods to detect the activity to identify the fall. Once the fall is detected, the information will be transferred to the control room and from there to the caregivers or to the health care professionals.

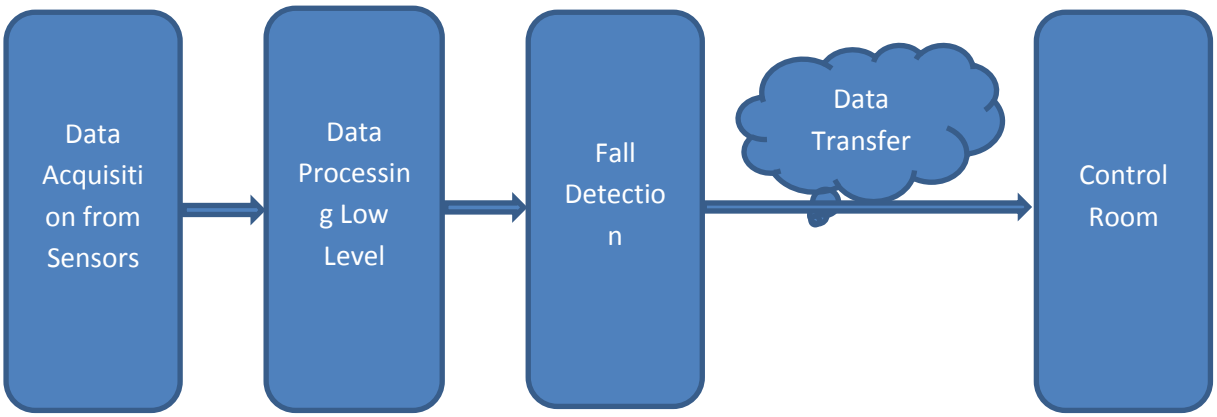


Fig.2.11. Framework for existing wearable sensor and ambience-based approaches [43].

The general framework for an existing vision-based approach is shown in the Fig. 2.12. Unlike the wearable sensor-based technique, here an image sensor or a video sensor is used to capture the images and these images are transferred into a data processing unit. This data processing unit may be located at the client apartment or at a remote location. The received images or video frames are then pre-processed to avoid the distortions. Once the image or video is ready to be analysed, this is passed on to the fall detection and analysis unit which will identify and detect the fall. The information is then passed on to the control room for high level processing. If there is any suspicious activities identified, then the control room operator will pass the message to the caregivers or to the health care professionals to take attend the elderly in less time.

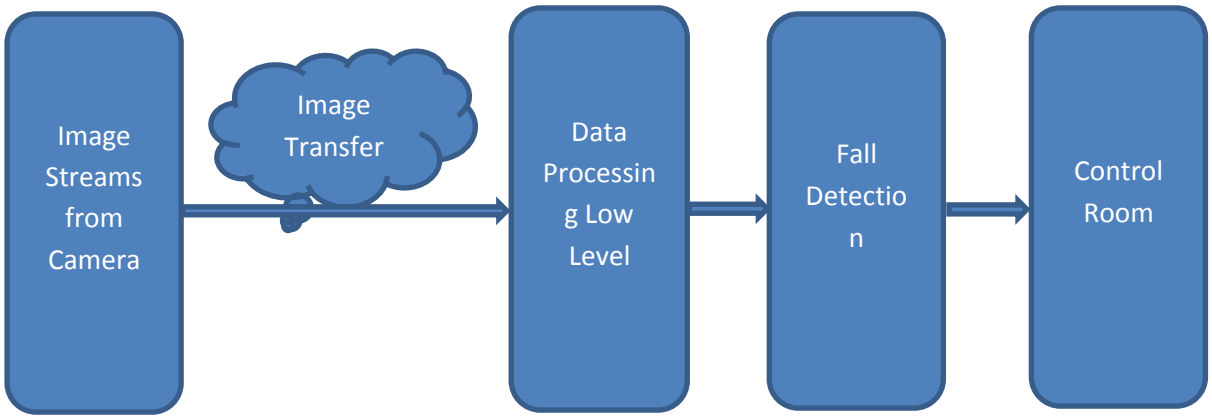


Fig.2.12. Framework for existing vision-based approaches [43].

Some of the existing vision-based fall detection system is analyzed and compared in the following section.

Kishanprasad Gunale et.al [47] has implemented a fall detection system using four extracted visual features like aspect ratio, orientation angle, Motion History Image (MHI) and threshold. The extracted feature set are then fed into the five different classification techniques like SVM (support vector machine), KNN (K-Nearest Neighbors), SGD (Stochastic Gradient Descent), GB (Gradient Boosting) and DT (Decision Tree) to find the most suitable technique to identify and detect a fall. The experimental results show that, the DT algorithm gives better F-measure value with minimum computational time and complexities. Most of the existing fall detection methods are dependent on posture extraction and classification [48-49]. However, in such cases, falls and non-fall activities can only be detected in some specific environments by the methods of pattern classification. All the postures associated with a fall related activity cannot be included in the system and trained, irrespective of the amount of training data used which is classified as one of the major disadvantages of this method.

Tao Xu et al [50] and Naswa El-Bendary [51] has conducted a survey on the new advancements and challenges of fall detection approaches and summarized and compared various approaches. However, their focus was on the sensor-based approaches which is not within the scope of this research work. Koldo de Miguel et al [46] demonstrated a method to detect fall among elderly people. They combined several algorithms such as background subtraction, Kalman filtering and optical flow and tested with 50 different videos captured from two different locations. Even though the accuracy of fall detection is more than 96%, the walking aids used by the elderly interpose between the sensor and the elderly person which confuses the algorithm by changing the shape of the perceived shape and size of the fallen person is one of the major limitations within this research work.

Lei Yang [52] proposed a method based on Spatio-Temporal Context Tracking of the head by using (3D) Depth Images that are captured by the Kinect sensors. The head position is tracked by applying dense spatio-temporal context (STC) algorithm. Distance from the head to floor plane is calculated and compared with the adaptive threshold method. The centroid height of the human body will be then used as the second judgement criteria to decide whether a fall incident has happened or not. The computational complexity associated with

this system is low. However, the major limitation is associated with the tracking scale since scales are highly variable during the tracking process.

Yoosuf Nizam et.al presented a novel method for human fall detection using position and velocity of the subject from a depth image [53]. In this method, the object and floor plane are extracted and tracked on a frame by frame basis. The tracked joints of the subject are then used to measure the velocity with respect to the previous location. The fall is confirmed, when the joint positions of the object are on the floor after an abnormal velocity. The center of the subject's head at any given time is the head position and the change of head position between frames are computed as the velocity as well. Fall is detected from multiple frames and hence any non-detected joints within a frame will not reduce the accuracy. The fall of a person is identified and detected accurately within the view of the sensors. Even though the accuracy is high, one of the major limitations is that the system lacked in classifying activities that possess similar patterns such as fall while standing and lying down on floor from standing.

Zhen-Peng et.al [54] demonstrated a fall detection method based on tracking the body part using a depth camera. In this research, the tracked key joints of human body is analyzed using a single depth camera. This method is independent of light illuminations which means the algorithm can work even in a dark condition which is the major advantage. For key joint extraction, a pose-invariant randomized decision tree algorithm is used. A support vector machine (SVM) is employed to determine whether a fall motion occurs, whose input is the 3D trajectory of the head joint. Multiple depth cameras incorporated to the proposed approach can resolve the occlusion related limitations. However, the proposed approach cannot detect the fall ending lying on a furniture. Hoang Le Uyen et al [55] proposed a video-based method to detect human falls. There are three major steps in this algorithm. Videos are captured by using a camera and human presence is detected using adaptive background Gaussian Mixture Mode. This is then converted into a five-dimensional feature vectors using ellipse model. To analyze the features, Hidden Markov Model is trained with challenging stimulated fall/non-fall database set. Once a fall is detected, an SMS alert is sent to the assigned phone number. However, the major limitation lies within the quality and quantity of the training required to detect all possible kind of falls. Since, all the postures associated with the fall activities cannot be included and trained, irrespective of the amount of training data used, this method opens a wide range of areas for improvement.

Ya-Wen Hsu [44] proposed a vision based pedestrian fall detection system with back propagation Neural Network. The camera sensor system provides the initial images and these images are first used to build up a model of the background using Gaussian mixture model (GMM). A current image captured is the subtracted from the previously generated background image to generate a very high-quality foreground image. Morphological closing including erosion and dilation are used to repair the foreground images and connected component labelling is applied then, to eliminate any possible noise from the images. From the extracted foreground object, the aspect ratio of the bounding box, the orientation of the ellipse, and the vertical velocity of the center point are extracted to use as input features in a learning algorithm. Fall detection is based on the classification results of learning algorithm using a back propagation neural network. Maximum efficiency is achieved when all the three feature sets are used together.

G. Diraco proposed a method [8] of active vision system to detect the falls automatically and the recognition of several postures for elderly homecare applications. The calibration procedure searches for different planes in the scene to select the most appropriate one that accomplishes the floor plane constraints. Subsequently, by applying Bayesian segmentation to the whole 3D points cloud, the moving regions are detected in real-time. The previously defined calibration parameters are evaluated to find the distance of the 3D human centroid from the floor plane and this trend is used as a feature in the thresholding-based clustering to detect a fall. The posture recognition is achieved by using both the 3D human centroid distance from the floor plane and the orientation of the body spine, estimated by applying a topological approach to the range images. However, this work is based on the 3D range images which increases the complexity and cost of the outcome**.**

Michal Kepski [45] proposed a method for fall detection using a ceiling-mounted 3D depth camera. A K-NN classifier is used to separate the lying pose from the normal daily activities which was trained on features such as head floor distance, person area and shape's major length to width. And motion between static postures are included to distinguish between intentional lying postures and accidental falls. However, this paper used depth images which is again requires complex hardware requirements including the high cost.

Miao Yu et.al presented a method to detect human fall using convolutional neural network. Background subtraction is used to extract the outline of the human body from the captured images. This is repeated for a set of daily activities and this data is applied to construct a convolutional neural network, which is applied for classification of different classes of human

postures such as bend, stand, lie, sit etc. [56] CNN outperforms the SVM based methods for the majority of individual cases with higher classification accuracies. Adrian Nunez et.al also proposed a method based on vision-based approach to detect the fall of a human being with convolutional neural network [39]. The optical flow images are set as the input to the network followed by a novel three-step training phase. The main objective of this algorithm is to distinguish objects in a fall state. To achieve this goal, the algorithm extracts data from the object from a scene to recognize his/her current state. Data acquisition requires multiple preliminary steps: subtracting the subject from the background, progressively learning the subject's changing environment and identifying uninteresting objects (to facilitate their rapid recognition as background), following the subject through the scene and identifying subjects that are partially occluded by furniture. A Kalman filter is used to reduce the noisy and the repetitive periodic changes are absorbed which are common to various human actions. Finally, the data is passed through a machine learning system determine the current state of the object under observation. The third training step is limited to fine-tuning and further research on transfer learning with fall detection datasets is warranted in order to improve the generic feature extractor. Optical flow images provide a great representational power for motion but involves with the heavy computational complexity of preprocessing consecutive frames. However, the major drawback is concerning lighting changes. To compensate this limitation, appropriate training is required which will be a major overhead.

Jeffin Gracewell et.al [57] presented a fall detection based on posture classification for smart home environment. A model is generated using the training dataset that consists the samples of both fall and normal activities. A key frame is then extracted from the input video sequence that is then subjected to two stream classification. The classification results are approved if both the steams project the same results. If it fails, then additional information is used to classify the fall from the normal activity. The key frame selection depends on the displacement in the centroid of the detected object and a threshold greater than the predefined value. However, this process is complex due to the requirement of the large dataset required for training and complex hardware requirements such as cameras with multiple views. One of the major advantages of the system is that the accurate results are achieved without any foreground techniques.

Komal Singh et.al [5] reviewed various works related to fall detection based on machine learning methods. This paper explained the new advanced technologies in the healthcare sector. This paper summarizes various human fall detection methods and techniques observing people's daily routine activities. Three different technologies are reviewed in this paper such as (i) wearable based device (ii) context-aware fall detection systems and (iii) vision-based systems. The basic principle of each of the methods along with the algorithms and performance statistics are compared in this paper. Further, this paper focuses to the use of machine learning algorithms for the development of intelligent automatic human fall detection system.

2.2.4 Multimodal-Based Methods

The multi-modal based fall detection systems integrate more than one sensor to detect the fall. Most of these methods illustrate a sensor fusion method. A more general architecture of a multi-modal based fall detection system is as shown in Fig. 2.13. In this example, we are showing a model implemented in the reference [58].

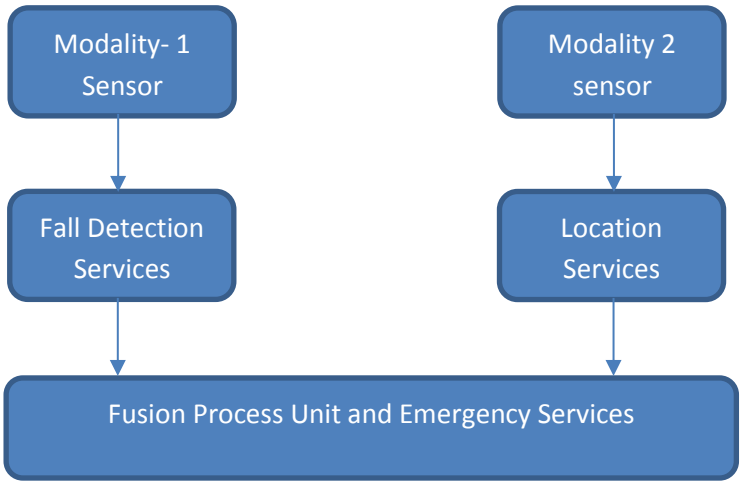


Fig.2.13. General framework for multi-modal fall detection

However, this area is not within the scope of this research work and hence we are not including this technique in the comparison table below.

A brief comparison of some of the different categories of fall detection approaches are tabulated in the table 2.1 which is given below.

Table 2.1. Brief comparison of different categories of fall detection approaches

Approach	Category	Cost	Intrusion	Accuracy	Setup	Robust
Wearable Devices	Tri-axial	Cheap	Yes	Scenario dependent	Easy	No
	Posture	Cheap	Yes	Scenario dependent	Easy	No
	Inactivity	Cheap	Yes	Scenario dependent	Easy	No
Ambient Sensors	Audio	Cheap to Medium	Yes	Scenario dependent	Easy/ medium	No
	Video	Cheap to Medium	Yes	Scenario dependent	Easy/ medium	No
Vision Based Sensors	Body Shape Change	Medium	Low/dependent	Higher/non specific	Medium	Yes
	Posture	Medium	Low/dependent	Higher/non specific	Medium	Yes
	Inactivity	Medium	Low/dependent	Higher/non specific	Medium	Yes
	Spatiotemporal	Medium	Low/dependent	Higher/non specific	Medium	Yes
	3D head change	Medium	Low/dependent	Higher/non specific	Medium	Yes

A thorough and extensive review and comparison on various fall detection systems using different techniques has been conducted in this section and the various characteristics and performance measures are tabulated in the above table. Vision based approaches in comparison to other methods are certainly the area to look forward to investing in terms of research and funds to develop an efficient fall detection system for elderly. Most of the existing vision-based approaches lack the flexibility. The existing approaches are often case specific and dependent on various scenarios. A comprehensive and robust fall detection system should possess both high sensitivity and good specificity. The above approaches have not comprehensively satisfied the level of accuracy as well as the robustness of a fall detection system. There is a big time need to develop a much reliable and robust generic fall

detection system. The existing approaches provides a basic framework to further analyse and develop techniques as well as to modify the existing algorithms to achieve better performance.

Some of the applications of a fall detection system includes:

1. Monitoring of health and wellness

   As the world population is aging and health care costs are increasing, several countries are promoting "aging in place" programs. This kind of programs allow older community with chronic disorders to remain in the home environment while they are remotely monitored for safety and for the purpose of facilitating the implementation of clinical interventions. Monitoring activities for elderly group with chronic conditions has been considered as a matter of high-level importance. We could able to classify the daily activities of the elderly people with the support of such monitoring systems.
2. Monitoring the safety of elderly

   The safety monitoring applications includes detecting falls and automatically sending alarm messages to a caregiver or an emergency health response team. If the system detects a sudden impact such as a fall, a mobile phone that is equipped with balance sensors which trigger automatic dialing SOS numbers can pass the message to the medical care team. Individuals with movement impairments require more specific approaches to detect or prevent the occurrence of a fall. Safety monitoring applications typically require detection of emergency events. The sensing technology used for such applications must be extremely robust and reliable.
3. Rehabilitation activities

   The implementation of rehabilitation programs often includes the combination of sensing technology and providing an interactive program or creating a virtual reality environment. A wireless inertial sensor system may be used to records the patient's movements. This is then analyzed for any deviations from the personal movement target and provides feedback to the patient and the therapist.
4. Assessment of the treatment efficacy

   A quantitative way of assessing treatment efficiency can be a valuable tool for clinicians in disease management. As an example, the use of a sensor-based system to monitor Parkinson's disease (PD) is a promising approach to improve the clinical management of patients in the late stages of the disease. The ability to automatically

estimate the severity of symptoms via processing sensor data recorded during activities of daily life is important for health monitoring.

5. Early detection of disorders.

   An area of growing interest in the field of sensor technology is the use of various sensors and systems to achieve early detection of changes in patient's status requiring clinical intervention. An example of this type of application of sensor technology is the management of patients with chronic obstructive pulmonary disease. Early detection and treatment of exacerbations are critical to prevent worsening of clinical status and the need for emergency services or admission in the hospitals. One approach to the problem of to detect exacerbation episodes at early stages is to identify and monitor the changes in the level of activity performed by a patient. A decrease in activity level would be an indicative of the likelihood of a worsening of the clinical status of the individual undergoing monitoring.

In this chapter, we have reviewed and compared different categories of fall detection systems in detail. We concluded that, vision-based system is more efficient and convenient for automatic fall detection. Most of the vision-based researches based on CNN. However, a large training dataset is required to efficiently detect a fall, and this increases the computational cost. But in a real-time scenario, the posture, shapes etc of falling are different. To increase the fall detection rate, more and more training data is required. The proposed method in our research is simple and we do not use any training dataset and hence easy to implement for real time application. The proposed architecture is less expensive compared to the models which required more training of huge data. The proposed architecture is explained in the next chapter.

CHAPTER 3

PROPOSED ARCHITECTURE

Fall is one of the biggest risks among the elderly population resulting in serious injuries, if not treated within less time after the fall happened. Fall detection plays an important role in the health care of the elderly people. The detection algorithm and the sensors used in a fall detection system can affect the accuracy of the overall performance and efficiency of the architecture [59]. We have concluded from the previous section that a heavy wearable sensor may causes inconvenience to the subject and these may not be a popular solution. Most elderly people are reluctant to wear the wearable devices due to the inconvenience and in such cases, vision based fall detection system places an important role and we believe that the future health care and assistance systems are controlled by vision based techniques where the cameras provide very rich information compared with other physical devices. So, computer vision-based fall detection technique is adopted to support elderly people.
Fall detection technologies enable rapid detection and intervention for individuals who have experienced a fall. This technique could potentially reduce the physical and mental damage caused not only by the fall but the delay in time after a fall before discovery. These technologies will help to reassure a normal life for those at a risk of falling as well as their caregivers and family [60]. The primary aim of this research work is to propose an accurate fall detection system and to analyse their level of success in real time applications.

In order to improve the quality of medical care, more efficient health care systems are developing intensely [16]. Existing studies in the literature have proposed a list of methods that require additional devices or large training mechanism to determine whether a fall has happened or not. The amount of data available to the researcher to do research on automatic fall detection to enable fast and proper assistance to the elderly people is immense. The number of elderly people living alone can result in increased healthcare costs which can Fall is a sudden and fast movement compared to other normal human activities. This is considered as an important factor throughout this research work.

The objective of our research is to develop a robust, cost effective and reliable algorithm to detect human fall from a video in a different environment without using depth images. The primary vital step of the fall detection system is to detect the presence of a human object from the frame captured by the sensor in the most accurate way. The proposed architecture uses

background subtraction to detect the presence of human objects. The system obtains the human object from the video frame using the background subtraction method. This is followed by a foreground segmentation and the elimination of any noise present in the output using noise elimination technique such as morphological operations. Morphological transformations on images can be used to remove speckle noise, isolate individual elements, and find intensity bumps or holes in an image. This results in a detected human object with no background noise. Once the presence of a human being is detected, the detected object of interest (human) is continuously analyzed with respect to the reference point using a bounding box around the object. The reference point within the scope of this research is defined as the ground point. The ground point is estimated using texture segmentation with a Gabor filter. The Gabor filter related segmentation paradigm is based on filter bank model where the input image is applied simultaneously to multiple filters. Each filter is focused on different range of frequencies. If an input image has two different texture areas, the local frequency differences between the areas will detect the textures in one or more filter sub-images. Gabor filters are extensively used for texture segmentation because of their excellent temporal and spatial-frequency localization. Simultaneously, the centroid of the object is detected and tracked using a Kalman Filter. The system then calculates the angle between the tracked point and the point from the ground plane which is the reference point. This angle of the object with respect to the ground point, estimates the rate of change of angle with respect to the centroid. The rate of change of angle also shows, how fast the centroid is moving with respect to the ground plane. The calculation of the rate of change of angle is performed over time consistently to confirm the fall.

The rate of change of value will have a lower value when the person is engaged in normal activities like lying down on the floor or sitting etc., compared to a sudden action like fall. When the system detects a sudden change in the rate of change of angle, this determines a fall. The system will consistently monitor the actions of the human object to confirm a fall. This system will them be able to trigger a mechanism to send an automated message to the care assistant or to the nearest health center or the ambulance provider to provide immediate medical care and attention to the person under the crisis. The block diagram of the proposed architecture is shown in Fig. 3.1 and a detailed flow chart is given in Fig. 3.2. The overall architecture is explained in detail in the following subsections. The outcome of this research will improve the support to older persons in modern societies.

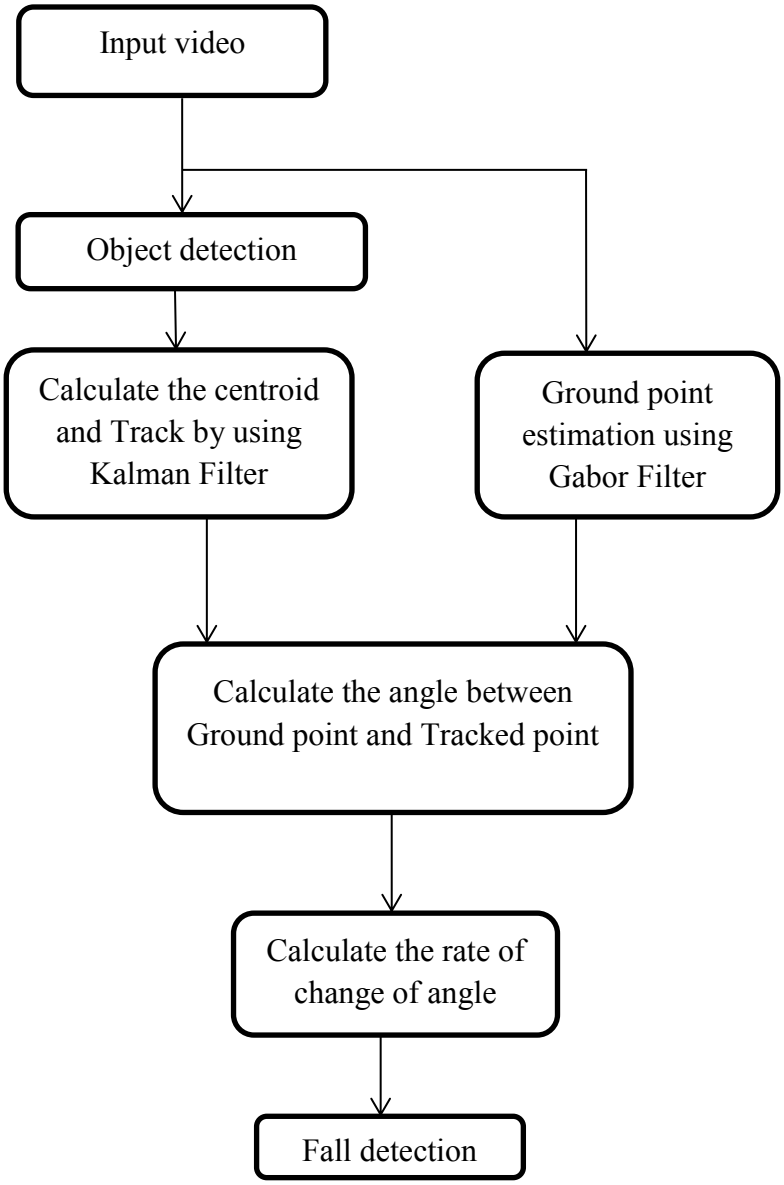


Fig.3.1. Architecture of the proposed fall detection system.

3.1 Input Video

Cameras plays an integral part in the vision-based fall detection systems. The vision-based approaches are mainly focused on the real-time execution of the algorithm using standard computing platforms using low cost cameras. The fall detection starts by collecting the data from camera-based sensors. The collected video or images are then processed further, and these processed images or video are the key for further image processing technique to detect a fall. One of the main highlights of our work is that depth images are not utilized to detect a fall. In this research, we are primarily using two publicly available dataset to detect the falls.

To test the efficiency and performance in real time scenarios, we have created our own data set under laboratory conditions and used this as an input to the proposed architecture.

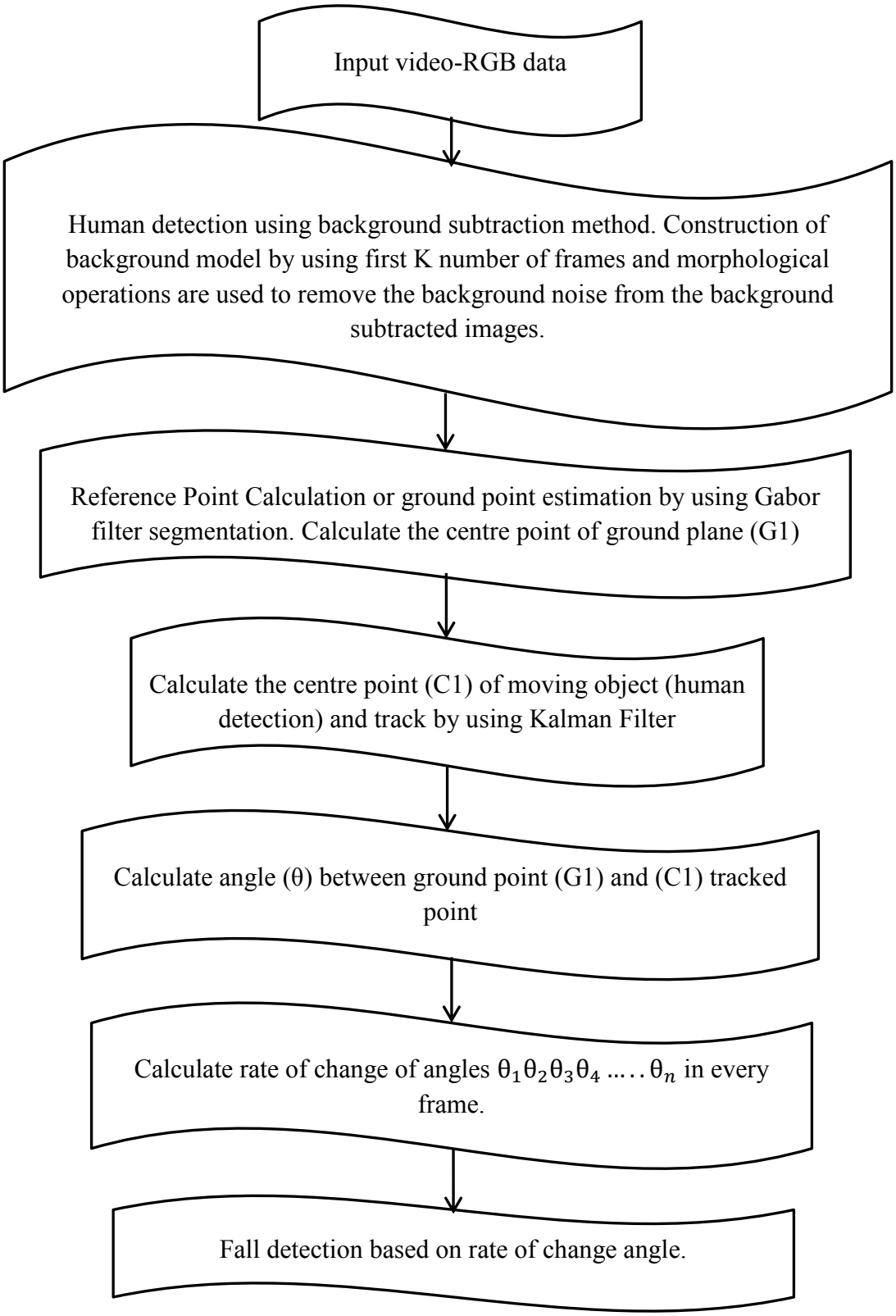


Fig.3.2. The flow chart of the proposed system.

Step 1: Input video-RGB data

Step 2: Human detection using background subtraction method. Background model by using K=5 consecutive frames and morphological operations are used to remove the background noise from the background subtracted images.

Step 3: Reference Point Calculation or ground point estimation using Gabor filter segmentation. Calculate the centre point of ground plane (G1).

Step 4: Calculate the centre (C1) of moving object (human detection) and track by using Kalman Filter.

Step 5: Calculate angle (θ) between ground point (G1) and (C1) tracked point.
$\theta = \theta_1\theta_2\theta_3\theta_4 \ldots\ldots \theta_n$ ['n' no: frames]

Step 6: Calculate rate of change of angles in every frame.

$$\theta_1\theta_2\theta_3\theta_4 \ldots\ldots \theta_n$$

Step 7: The last step is to detect the fall based on rate of change of angle.

3.2 Human Detection

Detecting a person from the video is the fundamental step of the fall detection system. We consider indoor videos to test our fall detection algorithm. So, background subtraction is the better option to detect the moving person from a video. The most popular approach from the literature review to detect moving object from the video sequences is to subtract the background. This approach utilized mathematical model to extract the static background and compare this with every single frame of new video sequence. The foreground objects in the sequence of video frames are separated from the background objects using background subtraction [61].

Background subtraction is one of the most popular and fastest methods to detect moving objects from a continuous sequence of video frames. This evaluates the current frame by either subtracting it from a reference frame or fitting it to a background model. Hossein Soleimani et.al reviewed different multiple state-of-the-art background subtraction algorithms and their principle of background modelling [62].

The main purpose of background subtraction is to generate a reliable background model to detect moving objects efficiently. Construction of the background model is the integral part of the background subtraction method. To calculate this, we are using the information of the first K number of frames and in this algorithm, we are using the value of k as 5. Various properties of a pixel such as the intensity, texture and the nearby pixel features are used to

generate the model. To detect the foreground, the information of the current frame in each location and the pixels or the region is compared to the generated background model to each of the corresponding location. If the current properties of the frame are significantly different from the model, i.e., the current pixel or region does not fit the model, then the location or region is classified as foreground and the rest is considered as background.

Background subtraction is the process of separating the foreground objects from the background from within a sequence of video frame as shown in Fig.3.2. The difference between the current frame and a reference frame or the background image is the fundamental logic used to detect moving objects. Fig.3.3 shows the general block diagram of the background subtraction algorithm. This is a widely used in traffic monitoring (counting vehicles, detecting & tracking vehicles), human action recognition (run, walk, jump), human-computer interaction (human interface), object tracking and many other computer vision applications such as digital forensics.

Fig.3.3. Image and background image

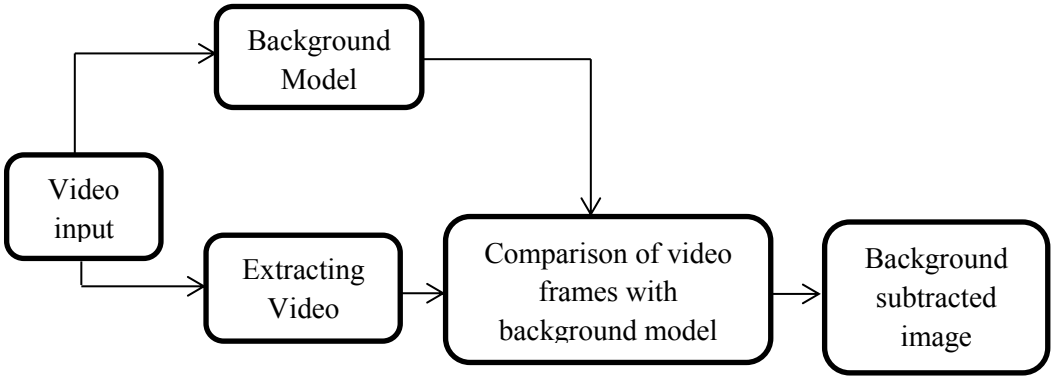
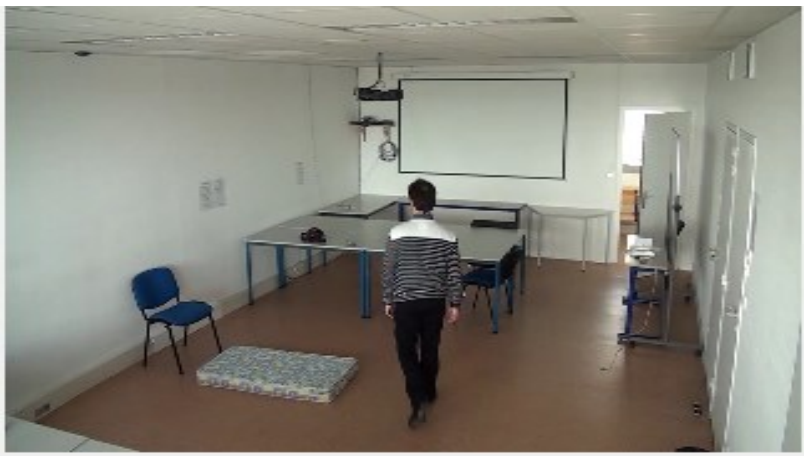


Fig.3.4. Block diagram representation of background subtraction

A practical application of the object detection using background subtraction method is shown in Fig. 3.4. A background image is estimated and is subtracted from the Fig.3.4.a to obtain the detected object as shown in Fig.3.4.b.



(a)

(b)

Fig.3.5. Background subtraction (a) input image (b) object detection

3.3 Morphological Operations

Morphological operations are used to remove the background noise from the background subtracted images. These background noises may trigger the false detection of the foreground object. As an example, the sudden changes of illumination may result on several moving objects detected from the frame. The morphological operations and filtering are the recommended methods to fill holes. Morphological transformations on images can be used to remove speckle noise, isolate individual elements, and find intensity bumps or holes in an image.

The two morphological operations used in post processing of background subtraction are dilation and erosion. Dilatation is described as the convolution of an image A with a kernel B. Basic effect of the kernel on the image is to gradually enlarge the boundaries of bright regions. Erosion which applies the converse processing to the foreground mask, causes darkness in the foreground mask. Fig.3.5 demonstrated the logic of using erosion and dilation. Based on the two previous morphological operations, Opening consists of applying erosion followed by dilatation on the image and closing consists of applying erosion followed by dilatation on the image. Erosion eliminates the isolated specks of noise. In simple words, erosion removes a layer of pixels from every blob in the scene and dilation adds a layer of pixels to every blob in the scene.

In some cases, the object may be fragmented into pieces, since some pixels were insufficiently different from the background. In this case, two passes of dilatation are applied to image and this fills in the cracks between the pieces, thereby creating a single, contiguous blob.

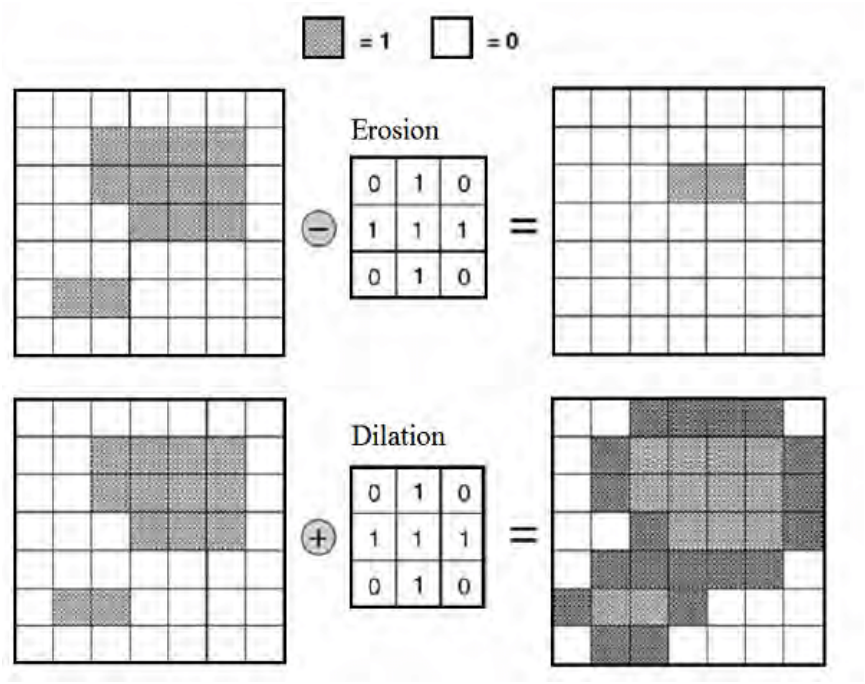


Fig.3.6. Demonstration of dilation and erosion in a matrix

3.4 Texture Segmentation using Gabor Filter

The goal of segmentation is to change or modify the representation of the given image into something that is more meaningful and easier to analyze. The given image can be divided or partitioned into various parts called segments. Once by dividing the image into segments; we can focus and use the important segments to process the image. An image is basically a collection or set of different pixels. The pixels that has same or similar attributes are grouped together using image segmentation process. A simple process of texture segmentation process is shown in Fig.3.6. A set of filter banks are tuned to different spatial-frequencies and orientations to cover the spatial frequency range. The image is then decomposed into several filtered images and the features are then extracted from them. The segmented image is generated by using the clustering of the pixels in the feature space.

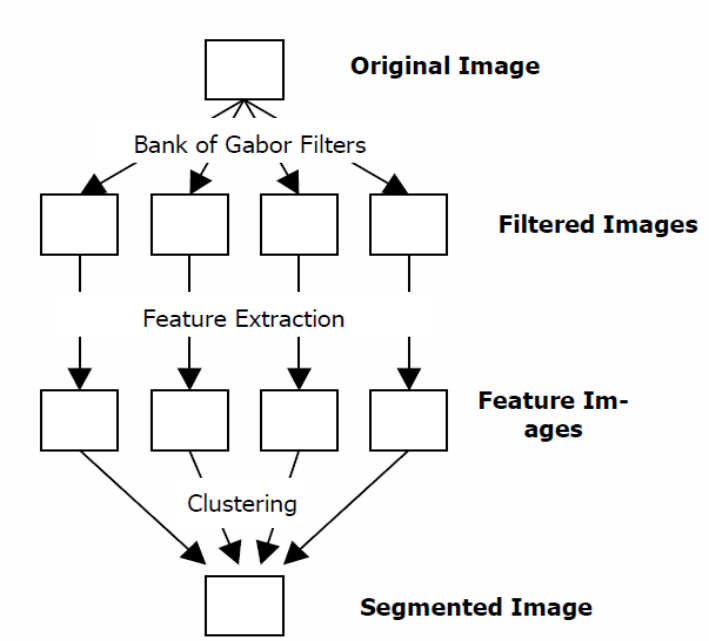


Fig.3.7. Texture segmentation process

In order to detect the ground plane from a video, we are using Gabor filter-based texture segmentation [63]. Gabor Filters are band-pass filters which are used for feature extraction, and texture analysis.

The input image is first passed through a Gabor pre-filter with impulse response $h(x,y)$, where

$$h(x,y) = g(x,y)\exp[-j2\pi(Ux+Vy)], \text{ and}$$

$$g(x,y) = \frac{1}{2\pi\sigma_g^2}\exp\left[-\frac{(x^2+y^2)}{2\sigma_g^2}\right] \quad (1)$$

The Gabor function $h(x,y)$ is a complex sinusoid centered at frequency (U,V) and modulated by a Gaussian envelope $g(x,y)$. The spatial extent of the Gaussian envelope is determined by parameter σ_g, Further the 2D Fourier transform of $h(x,y)$ is

$$H(u,v) = G(u-U, v-V), \quad (2)$$

Where

$$G(u,v) = \exp[-2\pi^2\sigma_g^2(u^2+v^2)] \quad (3)$$

is the Fourier transform of $g(x,y)$. The parameters (U,V,σ_g) determine $h(x,y)$. From equations (2) and (3),we see that Gabor function is essentially a bandpass filter centered around frequency (U,V), with bandwidth determined by σ_g.We assume for simplicity that the Gaussian envelope $g(x,y)$ is a symmetrical function. Other treatments have considered the impact of an asymmetrical Gaussian envelope.

The output of the pre-filter stage $i_h(x,y)$ is the convolution of the input image with the filter response

$$i_h(x,y) = h(x,y) * i(x,y) \tag{4}$$

Where * denotes convolution in two dimensions. The Magnitude of the first-stage output is computed in the second stage as

$$m(x,y) = |i_h(x,y)| = |h(x,y) * i(x,y)| \tag{5}$$

A low-pass Gaussian post-filter $g_p(x,y)$ is applied to pre-filter output $m(x,y)$ yielding the post-filtered image

$$m_p(x,y) = m(x,y) * g_p(x,y) \tag{6}$$

Where

$$g_p(x,y) = \frac{1}{2\pi\sigma_p^2} \exp\left[-\frac{(x^2+y^2)}{2\sigma_p^2}\right] \tag{7}$$

Generally, we will refer to $i_h(x,y)$ as the pre-filtered image, $m(x,y)$as the pre-filter output, and $m_p(x,y)$ as the post-filter output. Consider the input image $i(x,y)$ to be composed of disjoint regions of two dissimilar textures,$t_1(x,y)$ and $t_2(x,y)$.Then the problem is to find the Gabor function $h(x,y)$ that provides the greatest discrimination between the two textures in the filtered image $m_p(x,y)$.

Gabor filters has various properties that make them particularly suitable for texture segmentation. Gabor function is a band-pass filter that can be tuned to a narrow set of frequency ranges anywhere in the frequency domain. Thus, the most important features of a textured image can be reconstructed using the output of the parameterized Gabor channels.

A texture is defined as a pattern that is perceptually homogeneous. Each texture contains a narrow range of frequency and its orientation components. By filtering the image with a set of band pass filters, which are tuned to the most ruling frequency and orientation component of the texture, each texture can be located. The image is thus passed through multiple channels, where each of them are finely tuned filters. The output of these filter are used to determine the regions occupied by the textures.

The magnitude of the output of the channel provides accurate information about the location of the texture. A large magnitude of the channel output implies that, the texture exhibits the frequency and orientation characteristics of the tuned frequency of the Gabor filter associated within the channel. On the other hand, when the texture is not dominated by the characteristics, the magnitude should be negligible small. The region covered by the textures is obtained by comparing the magnitude of the channels.

More subtle transitions in the texture phase can be estimated using the phase of the channel responses. A discontinuity in the texture phase is indicated by abrupt change in the phase of the channel response. Such a discontinuity may appear when the object geometry on which the texture is applied, is irregular. Note that texture phase analysis is significant only within regions identified as belonging to a single texture in the previous analysis step. A large set of Gabor filters process the channel outputs. The resulting information is combined by clustering to perform texture segmentation.

3.5 Kalman Filter

Once the moving objects are detected, the next step is to track them using an appropriate tracking system. For vision-based tracking, the most commonly used method is motion estimators. It uses the position of a detected or tracked target in the previous frames to infer with the most statistically likely position of the target in the next frame. Mainly used estimators are Kalman Filter and particle filter.

In this research, we use point tracking (Kalman Filter). In point tracking, the detected objects in consecutive frames are represented by points. The tracking is performed by evaluating their state in terms of position and motion. Tracking is made possible by associating points across each frame. Association of points in one frame to another is based on the previous object state.

We prefer using Kalman filter in this research due of its prediction properties, noise reduction properties and fast response compared with other moving average filters. The Kalman Filter (KF) was introduced by Rudolph E. Kalman in 1960. Kalman Filter is used in places where there is uncertain information about some dynamic systems. In such cases, we can make an educated guess about what the system is going to do next using Kalman Filter. Even if a messy reality comes along and interferers with the clean motion that was guessed, the Kalman Filter will often deliver a better job by figuring out what happened. Kalman Filters are suitable for such systems which are continuously changing. One of the major advantages is that, they are light on memory (they don’t need to keep any history other than the previous state). Kalman Filters are very fast, which makes them well suited for real time problems and embedded systems. Kalman Filter helps us to obtain more reliable estimates from a sequence of observed measurements. The graphical representation of Kalman filter is shown in Fig.3.7 Kalman filter combine the two sources of information such as the predicted states and noisy

measurements, to produce optimal, unbiased estimates of system states. The filter is optimal in the sense that it minimizes the variance in the estimated states.

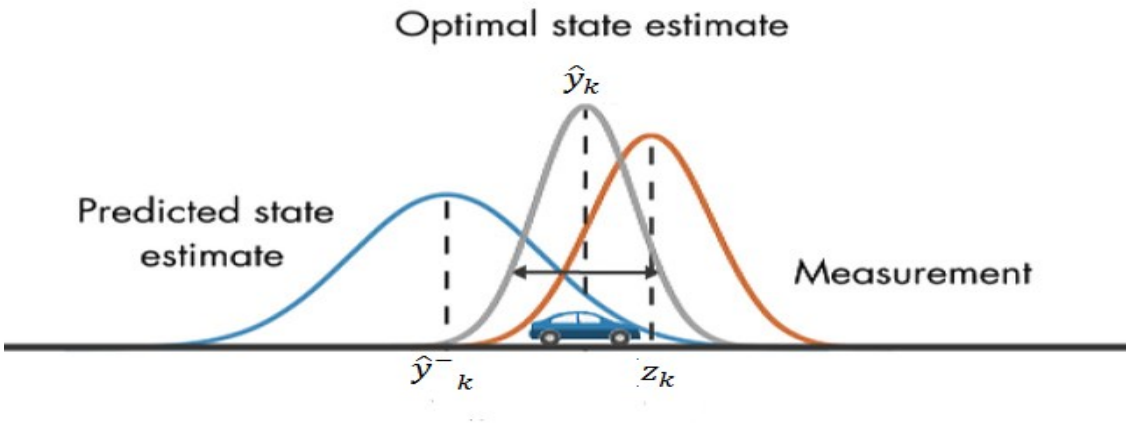


Fig.3.8. Graphical representation of Kalman filter

Kalman Filter (KF) is a state transition model and it is a recursive method and hence that new measurements can be processed as they arrive. It is a method of predicting the future state of a system based on the previous state. If all noise is Gaussian, the Kalman filter minimizes the mean square error of the estimated parameters. The state transition form of Kalman Filter is represented in Fig. 3.8. Kalman Filter has two main stages: First is the prediction step (time updates) and the second is the correction step (measurement updates). This operation form is like feedback control where the filter estimates the state in the prediction step, and then obtains feedback in the correction step based on the results of the measurements.

The prediction step is responsible to predict the states and obtain a priori estimation of the next step based on the projection of the current state. The correction step is responsible to improve the a priori estimation resulting in the prediction step, based on the obtained results of measurements and a posteriori estimation [64].

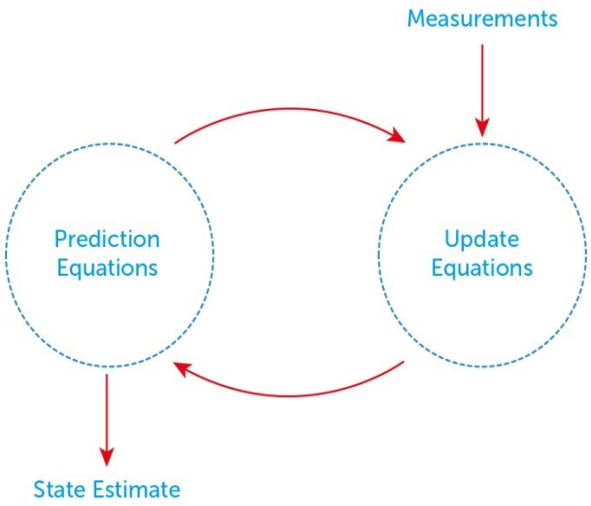


Fig.3.9. Kaman Filter representation

The predicted value and covariance matrix are estimated in the prediction step. The prediction and the correction steps are mathematically demonstrated in the section given below.

3.5.1 Prediction Step

The prediction step is otherwise known as time update step. The process model and the current state is used to predict the future state.

To project the state ahead Eq (8) is used

$$\hat{y}^{-}{}_{k} = Ay_{k-1} + Bu_{k} \qquad \text{and} \tag{8}$$

to project the error covariance ahead Eq (9) is used

$$P^{-}{}_{k} = AP_{k-1}A^{T} + Q \tag{9}$$

Where Q is the process noise covariance matrix, which is used to keep the state covariance matrix from becoming too small or going to zero.

3.5.2 Correction Step

The next step of operation in the Kalman filter is the correction step, otherwise known as the measurement update step. In this stage, the predicted state is corrected based on the difference between the real measured result and the expected measurement result from the measurement model .

In the correction step, the measurement values and used to do the correction. The correction step is estimated using equations Eq (10) ,(11) & (12), where

Kalman Gain is computer using Eq (10)

$$K = P^{-}{}_{k} H^{T} (H P^{-}{}_{k} H^{T} + R)^{-1} \tag{10}$$

Estimates are updated with measurements using Eq (7) and

$$\hat{y}_k = \hat{y}^{-}{}_{k} + K(z_k - H\hat{y}^{-}{}_{k}) \tag{11}$$

The error covariance is updated using Eq (8)

$$P_k = (I - KH)P^{-}{}_{k} \tag{12}$$

Where

- $\hat{y}_k$ and $P^{-}{}_{k}$ are the predicted mean and covariance of the state, respectively, on the time step k before seeing the measurement.
- $\hat{y}_k$ and P_k are the estimated mean and covariance of the state, respectively, on the time step k after the measurement.
- K is the filter gain, which tells how much the predictions should be corrected on the time step k.

An Important parameter of the Kalman filter is the Kalman gain (K) which was highlighted in the above equation. The Kalman gain is decided based on error from previous estimations, which of either the estimate or measurement to be given more weight. Intuitively, if we are making a reasonably good prediction, the Kalman filter gain works in a way to cancel out the effect of any new measurements. However, if the estimate is bad, then it gives weight to new measurements to make new subsequent predictions. The general flow and overview of the Kalman Filter is shown in the Fig 3.9.

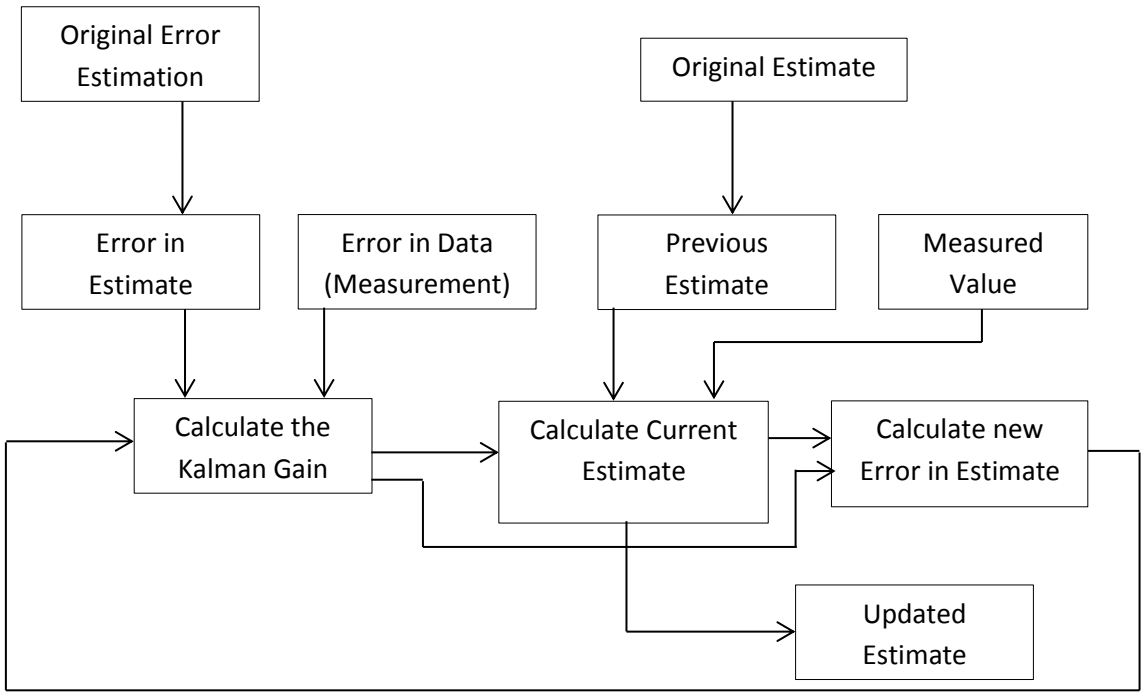


Fig.3.10. Flow chart of a Kalman Filter

One of the main applications of Kalman Filter is in object tracking [65] (e.g. missiles, vehicles, faces, heads, hands etc.).

In object tracking, the Kalman filter predicts the next position of the object from the information about the previous state of the object. This then verifies the prediction results using the result of the object detection process in the following steps .

After each time period and the measurement update pair, this process is repeated with the previous estimates which then project or predict the new priori estimates. This recursive nature is one of the most appealing features of the Kalman filter. This makes practical implementations more feasible than other methods such as Wiener filter (Brown and Hwang 1996) where this filter is designed in a way to operate on all the data directly for each estimate. The Kalman filter instead recursively conditions the current estimate based on all the past measurements. Generally, tracking indicates detecting an object from frame to frame.

For the fall detection system, the centroid of the moving object is calculated, and this is then tracked using the point tracker such as Kalman filter. An angle between the tracked point and the point from the ground plane is then calculated. The change of angle below certain threshold can be considered as a fall and on the other hand, a change of angle within the threshold represents the normal activities like lying down or seating in floor etc. The rate of

change of angle is calculated consistently to confirm a fall. The normal activity will not be a sudden action; however, the fall is a sudden action which results in an abrupt change in the rate of change of angle. So, constantly monitoring for any abrupt change in the rate of change of angle represents a fall detection. Our model is capable to detect and track a person even if the person is partially occluded. Fig.3.10 shows the partially occluded human detection and tracking.

Fig.3.11. Partially occluded human detection and tracking (FDD-lecture room-video14)

3.6 Rate of Change

Rate of change function is simply a relation between the points or members of two sets. One of the basic goals of calculus is finding and understanding these relationships. This is to understand the evolution of a system. From the research point of view, we can say that the rate of change will relates the position of a given object at a given time to the position of the same object 't' seconds later.

The rate of change is always considered as a change in the input variable, often with respect to at a fixed input value. This is a generalization of the notion of instantaneous velocity and essentially allows us to consider the question how we measure the pace with which a function is changing at a given point.

In simple words, the speed of an object is a measure of how fast it is moving or changing its positions. Noting that speed in this case , is simply the rate of change of position with respect to ground point.

The average rate of change of a function f over an interval $[x_0, x_1]$ is the ratio of its change in output $(f(x_1) - f(x_0))$ over change in input $(x_1 - x_0 = h)$.

Mathematically,

$$\text{Average Rate of Change} = \frac{f(x_1) - f(x_0)}{x_1 - x_0} = \frac{f(x_0 + h) - f(x_0)}{h} \tag{13}$$

The above definition and equation are in general context; however, we are interested in finding the rate of change in angle.

In this research work, we are calculating the rate of change of angle with respect to the ground plane. The normal operations such as sitting, standing and walking are consider as normal operations based on the rate of change, since the rate of change will not be abrupt. If there is an abrupt change in the rate of change this will be classified as a fall. Falls are normally supposed to happen very fast since it is an unexpected action. Hence these kinds of sudden actions can be easily detected by analyzing the rate of change.

To test this algorithm, we have used two public data sets (UR Fall Dataset and the Fall Detection Dataset) and our own dataset. Some of the sample images which we have used in this research is shown in Fig.3.11. For the purpose of testing, we have considered all type of videos in the public dataset including the sitting, walking, bending and falling videos.

Fig.3.12. Sample images from the public data set used for testing the algorithm

Falls are more dangerous for people who live alone in an apartment. Efficient fall detection system will give moral strength to those elderly staying alone and hence this will provide immediate medical attention when required in case of an emergency action detected. The results and the analysis of the results are demonstrated in the following section.

CHAPTER 4

RESULTS AND ANALYSIS

The proposed fall detection system is based on computer vision. The system was implemented in MATLAB with fundamental image processing performed using computer vision library.

The developed algorithm was implemented in MATLAB 2018b and the performance is evaluated in terms of sensitivity/recall, specificity and accuracy. We have validated our algorithm using two public data sets [The UR Fall Dataset (URFD[1*]) and the Fall Detection Dataset (FDD[2*])] and also our own dataset.

After human detection the centroid of the moving object is calculated, and this is then tracked using Kalman filter. An angle between the tracked point and the point from the ground plane is calculated. This angle is then compared with a threshold value and the change of angle below certain threshold can be considered as a fall. The rate of change of angle is calculated consistently to confirm a fall.

There are different causes for fall such as floors are wet (such as in the bathroom, or recently polished), the lighting in the room is dim, rugs or carpets are not properly secured, the person reaches for storage areas (such as a cupboard or is going down stairs), the person is rushing to get to the toilet during the day or at night etc. One of the other reasons of fall, particularly among older men, is falling from a ladder while carrying out home maintenance work.

The more risk factors a person has, the greater their chances of falling. Due to various types of falls, the body posture and body shape after fall will vary from time to times, and the body area in the floor will changed from person to person. So, it's difficult to identify the falls using most of the fall detection systems. Fall is a sudden and fast movement compared to other operations. We are taking this as an important factor throughout our research work. We are checking the rate of change of movement and in the rate of change movement for every frame is plotted in the graph. From this, we can easily identify the frame which the falls has happened. This sudden change is a clear indication for the caregiver of health care provide for immediate action. The rate of change will not show any abrupt changes while the person is in normal conditions. Some of the results are shown in Fig.4.1 and Fig.4.2.

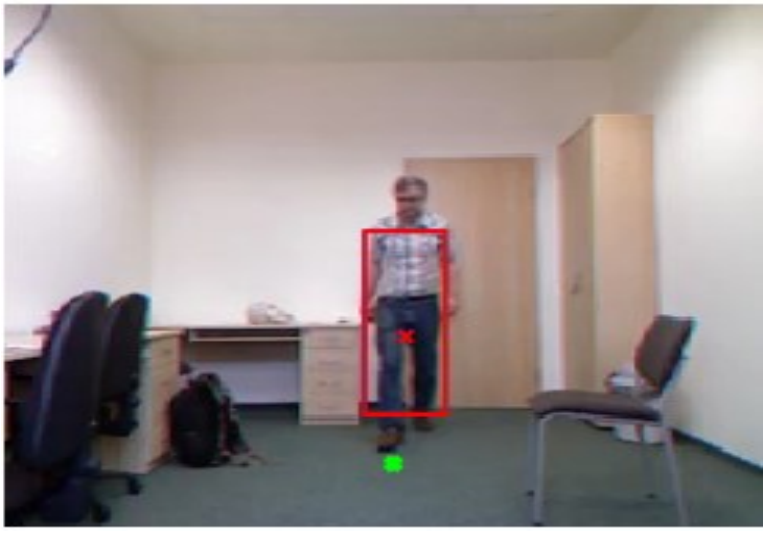
The UR Fall Dataset contains 30 fall videos and 40 Activities of Daily Living (ADL) videos. All the 30 fall videos are taken from two different locations by using two different cameras.

To test our algorithm, we have considered 15 fall videos from camera0, 15 videos from camera1 and 25 no fall videos.

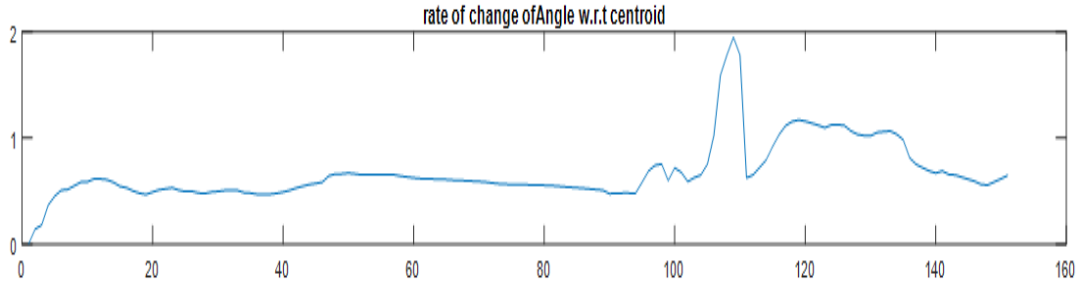
(a) URFD- (1)

[1*]http://fenix.univ.rzeszow.pl/~mkepski/ds/uf.html

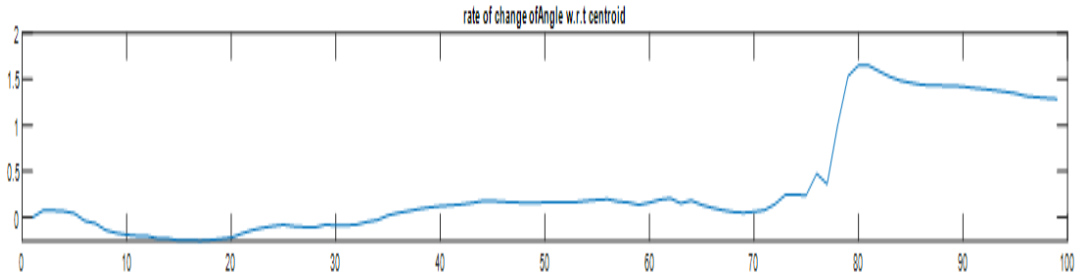
[2*]http://le2i.cnrs.fr/Fall-detection-Dataset?lang=fr



(b) URFD- (2)

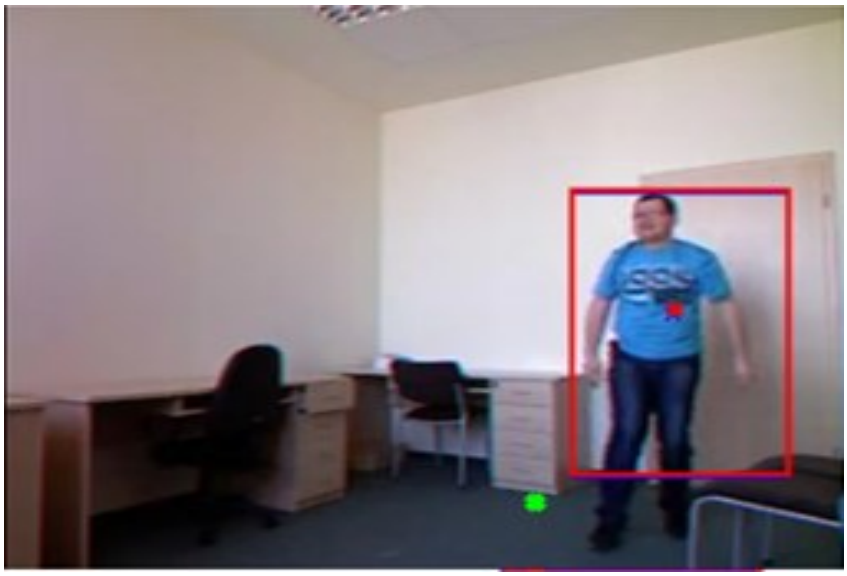


(c) URFD- (1)



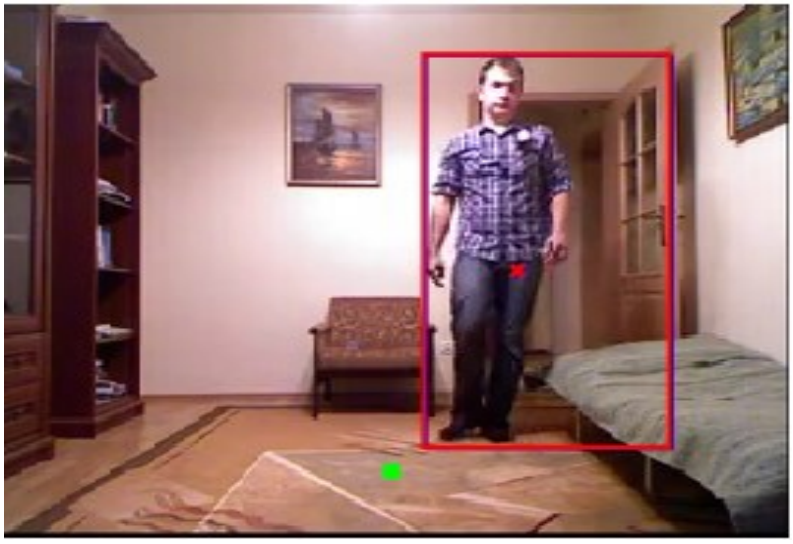
(d) URFD- (2)

Fig.4.1. Fall detection results URFD (fall) (a) & (b) represents tracking a person and (c) & (d) represents the rate of change of angle w.r.t. centroid.

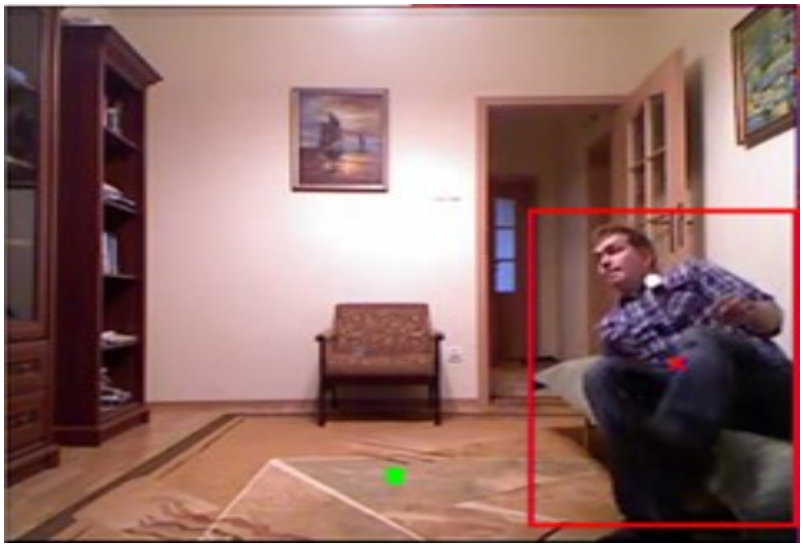


(a) URFD-1

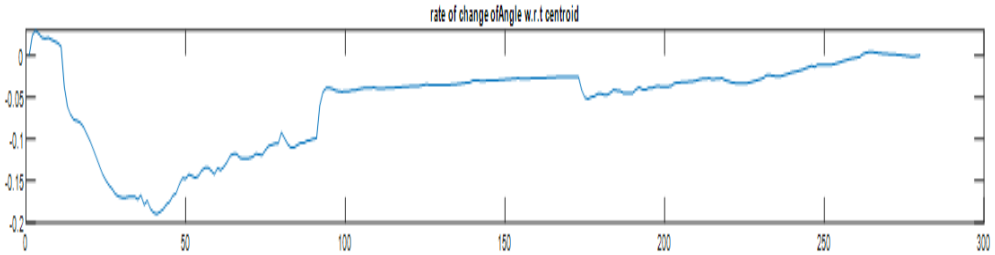
(b) URFD-1



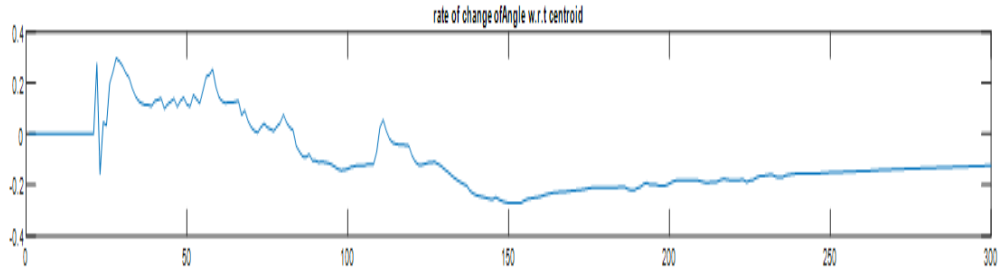
(c) URFD-1



(d) URFD-2



(e) URFD-1

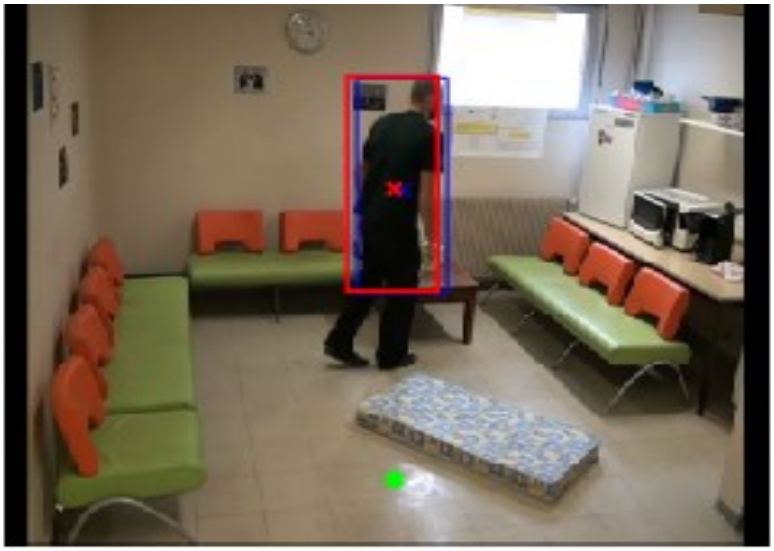


(f) URFD-2

Fig.4.2. Fall detection results URFD (no falls) (a), (b), (c) & (d) represents tracking a person and (e) & (f) represent the rate of change of angle w.r.t. centroid.

In the FDD dataset, the frame rate is 25 frames/s and the resolution are 320x240 pixels. The video data illustrates the major difficulties in a realistic video sequences that we normally can find at an elderly home environment or in an office room. This video sequences contain variable illumination, and most common practical difficulties such as occlusions or cluttered and textured background. The actors performed various normal daily activities and falls. The dataset contains 191 different videos to represent the normal daily activities. Dataset are taken from different locations, allowing to define several evaluation protocols such as "Home", "Coffee room", "Office", "Lecture room" etc.

FDD data set contain videos of 4 different locations with different actors. These available public datasets are recorded strictly in indoor environments with one person in a video. We tested 40 fall videos [10 falls from each group such as a coffee shop, office, home and lecture room]. Some of the experimental results shown in Fig.4.3.The falls appears in different positions at different scenario within the far and near regions of the camera.

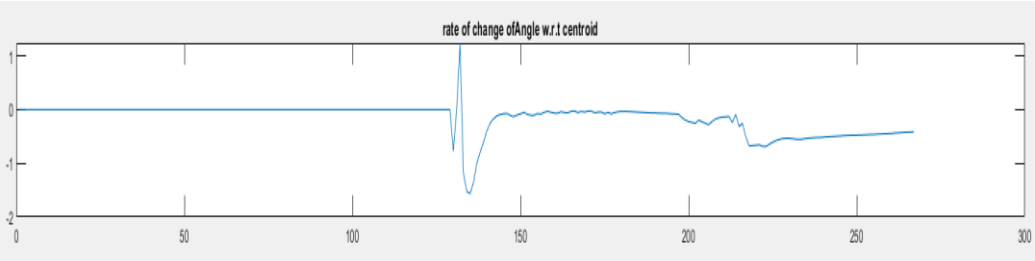


(a) FDD-coffee-video25

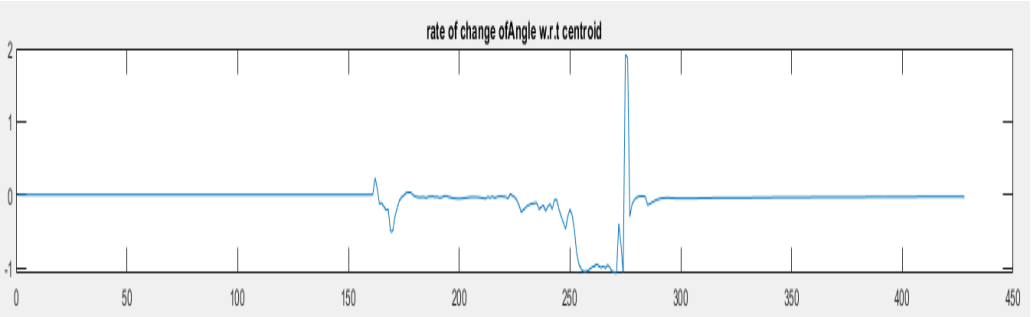
(b) FDD-office-video16

(c) FDD-home-video13

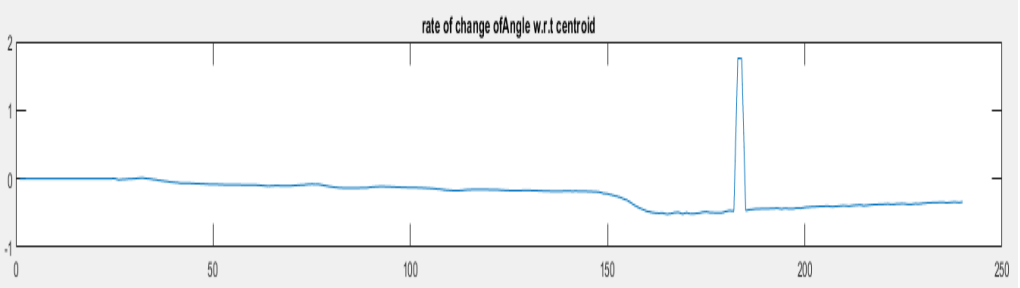
(d) FDD-lecture room-video16



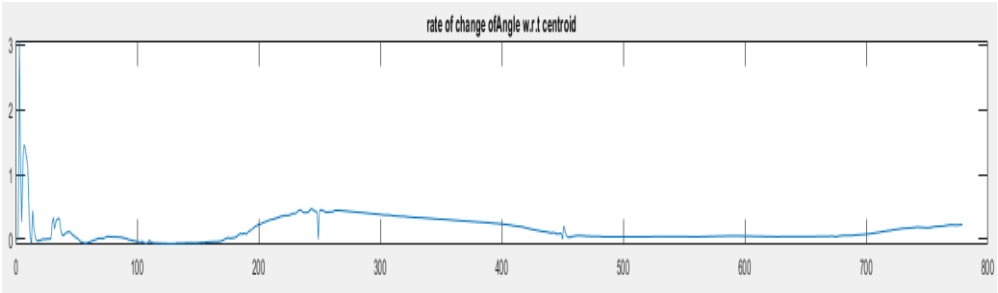
(e) FDD (fall) -coffee-video25



(f) FDD (fall) -office-video16



(g) FDD (fall) -home-video13



(h) FDD (no fall)-lecture room-video16

Fig.4.3. Fall detection results FDD (a), (b), (c) & (d) person tracking (e), (f), (g) & (h) rate of change of angle w.r.t. centroid.

Based on these graphs, it is possible to identify the fall activity which has happened, and a fall can be detected from this. A high peak in the graph represents a sudden change of tracked point with respect to ground point and the graph very clearly shows the detection of a fall. To identify the fall, the rate of change of angle with respect to ground point is calculated. For example, in Fig. 4.3 (h), there is no sudden peak above a threshold value which indicates no falling in that video input.

4.1 Performance Evaluation

We have used a total of 95 videos with different data sets to measure the performance of the system. Three different parameters such as sensitivity, specificity and accuracy are calculated to evaluate the accuracy of the system.

Sensitivity represents the percentage of fall events detected, specificity represents the percentage of events without falls detected correctly and accuracy represents the percentage of correctly detected events. These parameters are mathematically represented in the equations given below.

$$\text{Sensitivity/Recall} = \frac{TP}{TP+FN} \tag{14}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{15}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{16}$$

Where TP and TN refers to true positives and true negatives, similarly FP and FN refers to false positives and false negatives.

Sensitivity is an important parameter from the other parameters since the overall aim of this research is to detect all fall events. For measuring the performance of the algorithm, accuracy and precision are equally important as well.

For the performance evaluation, we tested a total of 95 videos. From URFD [30 fall videos and 25 no fall videos] and 40 videos from FDD. Results are represented in Table 4.1 and Table 4.2.

Table.4.1. Fall detection results

Datasets	No. of Events	TP	TN	FP	FN
URFD (falls)	30	27	-	-	3
URFD (no falls)	25	-	24	1	-
FDD	40	35	-	-	5
Total Events	95	62	24	1	8

The results of our proposed system are compared with the results obtained by the state-of-the-art technique in Table. 4.2 and the proposed system is more efficient.

Table.4.2. Performance parameters compared with the state-of-the-art technique

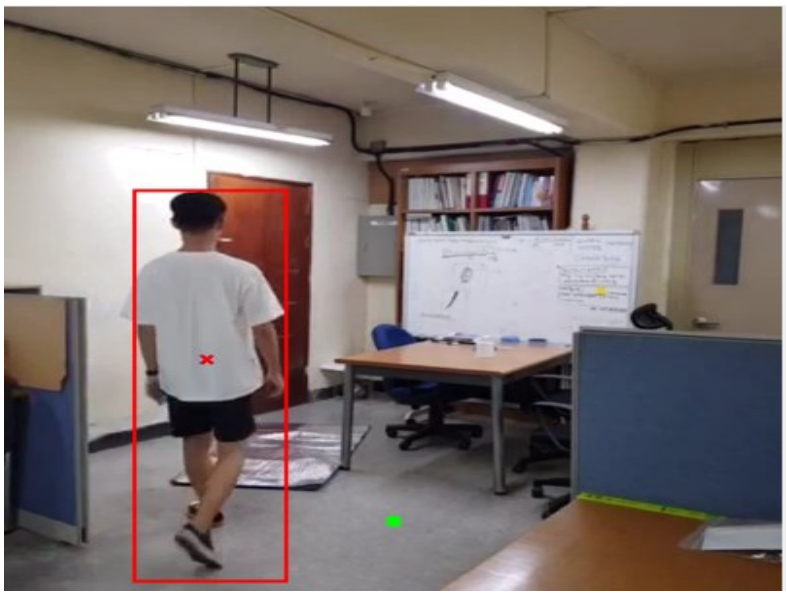
Parameters	Comparison of Results			
	Proposed Architecture	State of the art technique [13]	SVM-depth (URFD) [66]	Threshold LFT (FDD) [67]
Specificity	96.00 %	88.00%	80.00%	80.00%
Sensitivity/recall	91.17 %	82.85%	100.00%	93.33%
Accuracy	90.53 %	84.21%	90.00%	86.67%

To evaluate the performance of the proposed system, we have compared our results with the vision-based fall detection [13]. The proposed algorithm has shown superior performance parameters with the readings as shown in the table above.

FDD contains 4 different scenarios under different locations with different persons. The accuracy in detecting the fall thus proves the efficiency of our proposed system. We tested the algorithm with our real-time videos, and it has given accurate results as well. The

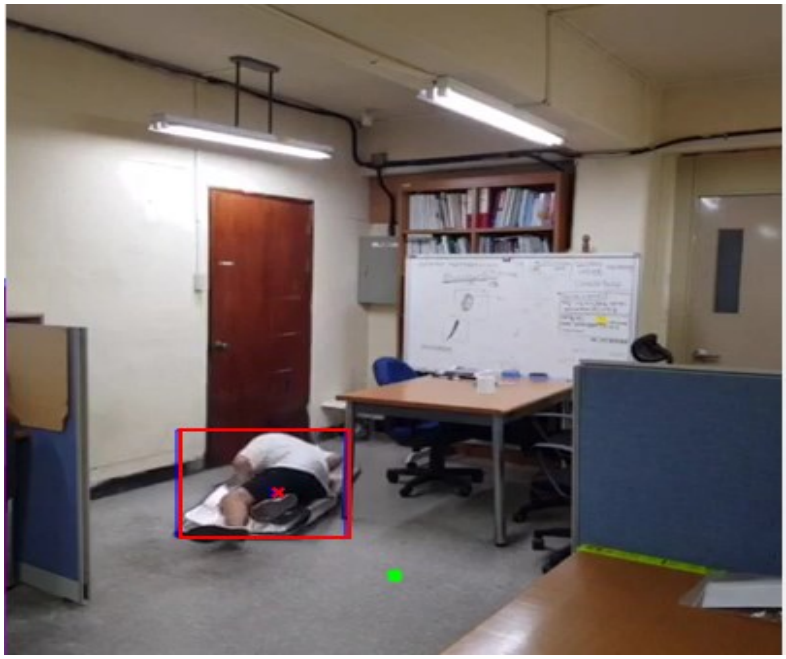
complexity associated with the 3D system can be overcome by the simple 2D camera design proposed in this paper.

For testing the accuracy of the algorithm, we have created some videos at our lab under various standard conditions and this real time data is fed as the input to the proposed architecture. The dataset is recorded in the laboratory environment with the help of my colleagues. We have recorded falls and non fall videos and tested different conditions such as sitting, falling, bending etc. and our algorithm has effectively and efficiently detected the falls from these scenarios. The experimental results shown in Fig.4.4

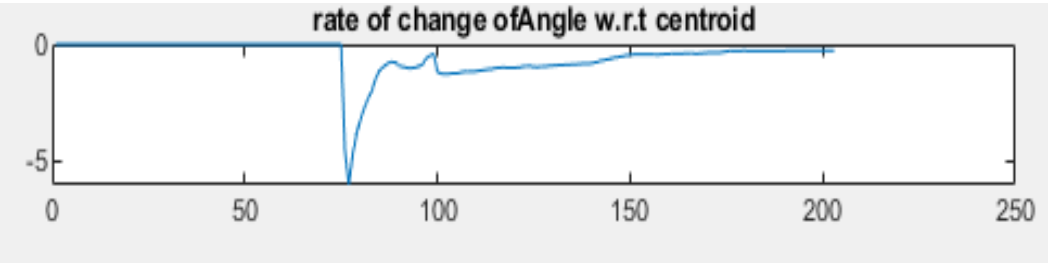


(a)

(b)



(c)



(d)

Fig.4.4. Fall detection results (a), (b), (c) person tracking (c) rate of change of angle w.r.t. centroid.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

South Korea saw its elderly population growing rapidly over the last one decade. Rapid increase in aging population in Korea between 2000 and 2050 is worrying as this increases the chances of life fatalities due to unexpected incidents such as falls. A large portion of experts share the view that the social burden of caring for the elderly will increase rapidly in the coming decade. This can be controlled by providing efficient techniques to identify incidents which can result in fatalities and provide urgent medical care. Falls represent a significant threat to the health and independence of adults 65 years of age and older. A wide variety and large amount of passive monitoring systems are needed to detect when an individual has fallen.

In this research work, we mainly focus to implement an efficient and low-cost real time fall detection system for the elderly people with the help of computer vision techniques. This system has been tested with two public fall detection dataset such as URFD and FDD and the dataset which we have created in our own lab for real time applications. We worked on RGB data to ensure that the fall is detected using 2D images (no depth maps or accelerometer data). The experimental results and discussion show that the proposed method is efficient and suitable for real-time fall detection. The proposed method detects a fall based on the combination of the centroid of a person in the frame and how fast the centroid is moving with respect to the ground plane. From the experimental analysis, our system was able to achieve an accuracy of 90.53% with a sensitivity of 91.17% and specificity of 96%. We believe that the proposed vision-based fall detection system will provide major advancements in smart real-time application.

One of the major advantages of our low-cost fall detection system is that the person under surveillance is not required to wear any physical device such as wearable sensors. We believe that this novel fall detection is a solid step towards the development of a solid support system for elderly people who are living independent. This technology provides a safe and smart environment for our elderly by getting an immediate support from the caregivers in case of an emergency situation arises.

However, there is still ground for improvement in order to bring vision –based fall detection to get 100% accuracy. We are suggesting some improvements as the future enhancement. As part of future enhancement, we are planning to improve the ground plane segmentation to reduce the false detections. The public data set is restricted with only one person per video. As part of enhancing the current work, we are investigating the possibility to detect the falls from videos where multiple people are present under various conditions and multiple falls within a single video. We are trying to incorporate a check in terms of occlusion, illumination changes, and nighttime videos. For obvious reasons, real datasets on fall patterns of the elderly are not available. So, to make this system fool proof, we need to collect real-time videos from a real situation since the walking speed and walking pattern of elderly aged people may completely be different from the dataset available. We are investigating the possibility of utilizing FPGA (Field Programmable Gate Array) for real-time processing as part of future enhancement.

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ACKNOWLEDGEMENT

First and foremost, I would like to thank almighty God for His showers of blessings to complete the research successfully.

I would like to express my sincere thanks to Prof. Sang Bock Cho, my Ph.D supervisor for his continuous support, patience, motivation during my doctoral study in University of Ulsan. It will be beyond the words if, I want to express my heartiest gratitude towards him for giving me the opportunity for pursuing my Ph.D under his guidance, keeping a constant faith on me during research tenure and also for providing full freedom to do research as per my own choice and eligibility. He always encourages me with my project designs and guilds me to make them more applicable and directional to solve the real problems. His care and concern for making my life better and better in Korea during my stay, I never can forget. His enthusiasm for introducing different kind of Korean foods helps me to have a good experience about Korean cuisines. Lastly, I would like to say that, this dissertation journey could never be accomplished without him. I want to thank you, Prof. Cho for being my supervisor.

I am extremely thankful to my research committee members; Dr. Myung Kook Yang, Dr. Chang Woo Nam, Dr. Hee Jun Kang, and Dr. Yun Sik Lee for their insightful comments, queries and encouragement during meeting.

I would like to thank all the faculty members in the School of Electrical Engineering for extending their research facilities, interactive discussions and teaching me varies courses. Especially, Dr. Hyung Yun Kong, Dr. Kim Han Sil, Dr. Kang Hyun Jo, having their courses which helped me to acquire valuable knowledge for my research and fundamental knowledge.

I specially thank my present and former labmates; Young-Min Jang, Peng Tao, Erdenetuya Tsogtbaatar, Tae-Hun Nam for their support and cooperation during my stay in South Korea. They create a homely atmosphere, which helps me stay far from home for a long time-period. I have found myself very fortunate having labmates like them.

A heartfelt thanks to all my friends who made the Ulsan experience more joyful, specially Sujith, Arjun, Rini, Jayasmitha, Ashok, Mahima, Soumya, Ajay, Rupesh, sourvav, and

Raddy. I would like to thank Moumita, Rajesh, Hrishikesh, Vipin and Jatinder for their awesome cuisines which keep my taste bud alive in South Korea.

I owe thanks to a very special person, my husband Anoop Suraj for his everlasting support, endless love, feedback, guidance, understanding, caring and motivation throughout my life which allows me to pursue my academic goals. You were always around at times I thought that it is impossible to continue, you helped me to keep things in perspective. I greatly value his contribution and deeply appreciate his belief in me. I appreciate my son, Aadi for abiding my ignorance and the patience he showed during my research studies. Words would never say how grateful I am to both of you. I consider myself the luckiest in the world to have such a lovely and caring family, standing beside me with their love and unconditional support.

I would like to thank my parents for everything to make me what I have become today, without them none of these would have been possible. Their encouragements, unconditional love and support, faith on me that I can do, helps me to reach this platform.

My heart felt regard goes to my father in law, mother in law for their love and moral support. Also I express my thanks to my sisters, brother in law for their support and valuable prayers.

Special thanks to principal Dr. Nixon Kurivila and vice-principal Dr. Ajith Cherian; Sahrdaya College of Engineering, Kerala, India for their sincere encouragement and support throughout my research studies.

My thanks and appreciations also go to my friends and everyone who have willingly helped me out with their abilities.

Financial support from University of Ulsan funded by the Brain Korea plus (BK) is greatly acknowledged.

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LIST OF PUBLICATIONS

1. Paper titled "Fall Detection System for Elderly People using Vision-Based Analysis" on the Journal Romanian Journal of Information Science and Technology (SCIE), Vol. 23, No: 1, pp.69-83, 2020.

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3. Paper titled "Vehicle Detection and Tracking from a Video Captured by Moving Host" on the Journal Indian Journal of Computer Science and Engineering, ISSN 0976-5166 (Manuscript Accepted).

4. Paper titled" Concrete Crack Detection Using Relative Standard Deviation for Image Thresholding" on the journal IEIE Transaction on Smart Processing and Computing, ISSN 2287-5255 (Manuscript Submission).

5. Paper titled "An Android Application for Real-Time Lane Detection System using JavaCV in Eclipse Development Environment" on the Journal The International Arab Journal of Information Technology, ISSN 2309-4524 (Manuscript Submission).

6. Paper Titled "Face Tracking using Unscented Kalman Filter" International Conference on Electronics, Information and Communication (ICEIC) 2020, DOI: 10.1109/ICEIC49074.2020.9102214, IEEE Xplore, ISSN: 978-1-7281-6289-8.

7. Paper Titled "Night-Time vehicle detection based on Brake/Tail light color" 2018 International SoC Design Conference (ISOCC), DOI: 10.1109/ISOCC.2018.8649981, IEEE Xplore, ISSN: 2163-9612.2018.

8. Paper Titled "A FPGA Verification of Improvement Edge Detection using Separation and Buffer Line" International Conference on Electronics, Information and Communication (ICEIC) 2020, DOI: 10.1109/ICEIC49074.2020.9051159, IEEE Xplore, ISSN: 978-1-7281-6289-8.

INTERNATIONAL AND NATIONAL CONFERENCES

1 "Face Tracking using Unscented Kalman Filter" at the 19th ***International Conference on Electronics, Information, and Communication (ICEIC 2020)*** hosted by IEIE and IEEE held at Barcelona, Spain on January 19 -22, 2020.

2 "A FPGA Verification of Improvement Edge Detection using Separation and Buffer Line" at the 19th ***International Conference on Electronics, Information, and Communication (ICEIC 2020)*** hosted by IEIE and IEEE held at Barcelona, Spain on January, 2020.

3 "Night-Time Vehicle Tracking based on Brake/Tail Light color" at the at the ***IEIE (Institute of Electronics and Information Engineers) SoC Conference*** held in Daejeon, South Korea on May 17-18, 2019.

4 "The Color Detection Method for Object Recognition using Dynamic Range" at the 18th ***International Conference on Electronics, Information, and Communication (ICEIC 2019)*** hosted by IEIE and IEEE held at New Zealand on January 22 -25, 2019.

5 "Night-Time vehicle detection based on Brake/Tail light color" at the ***ISOCC International Conference*** held in Daegu, South Korea on November 12 -15, 2018

6 "The FPGA Design with Color Detection using Noise Minimization for Real-Time Fire Extinguisher Detection" at the ***IEIE (Institute of Electronics and Information Engineers) Conference*** held in Suwon, South Korea on May 11, 2018.

7 "Number Plate and Character Recognition System using a Noise-Cancelling" at the ***IEIE Summer Conference*** held in Jeju Island, South Korea on June 27 -29, 2018.

8 "The Vehicle Tracking Method using Improved Image Correction in Harsh Environment" at the 17th ***International Conference on Electronics, Information, and Communication (ICEIC 2018)*** hosted by IEIE and IEEE held at Hawaii, USA on January 24 -27, 2018.

9 "Real Time Vehicle Detection and Tracking Using Fusion Approach" at the ***International Conference*** held in wellington, New Zealand on July 6 - 7, 2017.

10 "The FPGA Verification and Speed Improvement Algorithm of Edge Detection using Prewitt Edge" at the at the ***IEIE (Institute of Electronics and Information Engineers) SoC Conference*** held in Seoul, South Korea on May 26-27, 2017.

11 “A Center Line Recognition System to avoid Traffic Accidents in the Opposite Direction using Forward Image”, ***IEIE Fall Conference*** held in Incheon, South Korea on November 24-25, 2017.

12 “An Acquisition Method of Distance Information in Direction Signs”, ***2017 International SoC Design Conference (ISOCC)*** held in Seoul, South Korea on November 5-8 2017.