AN ANALYSIS ON HUMAN FALL DETECTION USING MAXIMUM SKELETON EUCLIDEAN DISTANCE TECHNICS

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ABSTRACT

Falls are the primary cause of death in older people, especially for those living alone. We are studies of falling patterns base on the vision-based system. That analyzes an extracted human body complied a new method with Maximum Skeleton Euclidean Distance technics (MSED) to investigate falls detection. The focus is to detect the human object from the contribution of different features in fall classification. First, the skeleton extract defines the region of interest and reduces an image to one pixel to increase processing performance. Then, specified maximum Euclidean distance and complied conventional shape analysis approach such as the velocity of the object, oriental with ellipse extraction, and time to recovery to fitting with fall algorithm. Maximum Skeleton Euclidean Distance Techniques (MSED) extracted features are tested 100 samplings from public fall datasets, including fall and non-fall sample sets. The result of this method is most accurate and suitable to recognize falls from skeleton features.

Keywords: Fall Detection, Skeleton Euclidean Extraction Distance, Image Processing.

1. INTRODUCTION

Computer vision is applied in daily life[1][2] to monitor and correct data in-home used, fall in elderly is a major public problem [3] the older people experience a least one fall every year. By the way, falls are the leading cause of accidental in the group of ageing moreover 65 years[4]. Therefore, a vision-based method has a significant advantage because it does not require older people to wear specific equipment. The Skeleton feature is prevalent [5] since the Kinect provides the skeletons, joining point, and accelerated as a primary feather. However, on video base does not have functionality. To improve the skeleton feature efficiency on conventional video is a challenge to fulfil this gap.

Many other computer visions and image processing to finetune algorithms to detect fall behaviour such as velocity, shape analysis but do not have algorithmic definition clearly and thus, this task can be challenging.

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2. BASIC CONCEPT

This paper aims to determine Maximum Skeleton Euclidean Distance technic by using human diagnosis factors and prevent serious consequences. Using body linkage feature to detect the harmful level, save time to avoid severe cases and keep the patient life as a basic concept we study on fall behavior and fall character.

2.1. Ageing Society in Thailand

A report of the 2017 survey of the older person in Thailand From the National Statistical Office Ministry Of Digital Economic And Society resulted from a study in the years 1994, 2002, 2007, 2011 and 2019 the result increasing rate 9.4 10.7 12.2 14.9 and 16.7 as current. The number of elderly pops. Increases continuously to refer to Table 1.

Early elder (60-69 yr) Contributes to half of the total number of elderly ppl. but is projected to be on the decline in the next 20 years.

Middle elder (70-79 yr) Contributes to about 1/3 of the total number of elderly ppl, projected to be fast increased over time.

Heightened elder (80 yr+) Despite a relatively small proportion, it is projected to be gradually increased.

People aged above 60 can be considered elderly [6], Elderly people have a high falling rate, and their speed of fall increases every year. About 70% of people over the age of 60 falls at least one, and in half of the cases, falls are recurrent (Thai research 2019). Over the last 25 years, the number of people ages 60 and over in Thailand has increased by 25%. In addition, the population age 85 and above have shown the highest population growth.

Table 1. Fall Record to Compare Thai Elder of Fall Case

CASE	1 Time	2-3 Times	4-5 Times	6 Times	Over 6 Times
Total	69.7	23.9	3.3	0.6	2.5
Male	70.2	24.0	2.6	0.9	2.3
Female	69.4	23.7	3.7	0.5	2.7
Middle elder (70-79 Yrs.)	68.4	26.6	2.0	0.1	2.9
Heightened elder (80 Yrs. Up)	71.9	21.5	4.5	0.2	1.9

2.2. Falling Incidence

Many fall incidents have caused severe injuries [7] [8] and even death in the past among older adults as they are more prone to diseases such as dementia and epilepsy. Society will have to face two significant threats due to ageing: firstly, the increase of care to ageing people means higher investments in elderly care services, and secondly, it will lead to a decrease in the working population which will eventually bring a shortage in skilled caregivers for older adults. This indicates that the ageing society is one of the biggest challenging society especially for those who chose to live alone because they would require dedicated medical care. Therefore, fall detection is an essential monitoring system. A monitoring system that could accurately detect a fall and provide an alert instantaneously is exceptionally desirable. This approach could be helpful to reduce the waiting time for medical treatment and save lives.

2.3. Fall Classification

Identifying falls is very challenging as some fall events are similar or normal activities of daily life. Fall detection may be generally considered as a sub-section of general motion estimation. Fall detection has distinguishable characteristics to that of general motion detection. There is a sudden change in height and width of the body after a fall incident and there is also an inactivity period on the floor. It can be noticeable by the sleeping pose or displacement of the head. Besides, the body's inclination angle and velocity before the fall can provide a significant clue for fall detection. Another attempt to distinguish falls from normal activities.[4] where unique features of the velocity profile which are the magnitude change, and the timing of the change was analyzed during normal and abnormal activities. Different scenarios are considered to analyses fall as fall can be observed in a different orientation, transitional postures, and acceleration of the body. Based on the orientation of the body, fall can also be classified into three different categories as referred.

- *Forward fall*: In this case, a person falls in the forward direction with face impacting the floor.
- *Backward fall:* In this case, a person falls in the backward direction with the back of the head impacting the floor.
- *Side fall: In this case*, a person falls towards the left or right side in a forwarding or backward direction.
- *Fall from standing:* In this case, a fall occurs from standing still pose or during walking. This kind of fall may have a higher impact on the floor during the fall due to the higher position of the head and torso region and hence can cause greater injury than other types.

- *Fall from sitting:* In this case, a fall occurs from the sitting position and the impact on the floor during the fall is lower and so is the level of injury in comparison to fall from the standing case.

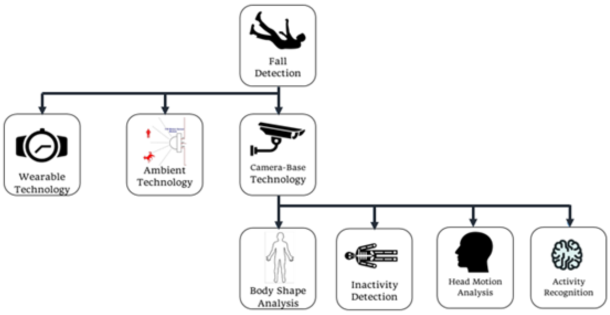


Figure 1. Approaches to Fall Detection and mainly the camera-based fall detection.

- *Fall from lying:* In this case, a fall occurs in a lying position from bed or sofa, and the impact on the floor and the level of injury during the fall is also lower than falling from a standing case.

- Fall from other transition postures: In this case, a fall occurs from a bending or crawling position, and the impact on the floor and the level of injury during the fall is also lower in comparison to a fall from a standing case.

2.4. Fall detection

There has been significant research carried on the development of fall detection systems in the past and most widely accepted systems based on a. Wearable technology, b. ambient technology and c. Camera-based technology as Figure 1.

I. *Wearable technology* – Base on Accelerometers, gyroscopes, oscilloscopes. They have presented the performance of 13 published fall detection algorithms applied to the database of 29 real-world falls. They have reported an average detection rate of 83% and a fall detection rate of 98% for the well-performing algorithms. the purpose of fall defection is commonly used wearable sensors. The sensors are easy to wear. But they some drawbacks such as sensitivity to the body movement, power consumption. This technology was not comfortable to daily using as they are attached to the body. [9][10]

II. *Ambient technology* – Ambient devices measure various parameters in the environment of the subject under protection using groups of infrared sensing devices, sound, vibrators, and so on. Base on this technology to install sensors to collect data from the related person when they are near. Most of the technology are pressure sensors which sense of high pressure due to the weight of the occupant

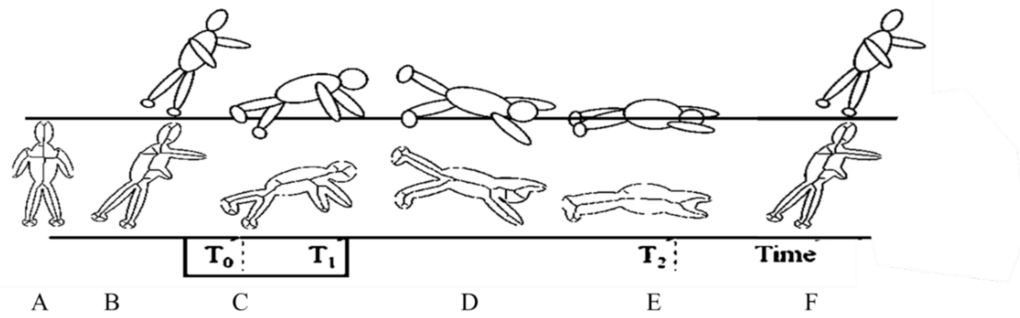


Figure 2. Fall characteristics and phase of falling in each step.

at the location, this technology can't be sure if the pressure observed is from some. another object the chances of false alarms due to lack of visual verification.[11] In reported a 100% fall detection ratio with the ability to distinguish activities through vibrations and have reported a 91% success rate using electromagnetic sensors in the floor plates that create an image of objects which touch the floor. The major drawbacks of the ambient devices are that they need to be installed in several rooms to cover the movement of the elderly to cater to all situations. In commercial fall detection devices, ambient technologies use presence.

III. *Camera-based technology* – Camera-based technology can monitor activities continuously in the living environment by applying image processing techniques. This technology is most popular because it avoids any physical contact with the body. They are installing on the building and not worn by the occupant. Cost-efficient due to the recent development is inexpensive with applying with RGB image processing as well as depth image. Data privacy is one thing that to be considered in monitoring.[12]

That Three types of technology as above, Researcher to consider to computer base approach is more appropriate for the development in a part of fall detection. However, this approach suffers from accuracy, occlusion, privacy, body part wearable, variation in the cloth. The image processing with camera techniques, this it possible to overcome obstacles to some extent and trace the occupant activities continuously. This idea leads to the need for activity recognition and poses estimation. Machine learning has set higher in the field of activities recognition and human pose estimation proposed a depth-based human fall detection using machine learning approach and were able to achieve 91% sensitivity and 86% accuracy [10] In recent years, fall detection research is mostly focused on vision-based technology, 3D human tracking almost develop based on multi-camera [11] to determined and detect a diversity of fall. Therefore, the camera or vision-based fall detection approach has been further explored in the past based on mainly these four techniques: Body shape analysis, Inactivity detection, Head motion analysis, and Activity recognition.

This research gap has Skeleton extraction very appreciated to perform to with image processing and not researcher to apply this technic to classification on fall detection this room to more opportunity to design and validate with Maximum Skeleton Euclidean Distance method through surveillance video sequences in scope vertical falling.

3. RESEARCH METHODOLOGY

Briefly stated, the method essentially involves with fall phenomenal of each characteristic of a person is reconstructed with a shape-from-silhouette approach. Then, a simple Skeleton Euclidean Distance threshold is used to determine a fall or not.

Our algorithm can be divided into 3 levels: Fall conceptual (step A), and recognition level (Step B-D), and fall detection level (Step E- F) to represent in Figure 2.

3.1 Fall conceptual.

To reduce the risk of falling, the early detection of falls in the pre-fall or critical fall phase, therefore, advances the interest of researchers. According to Figure 2. [13] had described a fall event in four phases as pre-fall phase, critical fall phase, post-fall phase, and recovery fall phase sequentially.

The Pre-Fall phase, corresponds to daily life motions, with occasionally sudden movements directed towards the ground like sitting or crouching.[14]

The Critical phase, corresponding to the fall, is extremely short. This phase can be detected by the movement of the body toward the ground or by impact shock with a floor.

The post-fall phase is generally characterized by a person motionless on the ground just after the fall, It can be detected by lying position or by an absence of significative motion.

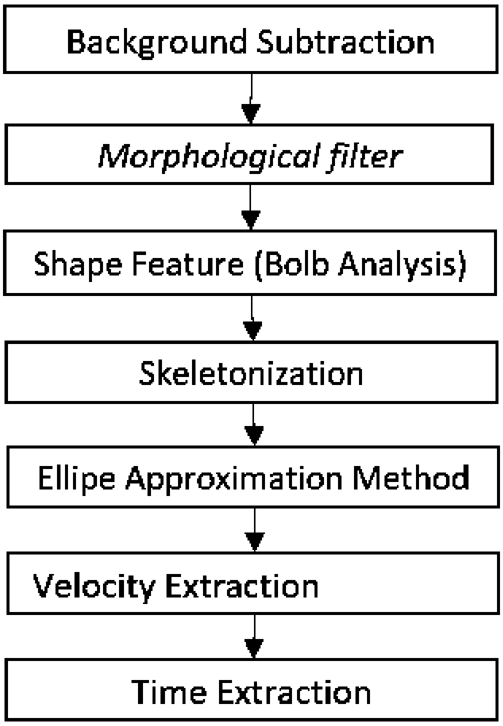


Figure 3. Flowchart of a fall detection system

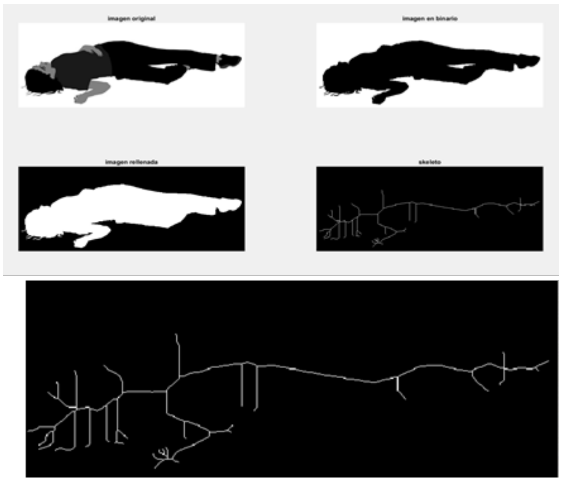


Figure 4. Image skeletal extraction on fall detection

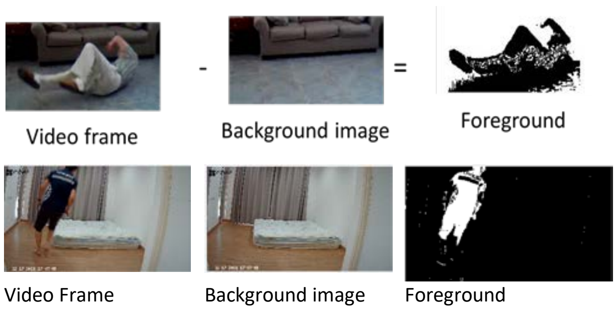


Figure 5. Background Subtraction for Foreground Image

A Recovery phase can eventually occur if the person can stand up alone or help other people.

Vertical and horizontal speeds during a fall are higher than other restricted movements and increase near concurrently during a fall. Next, the post-fall phase is posture after fall that can be detected by motionless after lying on the ground or lying position. Lastly, the recovery fall phase is the recovery phase that the falling person gets up from the post-fall phase. The goals of this study are to the analysis of falling patterns in prefill and critical fall phases based on distances of human skeleton joint positions. Study of fall reaction that is found by a high frequency of movement and some changes in human posture. For human posture during normal activity, the human shape will gradually change. While during a fall, the human shape will change rapidly. Our fall detection system detected a large movement of humans by using Skeletal Euclidean Distance. An approximated ellipse analyzed the posture of humans to classify fall and non-fall posture in image sequences. The flowchart of our system is shown in Figure 3.

3.2. Foreground Detector (Background extract and morphological filter)

The silhouette of the person is used for shape analysis. To extract this silhouette to define the moving person is then detected by finding the difference image between the incoming frames with the background model, the background subtractor algorithm is used to remove the background and obtain the foreground contour of the person in the scene. The background subtractor we use in the system described in this paper is aimed at daylight situations. For the night situation, we consider using a different algorithm, as expected in the future work section. Usually to apply median filtering method [15] to subtract the background of the scene disadvantage for noise and low-quality outputs [16]. we applied Gaussian Mixture Model (GMM) [17], which is established on background subtraction. The smoothing method was used for the pre-processing stage and a morphological filter was applied to remove the unwanted pixels out of the background in other to resolve the background noise disruption problem [18] and skeleton extract as Figure 4. An example of background subtraction is shown in Figure 5.

3.3. Blob Analysis

Blob Analysis is used to calculate statistics for label regions in an intensity image. It proceeds with quantities such as the centroid, bounding box, label matrix, and blob count [19]. The goal of this method is to detect corresponding regions in scaled versions of the same image. According to the goal, the scale selection mechanism is needed for finding characteristic region size that is covariant with the image transformation. For spatial selection, the magnitude of the Laplacian response will achieve a maximum at the center of the blob in which the scale of the Laplacian and blob is matched. Blob detection in 2D to show in Figure 6.

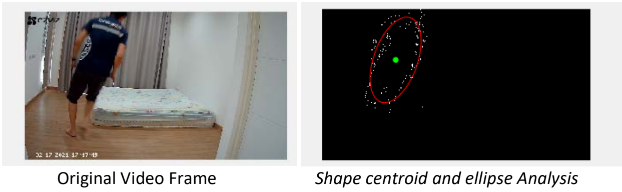


Figure 6. Shape feature extract with Blob analysis

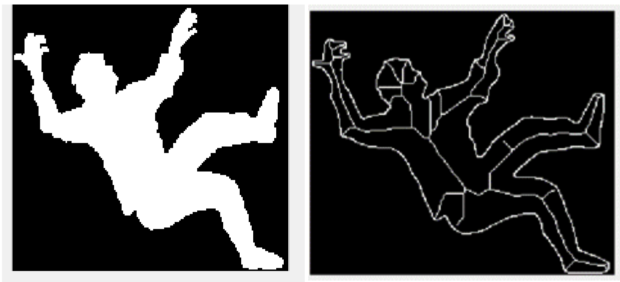


Figure 7. (a)Background Subtraction, (B) Skeleton Extraction

3.4. Skeletonization

Skeletonization [2] is the result of the thinning process, which peeling the contour of the object until reaches the most medial one-pixel width. The goodness of the thinning method is measured by how much the skeleton is extracted to preserve the topology of the shape without any interruption. Skeletonization is used in pre-processing phase for several applications such as writer identification, script identification, optical character recognition OCR. Skeletonization is divided into two main approaches: iterative and non-iterative. Iterative techniques, the peeling contour process iteratively parallel or sequentially; in the parallel way the whole unwanted pixels are erased after identifying the whole wanted pixels. Whereas in sequential techniques; the unwanted pixels are removed in determining the desired pixels in each iterative. In a non-iterative approach, the skeleton is extracted directly without examining each pixel individually, but these techniques are challenging to implement and slow to show in Figure 7.

Morphology Operation [20] is a broad set of image processing operations that process images based on shapes. In a morphological operation, each pixel in the image is adjusted based on the value of other pixels in its neighbourhood. By choosing the size and shape of the neighbourhood, construct a morphological operation that is sensitive to specific figures in the input image. Basket: Reduce all objects to lines in a 2-D binary image or 3-D binary volume. Bwmorph [21]: on binary images

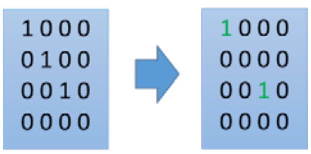


Figure 8. Ending point position

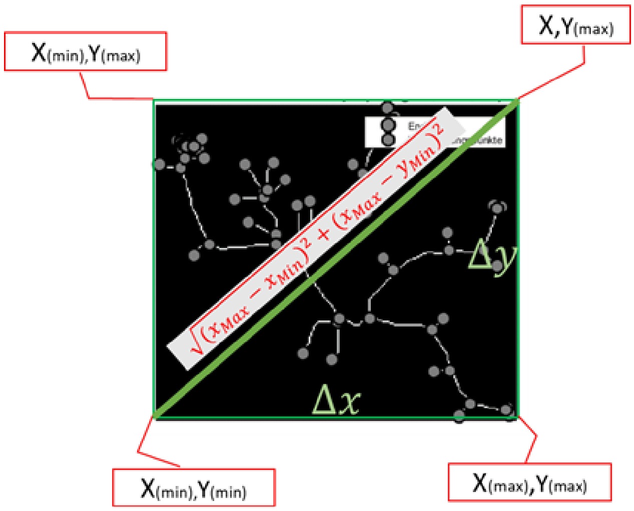


Figure 9. Skeleton Extraction Ending Point

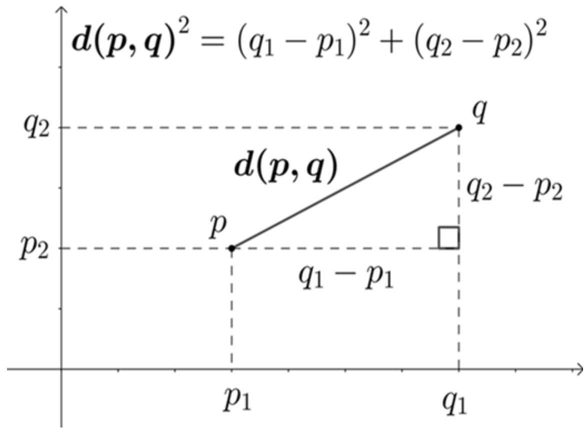


Figure 10. Euclidean Distance Method

3.5. Maximum Skeleton Euclidean Distance

From two selected edge points of Maximum point of image *qi* and Minimum point image *pi*, we find a large movement to detect fall with Maximum Euclidean Distance [8]. This method classifies abnormal activity from normal activities in all the video sequences. The Maximum Euclidean Distance is shown in equation (1).

$$MSED = (p,q) = \max(\sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \quad (1)$$

qi are points maximum point coordinate on skeleton extract and *pi* are minimum points on skeleton shape. We find a maximum distance by equation (1) for a large movement calculation to detect falls from the consecutive shapes. Sample of Maximum Euclidean Distance calculation find end point sample on Figrue 8. Skeleton Euclident method in Figure 9. And Figure 10. respectively. And extraction method for calculation within Figure 11. represent siting condition and Figure 12 represents pre falling condition.

Figure 11. Maximum Euclidean Distance on sitting

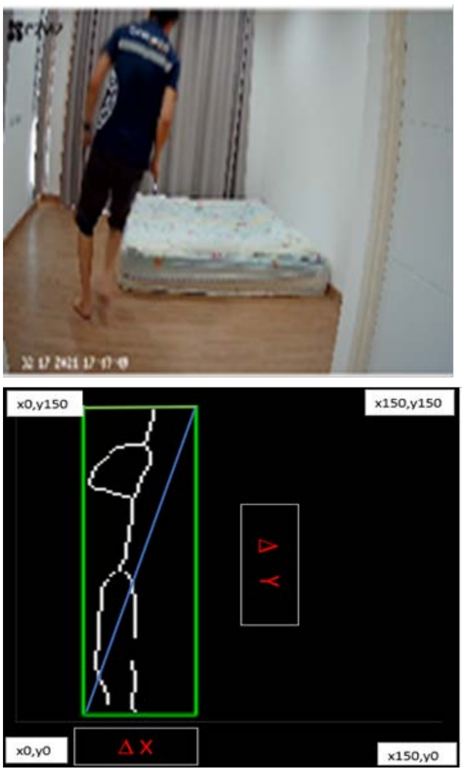


Figure 12. Maximum Euclidean Distance on pre-fall phase.

3.6. Ellipse Approximation Method

We use the Ellipse Approximation method [22] to analyze the changing of human shape in the current shape. An approximated ellipse is defined by the center of the ellipse $(\bar{x}, \bar{y})$, its orientation θ and the length a and b of its major and minor semi-axes. From the continuous image *f(x,y)*, movement in the current image is given by equation (2).

$$m_{ij} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} x^i y^j f(x,y)\,dxdy \qquad ; i,j = 0,1,2. \qquad (2)$$

The center of the ellipse is obtained by computing the coordinate of the center of mass with first order and the zero-order moments: $\bar{x} = m_{10} / m_{00}$, $\bar{y} = m_{01} / m_{00}$ The centroid *(x,y)* is used to compute the central moment in equation (3).

$$u_{ij} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} (x-\bar{x})^i (y-\bar{y})^j f(x,y)\,dxdy \qquad (3)$$

The angle between the major axis of the human shape and the horizontal x axis of the image gives the orientation of ellipse and can be computed from the second order of central moment as shown in equation (4).

$$\theta = \frac{1}{2}\arctan\left(\frac{2u_{11}}{u_{20}u_{02}}\right) \qquad (4)$$

The approximated ellipse provides information about the shape and orientation of the person in the current image. Figure 13. shows an example of the approximated ellipse of the person 13(a) and the calculated result during fall down 13(b). The orientation angle of a changed ellipse when a human falls down 13(c). In this experiment, the mattress was used to protect the person during fall simulation.

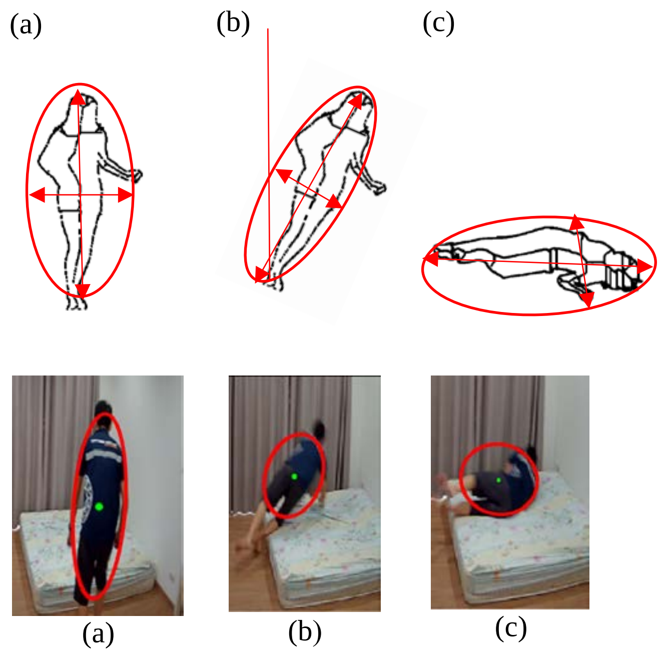


Figure 13. (a) Approximated ellipse of human shape, (b) human on criteria phase (c) human on fall down phase

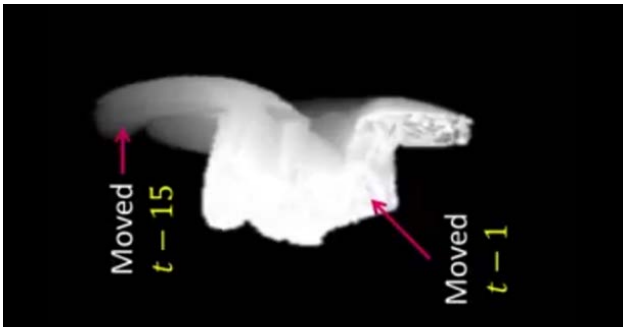


Figure 14. The figure of Motion History

(a) Original (b) BG subtraction (c) Motion history

Figure 15. (a) Original Image, (b) background subtraction, (c) Motion History

3.7 Velocity extraction on fall (Speed)

The velocity in the vertical direction (Vv) and horizontal plane (Vh) were calculated, [12] respectively, the method for human activity classification that we propose is based on the skeleton information of the human. Specifically, when the human performs a certain activity, the skeleton Euclidean moves as Figure 14 and Figrue 15 for MHI to base calculate speed extraction.

$$\begin{cases} \tau & if\ D(x,y,t) = 1 \\ max(0, H_\tau, (x,y,t-1) - 1) & Otherwise \end{cases} \quad (5)$$

$$Distance = \sqrt{(x_2 - x_1)^2 - (y_2 - y_1)^2} \quad (6)$$

$$Speed\ (Velocity) = Distance\ Travelled\ /\ Frame\ Rate \quad (7)$$

The speed or velocity of a moving object is calculating by the distance traveled concerning the time, Euclidean distance formula is used to calculate the distance between the sequences of frames. By using the values of distance concerning frame rate, the velocity of the object is defined by equation (5),(6) and (7) . [23]

3.8 Time Extraction

Time extraction to relate with input video frame rate.

3.9 Fall Detection Algorithm

The objective of our algorithm is to distinguish subjects in a fall state. To achieve this goal, the algorithm extracts data from the subject in a scene to recognize the 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. Next, a Skeleton extract is used to verify data repetitive periodic changes common to various human actions. Finally, a classification and algorithm will be applied to the acquired data to classify the subject's current state as a Model diagram in Figure 3 and a Flowchart of the fall detection system as Figure 16.

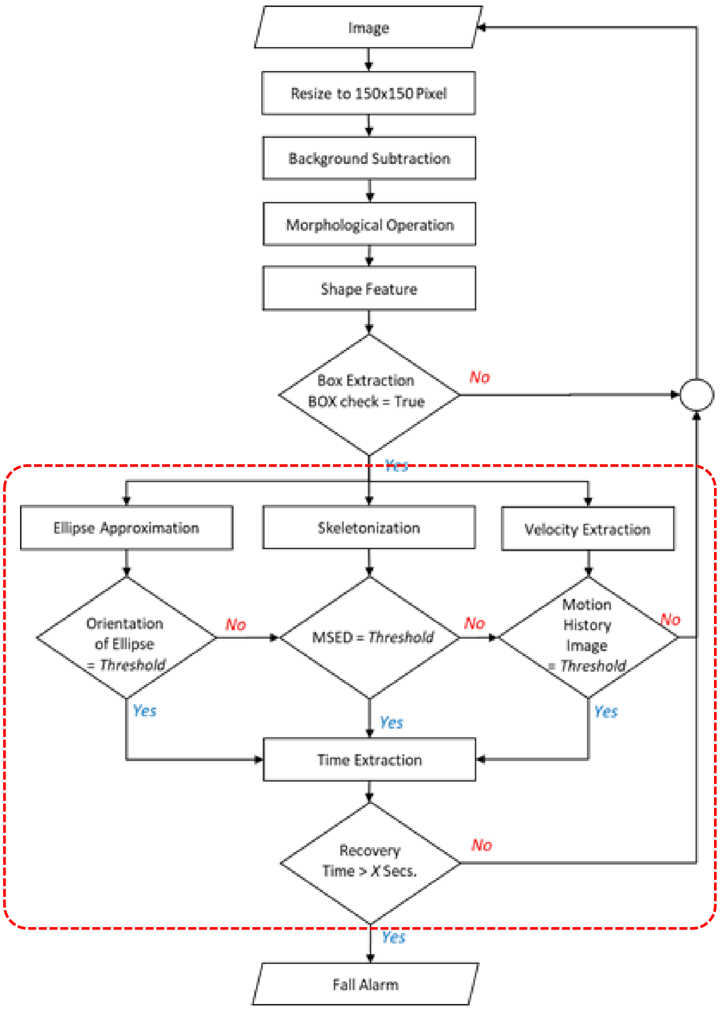


Figure 16. Flowchart of a fall detection system

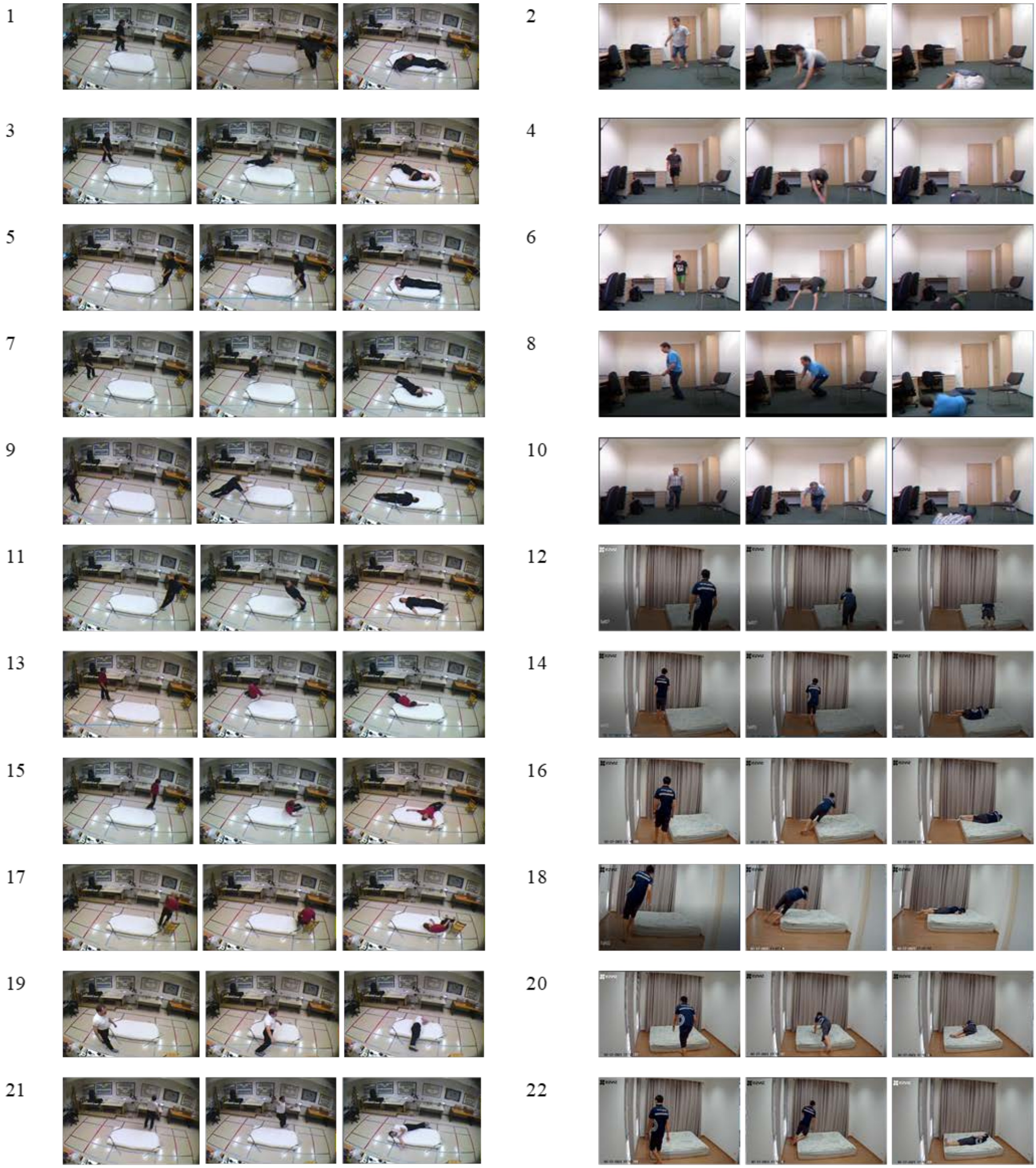


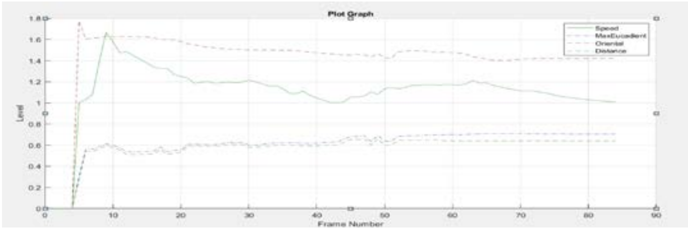
Figure 17. The data sampling of each scenario.

4. EXPERIMENTS

In this section, we project scope frontside view of public data sets and our IP camera (Ezviz C6N 1080p) into object and monitoring on fall criterial of laying on fall only. An experimental result of the proposed object tracking method. The proposed algorithm was implemented in MATLAB 2019b and tested in windows 10 with an Intel dual-core I5 CPU. We have used a video file that is publicly accessible; to convert video size to 150x150 pixels for standardizing. The procedure to fall detection to show in Figure. 16. To extract data and plot to 2D graph follow the character by each criterion. Our data set to include 100 video sequences representing activity normal daily life (ADL) and abnormal activity (Forward falls with occlusion). All these sequences capture the person who enters the room.

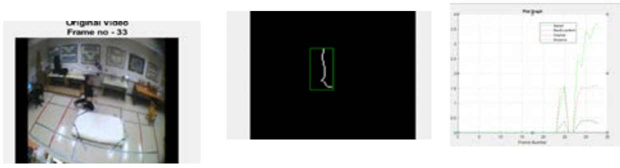
To evaluate the method proposed in this paper we have captured several videos containing a wide set of falls (see Figure 17) for each situation, we used several synchronized Camara and data sets to identify the sample of falls. However, it is impossible to capture the real-life situation where people who in fall incident. This is a way we must design scenarios that were carried out by actors who performed that falls in sample data sets of laboratories and our data from our design in the testing room with appropriate protection. One must notice that the realism of the falling motion is not a key issue here as our approach focuses on the post-fall phase. In the experimental setup, this dimension to reference our data sets to perform area to test condition to room size 7 m per 4 m. including a chair and a sofa were introduced in the capture area to reproduce a normal room. Where people live. Additional such as furniture and amenity introduce occlusions in the videos for most of the scenarios. We assumed that a commercial system based on our technique would be a make-up of internet protocol (IP) video surveillance cameras with a large field of view lenses. In fall scenarios setup, this decides to propose a wide range of realistic fall scenarios according to many previous public works [24]. Each scenario is defined by a set of characteristics, such as main falling direction (Fall, fall forward, fall backward) and departure position (stand up, sit on the floor or chair or sofa). Each scenario is depicted in Figure 17. Some situations, which could lead to false alarms, such as occlusions due to furniture, crouching down on the floor, and lying on the sofa have complexified the scenarios. Overall were provide 100 scenarios of realistic falls and non-fall. These technic data sets are documented. Each scenario was performed once by one subject and approved by a clinician.

(a) Nonfall *(b) Skeleton extract* *(c) Data Generate*



(D) 2D plot result of each criterion

Figure 18. *Example of ADL activity plot*



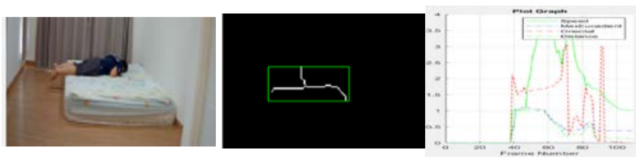
(a) Critical fall *(b) Skeleton extract* *(c) Data Generate*

(d) fall original *(e) Orientation image* *(f) Motion speed*

Figure 19. Example of Fall sample sets

*** *Datasets:* http://www.iro.umontreal.ca/~labimage/Dataset/

(a) Critical fall *(b) Skeleton extract* *(c) Data Generate*



(d) fall original *(e) Skeleton extract* *(f) Data Generate*

Figure 20. Example of Fall sample by IP camera

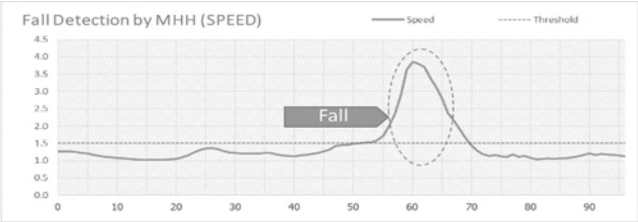


Figure 21. Threshold of Speed by MHI extract

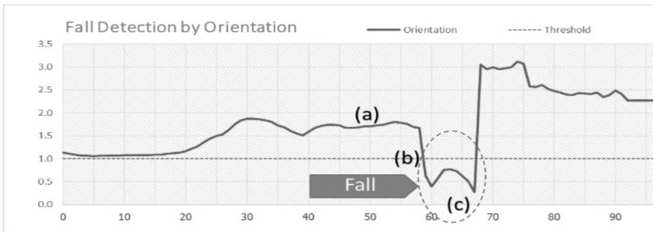


Figure 22. Threshold of Orientations

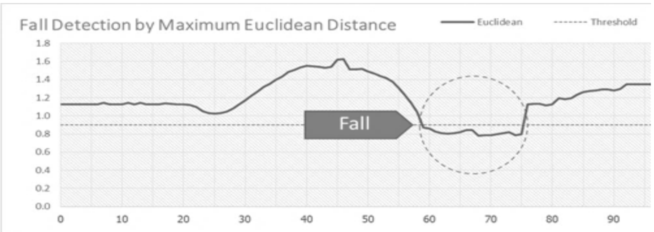


Figure 23. Threshold of Maximum Skeleton Euclidean Distance

Whose research is interested in older adults affected by musculoskeletal and cognitive disorders living in the community. This awareness of different natural falls features in older persons and taking care of performing the simulation fall accordingly. Sequence images of fall have a pattern or fall character Figure.21. on ADL speed depends on object movements such as run jump or lying.

Our fall detection mechanism is based on Maximum Skeleton Euclidean Distance (MSED), the orientation of ellipse (0), Object velocity (Speeds) before time recovery on the last step to confirm fall to alert. This algorithm can detect a change fall characteristic by 4 conditions to confirm falls as follows.

4.1.1 Object speed is higher than a threshold ($V > 2$), This indicated that large motion was detected (Figure 21).

.

4.1.2 The value of orientation of ellipse is lower than the threshold ($\theta < 0.8$ rad), The fall criteria maybe occur(Figure 22.).

4.1.3 Maximum Skeleton Euclidean Distance (MSED < 1.0) (Figure 23.)

4.1.4 Time to recovery is detected by no more motion under the above condition for 5 seconds, The fall defect system will send a notification to the helper.

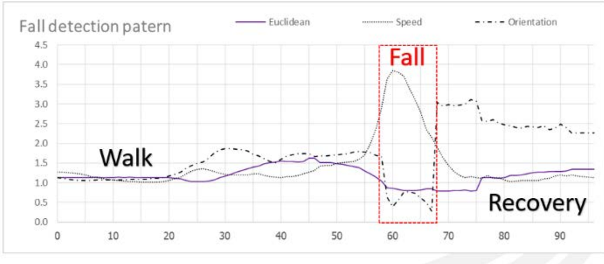


Figure 24. Fall pattern and recovery time.

A fall defected if this criterion is within the threshold during a predefined period (5 Seconds) in our case. This predefined period of 5 s is not a sensitive parameter and could be longer if needed. We chose 5 s because after that period the subject stood up after fall (we do not survey to this information to ask him to stay on the floor to identify) and confounding events were lasting shorter periods. This parameter should by the clinician considering the habits of the elderly person with suitable a time with case by case.

$$Fall = (V > 2)\&(\theta < 0.8\ rad)\ \&\ (MSED < 1.0)\ \&\ (T > 5\ Sec.) \quad (8)$$

We compute the Fall algorithm equation (8) for all images coming from the sequences. As shown in Figure 24 For lying down, the position is a clear difference from others, such as standing up, Sitting down, or crouch. This statement is true for whatever the number of algorithms even threshold to acceptable, this time is defined as the beginning of the post-fall phase when the body hist the ground. Our method can detect a fall event after $t_{fall.}$ The detection is supported to be correct (True positive). If the technique, not see any falls. It is supported to failed (False negative). If it detects a fall event before t_{fall} this time interval, it is supposed to have generated a false detection (false positive) If no fall is detected before t_{fall}, it is considered as TN.
The MSED threshold to set fall detection was simply taken as the result of 100 sample sets. To analyze our recognition result, we compute the sensitivity and the specificity as follows.

Where:

1) True Positive (TP): Number of falls correctly detected (among the 50 fall events)
2) False Negative (FN): Number of falls not detected.
3) False Positive (FP): Number of activities daily lives (ADL) defect as fall (among the 50 activities on this scenario)
4) True Negative (TN): Number of activities daily lives (ADL) does not defect as a fall.

$$\text{Sensitivity: Se} = \frac{TP}{(TP+FP)} \quad (9)$$

Specificity: $Sp = \frac{TN}{(TN+FP)}$ (10)

5. RESULT AND DISCUSSION

To measure systems performed to tall, 100 videos were recorded in two locations (Open public as the laboratory) and house. This section present result obtained from experimental with the data sets previously present. In the first part, the ability of the MSED to detect a fall is examined. Then the result constraints are tested with a new method applied.

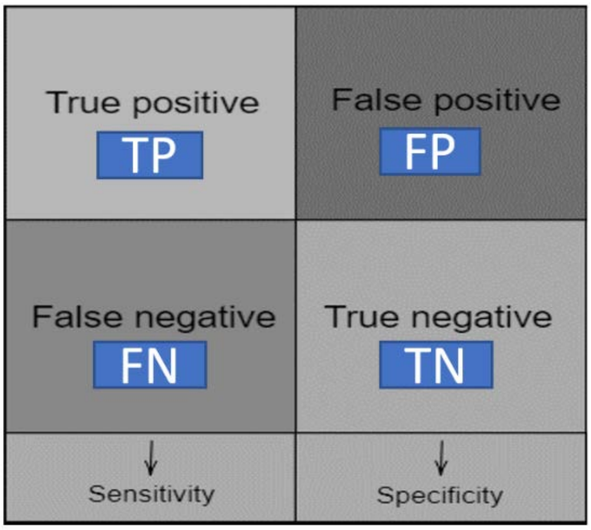


Figure 25. Fall pattern and recovery time.

Table 2. Experiment Result.

Fall indicated	*Fall*	*Non-Fall*
Detection as fall	*50*	*0*
Detection as non-fall	*1*	*49*

Table 3. *Explanation result on true false sensitivity.*

TP (50)	*FP (1)*
FN (0)	*TN (49)*

Table 4. *Summary Result*

Parameter	*Result*
Sensitivity = TP / (TP + FN)	*100%*
Specificity = TN / (FP + TN)	*100%*
Specificity = TN / (FP + TN)	*98%*
Accuracy = (TP+TN)/ (Total Even)	*99%*

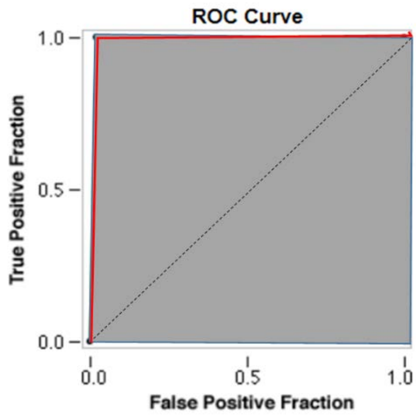


Figure 26. True and False Position Fraction.

ROC Curve

DATA CHARACTERISTICS:
Data collected in 2 categories with category 2 representing.
strongest evidence of positivity (e.g., that abnormality is present).
Number of actually negative cases = 50
Number of actually positive cases = 50

RESPONSE DATA:

Category	1	2
Actually, negative cases	49	1
Actually, positive cases	0	50

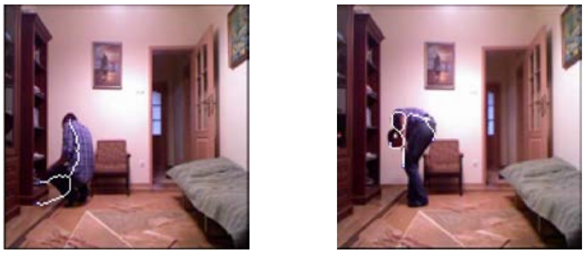
OBSERVED OPERATING POINTS:
FPF: 0.0000 0.0200 1.0000
TPF: 0.0000 1.0000 1.0000
Number of Cases: 100
Number Correct: 99
Accuracy: 99%
Sensitivity: 100%
Specificity: 98%
Pos Cases Missed: 0
Neg Cases Missed: 1
(A rating of 2 or greater is considered positive.)
Fitted ROC Area: degenerate
Empiric ROC Area: 0.99

Table 5. Comparison with another algorithm

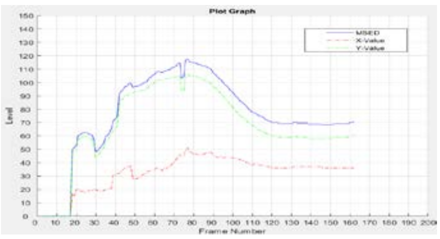
System	**Sensitivity (%)**	**Specificity (%)**	***Accuracy (%)***	***Cpu***
[25]	96.6–100	72.2–86.*4*	86.3–94.1	Intel_R CoreTM i5 2.6 GHz
[26]			79.6–85.4	CortexTM -A9 + FPGAs
[27]	*71-100*	*73*	94	Several
[28]	96	96.9	97.6	CortexTM -A7 900 MHz
[29]			92	Human droid
MSED	100	98	99	Intel_R CoreTM i5 2.6 GHz

The experiment result of the fall detection system is shown in Table 2, and the Explanation result on true false sensitivity is in Table 3. The result indicates a high fall detection performance with 98.0% sensitivity and non-fall detection with 100 % specificity accuracy on Table 4. and Figure 26 to show ROC True and False Position Fraction. Table 5 to a comparison of each algorithm to be performing with MSED by Sensitivity (%) could be identified with conventional threshold [25] and better accuracy (%) to compare with another algorithm.

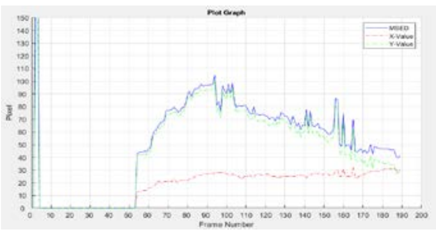
Our methods are tests on falls and some routine daily activities indoor. The activities test are walking, running, sitting on the floor, falling, standing after fall, bending, etc. The Figure 18. To show screenshots of some of the activities performed. The Maximum Euclidean Distance between daily activity lives in Figure 19 and the Fall incident in Figure 20 changes velocity and orientation for everyday activities. The section ‘a’ To show original input ‘b’ for the preparation process and ‘c’ for data extraction to plot with 2D the skeleton of distance from ordinary standing in front of the camera represents the changes to the same space for walking across the camera. Likewise, the part of distance changes for the activities such as sitting down, Figure 27(a). and they are bending on Figure 27 (b) to shows the MSED pattern for the activities to apply to future work.



(a) Sitting Down (b) Bending Down



a) Sitting Down



b) Bending Down

Figure 27. Maximum Euclidean distance ADL pattern

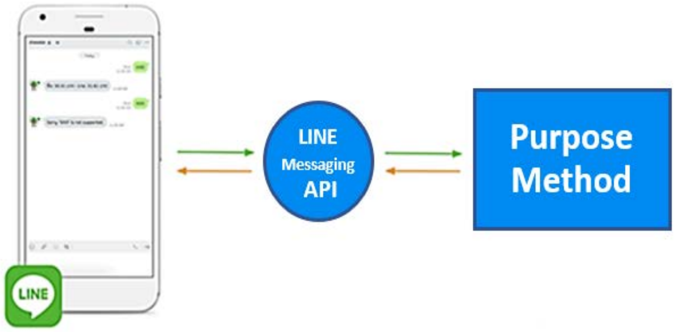


Figure 28. Apply Line notify for our Purpose method.

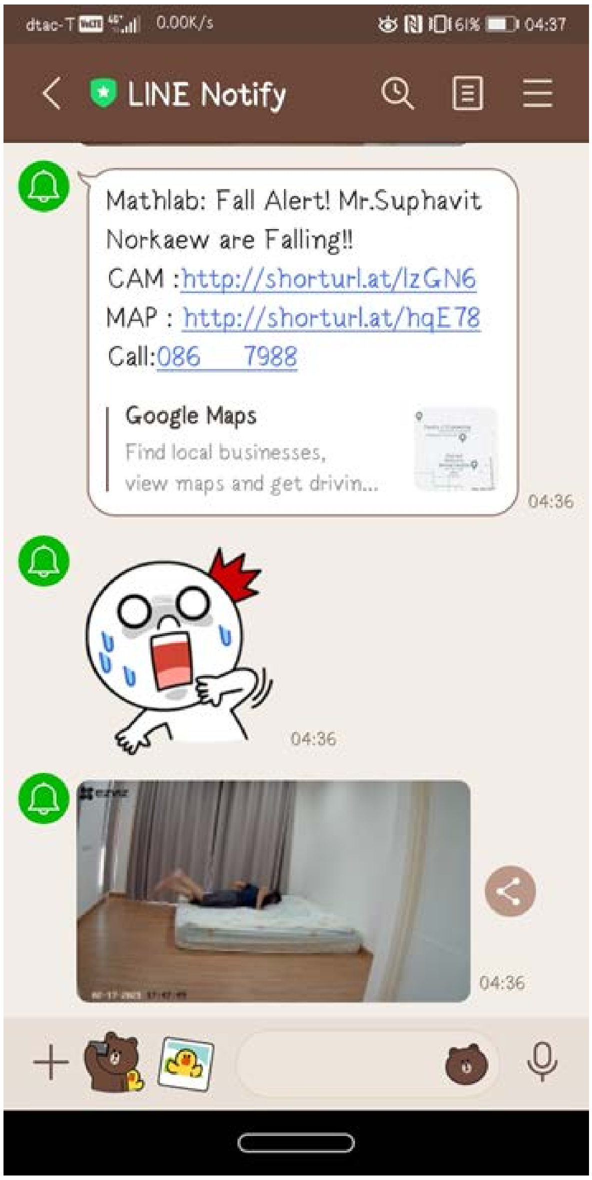


Figure 29. User Screen for Fall Alert system

5.1 Alert system

For the system to be useful, it imust reply to fall events to specific responsible or entities, at this moment the dedicated software for fall detection will apply communication to API messages that transfer the fall result to outside.

The Alert system can communicate with who is monitoring the patient. The alert system features a 2s delay to sending fall alert to avoid sending alert under a peripheral condition where a subject is shifting from a regular state to fall state the minute seconds delay also remove a small number of false-positive currently classified as unstable stage such false positives are a focus area for system improvements and are further detailed in the results and annotation section. The delay system also can address when a fallen subject unsuccessfully attempts to rise, causing a recovery event followed by a subsequent fall even a few seconds later. An example message is shown in Figure 29.

Although privacy in communications has not yet been taken into consideration, the system is based upon the concept of sending only the subject's information once an accident has happened, thus avoiding active monitoring and streaming of data. At this point, we were in favour of using untreated images of fall events, even for locations such as bathrooms, if it results in an improved response to a fall event. However, the experts acknowledged that using filters to reduce image details to the minimum required for fall recognition would be preferable. By the way, for the sample image, we would like to show the captured picture, location, and IP camera URL for those who have a monitor who can direct live access video and real follow-on situations on happening.

In this paper, we wish to evaluate the ability to discriminate lying on the floor position. We perform the fall charter when the body hits on the floor. Our proposed approach considers 3 scopes: (1) Box Extract gets the body shape information of the human body; (2) Extract gets the result of Orientation, MSED, Speed; (3) Time to recovery. Our fall detection system to compile with public data set of Activity Daily life (ADL) public data set to provide walking, sitting, and bending down. and Fall incident to (Fall) to focus only laying on the floor. Figure 18(a) to show activity daily activity by sitting on the fall the result after inputting normal present activity (ADL) by extract of speed, orientation, and Maximum skeleton Euclidean distance. Figure 18(b) to using skeleton extract to determine Maximum Skeleton Euclidean Distance and Figure 18(c),18(d) to generate a 2D plot of activity. Figure 19(a). representing abnormal activity by processing public data set and our data with fall occurred. Figure 20. Figure 19(c),19(f) and 20(c),20(f) show the result of the Video input of the Fall sample and extraction of each criterion by following to generate a 2D plot by following ADL, Fall critical phase, and fall.

5.2 Future work

This research to more develop on next step should be considered by following. Outdoor monitoring and multiple objects with reliability and ambient situation and apply to multicamera to across perspective view to processing to improve night vision mode to comply with individual algorithms to perform on the standalone module and self-operation as workstation or operation on a cloud-based system to full running monitoring and tracking system to be developed. To cover all falling types such as lying on bed or sofa, backward falling. Implementation of fall alarm and monitoring system by individual and complied with the second-order of speed with acceleration algorithm.

6. CONCLUSION

The system performs within this research. We proposed a fall detection can recognize fall from normal activities by using Maximum Skeleton Euclidean Distance (MSED), Ellipse approximation, Velocity and Time to recovery method. And the four conditions with calculation confirm a fall. The 1st condition indicates a significant human motion, 2nd detects a human posture, 3rd sees a velocity even fall 4th condition checks the movement after fall occurs, if no action is detected, the fall will be confirmed, and the notification will be sent to a helper. Furthermore, our fall detection system was proven its robustness in a realistic situation for human fall detection with occlusion from other regular activities.

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