Pre-Impact Fall Detection System Using Real Time Dynamic Threshold and Human Body Bounding Box by Multiple Kinects

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Abstract This work contributes to the fusion of multiple Kinect based skeletons, based on dynamic threshold and bounding box posture analysis, which is the only research work reported so far. As the second leading cause of accidental death, extensive is unintentional falls, which is a vital cause of personal harm, particularly with the venerable. Accordingly, many studies in healthcare are achieving on the improvement of the pre-fall detection system to secure the protection of those who are possible to be concerned. The pre-impact fall detection system has to overcome many difficulties to improve an effective method. Some of the particular difficulties are obtrusion, occlusion, and overlap in the vision-based method.

In this research, the purpose of adopting the bounding box and head velocity method compare with a real-time dynamic threshold is for analyzing the fall and non-fall incident accurately. Furthermore, the skeleton joint position provided by multiple Kinect viewpoints is utilized for the reason of resolving in obtrusion, occlusion, and overlap issues without demanding of markers. Though, the various fuzzy rule base methods also are applied for the final decision of lead time detection and triggering fall alarm. The demonstration of subjects completion is performed 1,100 actions were included 700 times for activities of daily living and 400 times for falling. All activities performed by ten different volunteers, seven healthy young males, and three healthy young females.

The results have shown that 98.55% of the proposed method is higher accurately detected. However, the proposed method provided the lowest specificity at 97.71%, vice versa, and it offered the highest sensitivity at 100.00%. It implies that during system provided higher accuracy and sensitivity in pre-impact fall detection, the recognized precision of normal activities will be reduced. Moreover, the multiple Kinect methods not only provide higher accuracy and sensitivity but also offer higher average lead-time as 505.86 ms.

***Keywords* :** Fall Detection, Elderly, Dynamic Threshold, Bounding Box, Posture analysis

1. Introduction

Human motion detection is one of the most challenging topics in the fall detection system. According to Mastorakis & Makris [11] and Otanasap & Boonbrahm [13], the second leading cause of accidental death extensive is unintentional falls [18], which is a vital cause of personal harm, particularly with the venerable. Accordingly, many studies in healthcare are achieving on the improvement of the pre-fall detection system to secure the protection of those who are possible to be concerned. There are many ways used in human motion detection and identification. These include not only vision markers and marker-less but also wearable devices for the identification of fall. Nonetheless, pre-fall detection often includes wearable devices such as accelerometer and gyroscope [4, 17] for the disclosure of fall incidents in the beginning scene. But the main difficulty [17] of these kinds of technique is the most people have frequently forgotten to consume the devices during the accidents happen.

Accordingly, some researchers try to resolve these obstacles by utilizing vision-based techniques such as Omni-camera [7] and Kinect camera [10, 16] that do not need the individual instance to wear any materials. Appropriately, Kinect cameras proposed by Microsoft for human pose analysis and fall disclosure are enhancing famous as it is moderately low-priced and free Software Development Kit (SDK) is also convenient for improvement objectives. Though, vision-based methods still possess their obstacles such as overlay to happen in some areas and directions within camera viewpoint and the instance. The primary purposes of this investigation are to detect fall incident in the initial scene attending to the pre-impact fall stage and decreasing the overlay issue by using multiple Kinect cameras.

2. Related works

2.1 Pre-impact fall detection system: Pre-impact fall detection system has to overcome many difficulties to improve an effective system [15]. Some of the particular difficulties are obtrusion, occlusion, and overlap in the vision-based method [13]. Additional associated problems are interests in privacy, price, noise, computation complexity, and definition of the threshold based values [15]. Most fall detection systems currently are using both wearable sensors or external sensors that include vision-based or ambient based systems. Wearable sensors [5] are low price and small size electronic devices such as accelerometer and gyroscope [4], are used for collecting individual motion signs from the subjects. External sensors are devices used to transmit environmental signs and movement information of the subject for fall-event detection purpose [1]. Due to their non-intrusiveness and low cost, ambient sensors such as pressure sensors are usually used for tracking the falling occurrence of the subjects [16]. Multi-Kinect based system has also be improved and used to collect signals of interaction in the near or surrounding of the occurrence.

2.2 Velocity characteristics: According to the automatic detection of falls using the velocity profile as a unique feature identification, that has been proposed by Wu [19]. Activities of Daily Living (ADL) being observed include walking, standing up from a chair and sitting down, picking up an object from the ground and lying down on the bed. Falling movements informed include slipping, forward, and backward fall from standing. The determinations are based on vertical and horizontal speeds of the body movement. While falling transitions, the magnitude variation and the timing of the magnitude diversity of both speeds will be higher than usual activities, and the data will be applied to trigger the warning.

2.3 A threshold-based algorithm: As a threshold-based algorithm proposed by Bourke et al. [4], it discriminates between Activities of Daily Living (ADL) and fall events. They utilized a bi-axial gyroscope sensor fastened to the personal body for fall appearance using a threshold-based algorithm. It also estimates pitch and yaw angular speeds to separate among fall events and ADL that was invented by young instances. There are three thresholds applied to predict fall event, angular speeds, angular acceleration, and the difference in trunk-angle. Though there are topics concerning the measurement of the threshold rates, and this affects other improvements.

2.4 Dynamic Threshold and other related approaches: Dimou, Nemethova, & Rupp [6] and Youm & Kim [21] performed a different view of transition detection analysis. Their task determines an automated dynamic threshold model which is valuable for tagging view transitions. Regularly, the speed variation of the mean rate for fall detection could be identified by applying a suitable threshold. Although, the fixed threshold based on the mean rate did work fine for all speed variation of the pre-fall event in this research. According to the dynamic threshold method (DTM) [6, 21], changeable parameters are appropriated to adjust the threshold dynamically. The results show that DTM has demonstrated low calculation demand and robustness into false alarms. Then again, a 3D bounding box technique recommended by [11], which exhibited a different fall detection method based on Kinect sensors. The fall event is determined by velocity and inactivity estimation based on the extension of width, height, and depth of 3D bounding boxes. Furthermore, their proposed method does not need movement history to complete the process of fall detection. Their real-time process [14] has demonstrated improvement in the accuracy and robustness against false positive activities. Moreover, a fall detection method adopting a single camera, based on the 3D trajectory of the head was proposed by Rougier et al. [15]. Their approach could classify fall movements from normal activities by measuring the speed of the 3D head. Furthermore, Li et al. [9] introduced a data blending technique from various Kinects to calibrate the depth of the camera viewpoint with 3D locations of joints on an individual body. Though, Kinect skeleton blending utilizing a Kalman filter is required to estimate the action detection based on 3D positions of skeletal joints. The 3D human skeleton monitoring and ground plane detection based on depth visions obtained by a Kinect method also were used by Yang and Chuang [20]. A skeletal centroid was defined as the mean of 3D body mass for an estimate of the motion vector of 3D centroid speeds within continuous frames. Several significant degrees of velocity were identified most feasible as the chance of falls. Moreover, the levels of lean and sway of the human trunk also mean the rise in the chance of fall significantly.

Moreover, the fuzzy rules based technique compete for the cognitive process of resolving to efficiently proper methods of thinking that are evaluated preferably than particular [8]. Within fuzzy logic, we can imply correlating rules accompanying semantically reasonable variables rather than quantities. Treating the descriptions affords us the feasibility to exhibit incorrection, uncertainty, biased precision, and threshold [22]. In a while, fuzzy logic-based inference methods are expert in working actively and achieve a relationship with human-like decision composition in ambiguous conditions.

3. Methods

Aggarwal and Ryoo [2], demonstrated that 2-dimensional models are comparing to the projection of 3-dimensional real-world view and spatial arrangements of human and objects. A video is a series of 2-dimensional images recorded in sequential order. Furthermore, there are various changes in the space-time description of pure 3-dimensional quantity. Accordingly, a method could describe the motion as a route in a space-time dimension, instead of a volume. Characteristic points determined skeleton joint positions tracked by Kinect could be applied to describe actions of human body parts in features as a set of trajectories. The quantity or path could be derived from the feature set of movement for more processing.

3.1 Head Velocity and Dynamic Threshold Methods. The using of velocity characteristics, both vertical and horizontal directions in a coordinate system using wearable markers to separate falls from normal activities had been proposed by Wu [19]. However, the utilizing of wearable tags is unsuitable for actual life. In this study, 3D head poses recognized from various skeleton structures of Kinect SDK is applied to measure these properties without demanding markers. According to previous research had proposed fixed threshold base methods for comparing with head velocity in various cases. Because of the fixed threshold definition may be suitable for an individual one only, due to personal behavioral, it is not a stereotype. Therefore, the utilizing of a real-time dynamic threshold based on the head position velocity is proposed for classified fall incident from ordinary activities. The head position velocity among frames can be determined from the following equation.

$$RTVel, ADLVel = \left|\sqrt{(x_{i-1}-x_i)^2+(y_{i-1}-y_i)^2+(z_{i-1}-z_i)^2}\right| \quad (1)$$

with *RTVel* being the real-time velocity and *ADLVel* being the activities of the daily living velocity calculated by head position in the frame by frame, x_i, y_i and z_i being the head position in the current frame and x_{i-1}, y_{i-1} and z_{i-1} being the head position of the previous frame. Euclidean distance algorithm was applied as equation (1). As the skeleton data provided by Kinect in 30 frames per second, therefore fps is the time spent per frame, which is about 33.33 msec.

Then, the mean value of velocity in 1 second is computed by applying

$$\bar{X}_{ADLVel} = \frac{1}{n}\sum_{i=1}^{n} ADLVel_i \qquad (2)$$

with $\bar{X}_{ADLVel}$ being the mean value of the head position velocities during performing activities of daily living (ADL) of instances, n being the number of frames in ADL dataset and $ADLVel_i$ being the ADL head velocity of each frame in the ADL dataset.

$$\bar{X}_{RTVel} = \frac{1}{n}\sum_{i=1}^{n} RTVel_i \qquad (3)$$

with $\bar{X}_{RTVel}$ being the mean value of head position velocities while performing real-time activities of instances, n is the number of 30 previous frames in 1 second stored in the buffer.

$$SD_{RT} = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}(RTVel_i - \bar{X}_{RTVel})^2} \ldots(4)$$

$$DT = ((\bar{X}_{RTVel} + \bar{X}_{ADLVel})/2) + SD_{RT} \ldots(5)$$

Next, the standard deviation (SD_{RT}) of each series has been processed as equation (4) then added by an average of $\bar{X}_{ADLVel}$ and $\bar{X}_{RTVel}$ as a result for defining the dynamic threshold (*DT*) of each frame was determined. In equation (5), let *DT* being the real-time dynamic threshold, that estimated by consolidating with a mean value of ADL velocity and real-time detection value supplemented by the standard deviation value of real-time detection.

For head velocity detection, the head position velocity of the current frame ($RTVel_i$) has been compared by dynamic threshold (*DT*), if the $RTVel_i$ value is higher than *DT*, it indicates a danger gesture is recognized. Then, the result of velocity comparison is passed to the step of comparison in fuzzy rule between velocity and bounding box technique. However, only head velocity characteristic insufficient for separate fall and non-fall motions cause of some normal activities also produce speed boosting rapidly higher than the threshold such as starting to run or jump.

As Fig.1 for more understanding, it describes the sample outcome of the previous trial of comparison in regular activity between the dynamic threshold and ADL velocity. The moving average of the dynamic threshold was increased or decreased based on the extreme speed in 1 second or 30 frames provided by Kinect. In the fall phase, during the velocity of the human body higher than the dynamic threshold that adaptive increasing based on previous average speed. It implied that a falling accident is happening. Lead Time, Impact Time, and Pre-Impact Fall detection have also been presented. The time between the first detected and peak time of head velocity was defined as lead time. That indicates it relevant if lead time or pre-impact fall recognized time was detected as long as possible.

3.2 Human Posture Bounding Box: According to a fall detection algorithm utilizing a bounding box proposed in [11], it was applied to recognize during fall appearance by mixing two expanding dimensions of depth and width. While falling incident, the height of the body will be decreased while the width will be increased, where the beginning and ending bounding box dimensions are changed. However, in a single camera viewpoint, the bounding box may contribute inaccurate length of in various directions of perspective. Moreover, the bounding box unable to separate between laying down and falling incident, due to they have the same change rate of width and height. Furthermore, the head velocity could be utilized for separate between routine activities and fall incident, but the change rate of head velocity during the fall may same as jumping and running also. It is the reason for our proposed method in combination with 3D head velocity and bounding box techniques, due to only applying one feature is unable to classify fall accurately. In this research, the purpose of adopting the bounding box and head velocity method is for analyzing the fall and non-fall occurrence precisely.

As equation (6), let *LShoulderX* is the *x* value of left shoulder skeleton position, *LAnkelX* is the *x* value of left ankle skeleton position, *RSholderX* is the *x* value of right shoulder skeleton position, and *RAnkelX* is the *x* value of right ankle skeleton position in the coordinate system. The range of body width is calculated by the maximum comparison of the *x* value by the left shoulder, left ankle, right shoulder, and right ankle then subtracted by the minimum comparison of the *x* value by the left shoulder, left ankle, right shoulder, and right ankle. As equation (7), let *LShouldery* is the *y* value of left shoulder skeleton position in the coordinate system, *LAnkelY* is the *y* value of left ankle skeleton position, *RSholderY* is the *y* value of right shoulder skeleton position, and *RAnkelY* is the *y* value of right ankle skeleton position in the coordinate system. The range of body height is calculated by the maximum comparison of the *y* value by the left shoulder, left ankle, right shoulder, and right ankle then subtracted by the minimum comparison of the *y* value by the left shoulder, left ankle, right shoulder, and right ankle.

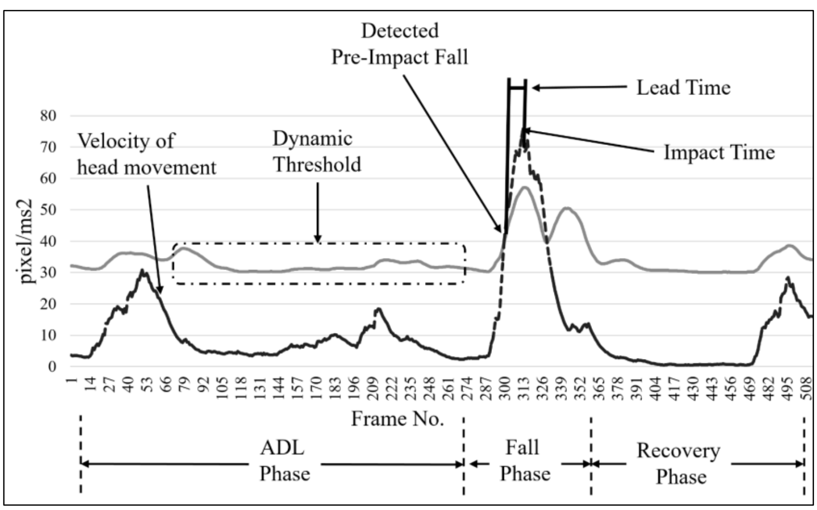

Fig.1 Pre-impact fall detection utilizing head velocity compare with dynamic threshold and bounding box

$$BodyWidth = Max(LShoulderX, LAnkleX, RShoulderX, RAnkleX) - Min(LShoulderX, LAnkleX, RShoulderX, RAnkleX) \tag{6}$$

$$BodyHeight = Max(LShoulderY, LAnkleY, RShoulderY, RAnkleY) - Min(LShoulderY, LAnkleY, RShoulderY, RAnkleY) \tag{7}$$

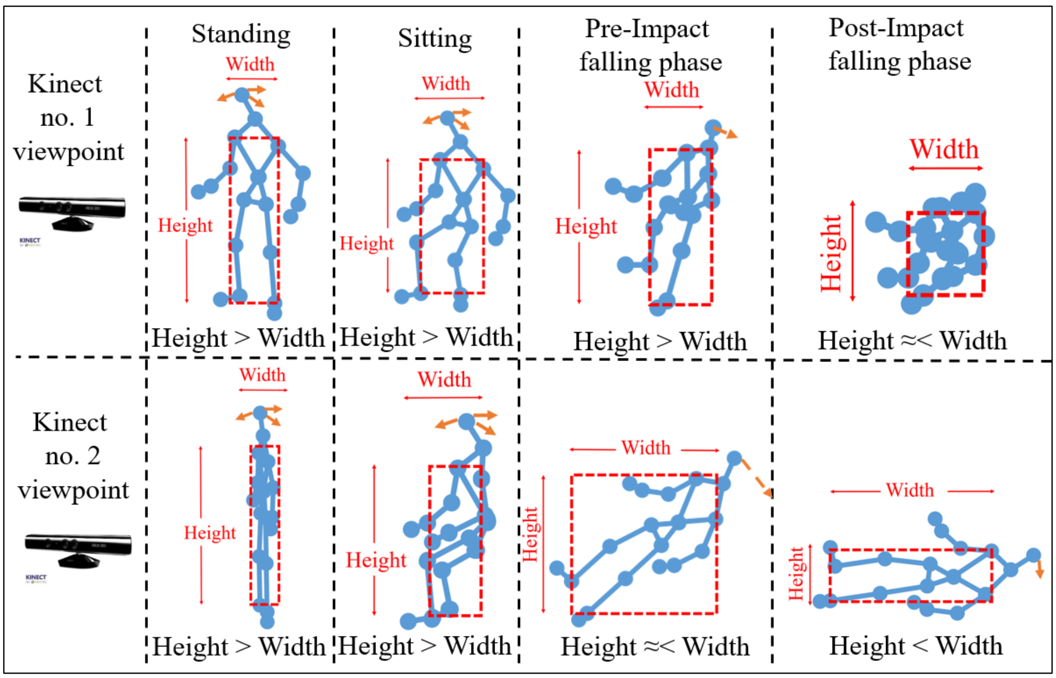

Fig.2 Various posture and bounding box provided by different viewpoint of multiple Kinect.

Table.1 Fuzzy rule for Pre-impact fall detection utilizing multiple Kinect viewpoints.

Methods	**Input variables**	**Fuzzy Rule**
Single Kinect number 1	velocity of head and bounding box from Kinect number 1	*If(BodyHeightKN01 <= BodyWidthKN01) And (VelKN01 > DTKN01)*
Single Kinect number 2	velocity of head and bounding box from Kinect number 2	*If(BodyHeightKN02 <= BodyWidthKN02) And (VelKN02 > DTKN02)*
Multiple Kinect number 1 and 2	velocity of head and bounding box from Kinect number 1 and 2	*If((BodyHeightKN01 <= BodyWidthKN01) And (VelKN01 > DTKN01) Or (BodyHeightKN02 <= BodyWidthKN02) And (VelKN02 > DTKN02))*

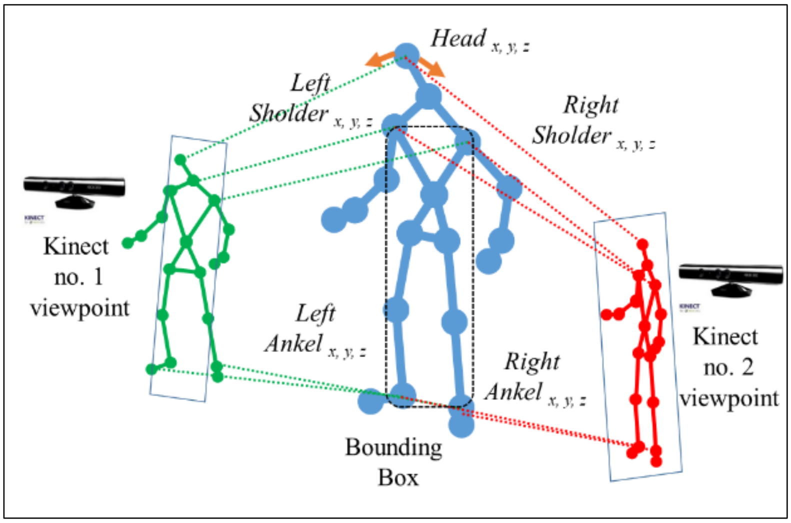

Fig.3 Different viewpoint of Kinects

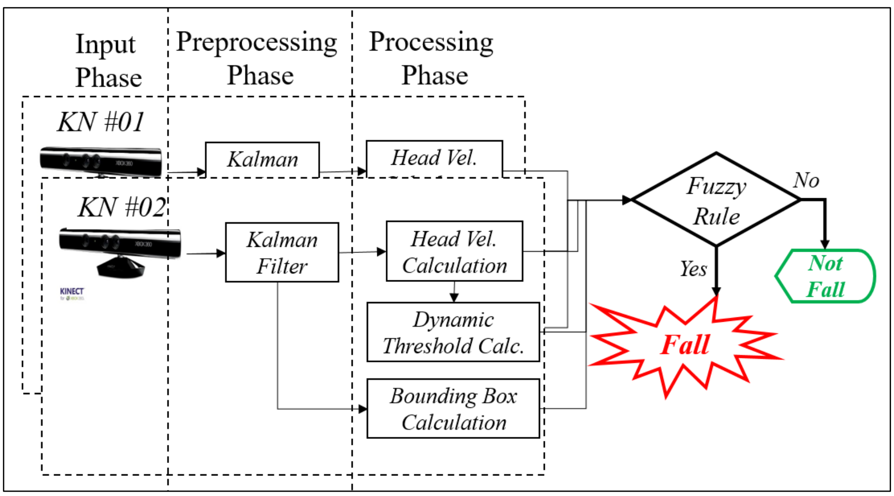

Fig. 4 System block diagram

Fig.5 Lab simulation of falls performs on the top of the thick mat poured with soapy water.

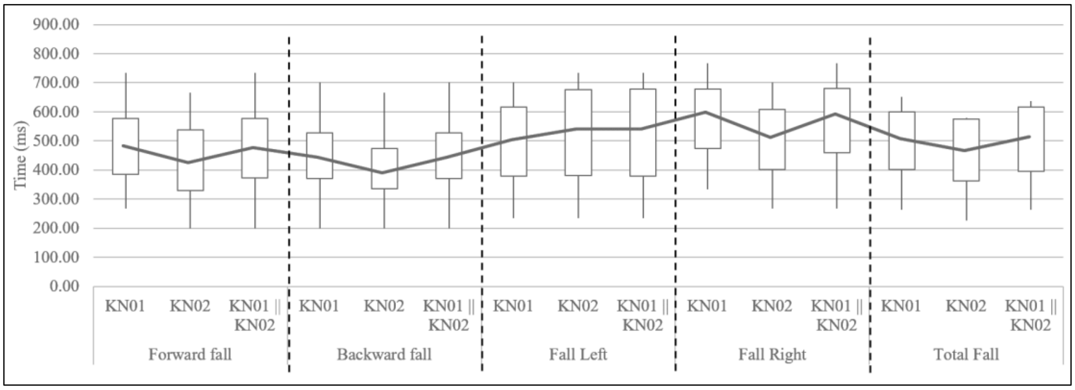

Fig.6 Presents the comparison of pre-impact fall detection lead time in various methods.

3.3 Fuzzy inference based methods for classification between ADLs and fall occurrences: As the amount of fuzzy inputs and semantic variables of each fuzzy set expansions, the number of fuzzy rules expands exponentially. For n variables each of which can estimate *m* values, the number of rules is *mn*. The 3 Sugeno fuzzy sets describing the falling posture, movement changes, and measurement of the various aggregate of methods are indicated first, whereas the final judgment is delivered through thought and trigger on such fuzzy sets, as shown in table 1. For the explanation of each input variable for different methods, let xi is the head velocity from Kinect number *i*. Then let *BodyHeightKN* is height range, and *BodyWidthKN* is the width range of the human body from Kinect number *i*. Furthermore, let *VelKN* is the value of head position velocity, and *DTKN* is a real-time dynamic threshold.

4. Experimental results

Refer to the research review of pre-impact fall detection methods based on a vision-based technique that has been improved and utilized for acquiring data of body movements in ADL and fall occasions [3]. Thus in this research, the various viewpoints that performed by different Kinect© sensors are advanced as exhibited in figure 4. The experimental settings in this research were comprised of two Kinect sensors that were installed on tables of equal elevation of 80 centimeters from the ground. The range between them is 200 centimeters distant at 90 degrees of angle. They were adapted to accommodate monitoring centered around 400 by 400 centimeters space. The 3D coordinates of skeletal joints were produced utilizing Kinect SDK automatically. Several Kinect cameras obtained 20 joint positions at 30 frames per second separately. The trial settings of the method and system block diagram are presented in figures 1 and 2 sequentially.

The demonstration of subjects completion are presented in figures 3 for evaluation purpose, 1,100 actions were included 700 ADL as 100 sitting down, 100 standing up, 100 object picking, 100 walking, 100 jogging, 100 standing still, and, 100 jumping activities and 400 falling activities included 100 forward falls, 100 backward falls, 100 lateral falls left and 100 lateral falls right. All actions performed by ten different volunteers, seven healthy young males and three healthy young females, age between 18 to 22. The data were calculated in real-time to simulate various viewpoints contributed by multiple Kinect cameras. For realistic of falls, all volunteers have performed the fall performances on a 4 x 4 meters width and length, and 10 centimeters thick mat that was pouring with soapy water as shown in Fig.5. In Fig.2, falling occurrences were identified while the speed of head moving was higher than the real-time dynamic threshold and approved by lying down pose applying the bounding box method that provided by multiple Kinect in different viewpoints. The peak velocity value of the head position was moving higher than the real-time dynamic threshold (RDT), and bounding box posture judgment from the 400 falls is summarized in Table.1. The comparison of head velocity with a dynamic threshold and bounding box posture investigation were also combined to separate fall or non-fall detection accurately.

Table.2 Presents the comparison of pre-impact fall detection lead time in various methods.

Fall Type		**Kinect No. 1 (ms)**	**Kinect No. 2 (ms)**	**Kinect No. 1 || No. 2 (ms)**
Forward fall	$\bar{X}$	481.22	433.01	475.41
	SD	95.99	103.97	102.58
Backward fall	$\bar{X}$	449.37	405.18	449.70
	SD	78.50	69.13	78.29
Fall Left	$\bar{X}$	497.91	528.33	528.33
	SD	118.76	147.52	149.14
Fall Right	$\bar{X}$	576.04	505.00	570.00
	SD	102.48	103.78	110.87
Total Fall	$\boldsymbol{\bar{X}}$	**501.13**	**467.88**	**505.86**
	SD	**98.93**	**106.10**	**110.22**
	Min	**263.33**	**225.93**	**263.33**
	Max	**651.85**	**580.00**	**636.67**

According to Table.2 and Fig.6, the comparison of pre-impact fall detection lead-time in various methods are presented. The results show that the longest total average lead time of pre-impact fall detection is the fusion method of multiple Kinect as 505.86 ms before body impact to the ground. The second longer total average lead time is provided by a single Kinect number one as 501.13 ms, and the last longer total average lead time is provided by unique Kinect number two as 467.88 ms. Furthermore, the results have shown that 98.55% of the proposed method is higher accurately detected, as shown in table 3. The second accurately detected is single Kinect number one as 97.82% and Kinect number two as 97.45%% consequently. However, the proposed method provided the lowest specificity at 97.71%, vice versa; it offered the highest sensitivity at 100.00%. It implies that during system provided higher accuracy and sensitivity in pre-impact fall detection, the recognized precision of normal activities will be reduced. Moreover, the multiple Kinect methods not only offer higher efficiency and sensitivity but also provide higher average lead-time as 505.86 ms.

Table.3 Recognition results of accuracy, specificity, and sensitivity of ADL and falling incidents

Activity Types	**Methods**	**Kinect No. 1**	**Kinect No. 2**	**Kinect No.1 || 2**	**Total Performs**
Sitting down	TN (time)	98	97	95	100
	FP (time)	2	3	5	
Standing up	TN (time)	99	99	98	100
	FP (time)	1	1	2	
Object picking	TN (time)	98	98	96	100
	FP (time)	2	2	4	
Walking	TN (time)	100	100	100	100
	FP (time)	0	0	0	
Jogging	TN (time)	99	98	97	100
	FP (time)	1	2	3	
Standing still	TN (time)	100	100	100	100
	FP (time)	0	0	0	
Jumping	TN (time)	99	99	98	100
	FP (time)	1	1	2	
Total ADL	TN (time)	693	691	684	700
	FP (time)	7	9	16	
Specificity		**99.00%**	**98.71%**	**97.71%**	
Forward fall	TP (time)	95	93	100	100
	FN (time)	5	7	0	
Backward fall	TP (time)	99	91	100	100
	FN (time)	1	9	0	
Lateral fall left	TP (time)	91	99	100	100
	FN (time)	9	1	0	
Lateral fall right	TP (time)	98	98	100	100
	FN (time)	2	2	0	
Total falls	**TP (time)**	**383**	**381**	**400**	**400**
	FN (time)	**17**	**19**	**0**	
Sensitivity		**95.75%**	**95.25%**	**100.00%**	
Accuracy		**97.82%**	**97.45%**	**98.55%**	

5. Discussion and Conclusion

Regarding human movement using vision-based is a challenging task due to partial or entire overlay effected either by the direction of the angle between targets or body parts and camera. Additionally, more complication due to calculations of overlay components may happen in irregular poses and positions. This article details the advantage of multiple Kinect sensors for human pose analysis and pre-impact fall detection utilizing a dynamic threshold based and bounding box posture analysis method. The advanced practice used only two Kinect sensors for obtaining appropriated images and skeleton joint positions to determine between routine activities and falls. The peak rates of head velocity compared with a real-time dynamic threshold value, and analysis of the bounding box posture are used to confirm fall incidents.

Moreover, the skeleton overlay difficulty due to the single Kinect camera was approached by utilizing multiple Kinect cameras installed in a right angle. It is a different approach appropriating a fusion of various Kinect based skeletons, dynamic threshold, and bounding box posture analysis for fall detection. Future work will focus on not only extending longer lead-time for pre-impact fall detection but also increasing accuracy with a combination of other devices techniques such as wearable devices for resolving the invisible viewpoint issue in vision-based.

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