Pre-Impact Fall Detection System Using Logistic Regression Model

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Received: 1 March 2023 / Revised: 1st: 14 March 2023 / Revised: 2nd: 26 March 2023 / Accepted: 29 March 2023

บทคัดย่อ ด้วยปัญหาการหกล้มในผู้สูงวัยที่มีอัตราเพิ่มขึ้นเป็นอย่างมาก เพื่อป้องกันผลกระทบที่ตามมาจากการหกล้มนักวิจัยจึงพยายามค้นหาวิธีการที่เหมาะสมในการเฝ้าติดตามและแจ้งเตือนก่อนการหกล้มเพื่อสามารถปกป้องร่างกายจากการกระแทกด้วยถุงลมเป็นต้น ในบทความนี้จึงนำเสนอแนวคิดการเฝ้าระวังและตรวจจับก่อนการหกล้มโดยใช้คินเน็กซ์จำนวน 3 ตัวติดตั้งในมุมมองที่แตกต่างกันทำให้สามารถตรวจจับโดยไม่ต้องใช้อุปกรณ์ที่ติดตามร่างกายซึ่งก่อให้เกิดความรำคาญ อีกทั้งด้วยการตรวจจับของคินเน็กซ์ที่ใช้เฉพาะค่าตำแหน่งของร่างกายคือศีรษะ จุดศูนย์ถ่วงของร่างกาย และตำแหน่งของเท้าทั้งสองข้างเพื่อคำนวณฐานรองรับจึงไม่เกิดปัญหาการละเมิดสิทธิส่วนบุคคล โดยโมเดลที่ใช้ในการตัดสินใจเหตุการณ์หกล้มคือการวิเคราะห์ถดถอยโลจิสติกที่ใช้ตัวแปรทำนายจากการเคลื่อนที่ของศีรษะเปรียบเทียบกับไดนามิกเทรชโชลด์และจุดศูนย์ถ่วงของร่ายกายเทียบกับพื้นที่ฐานการรองรับ จากผลการทดลองทำนายเหตุการณ์ก่อนการหกล้มมีความแม่นยำที่ร้อยละ 98.17 ค่าความไวร้อยละ 87.97 และค่าความจำเพาะร้อยละ 98.98 จึงสามารถสรุปได้ว่าระบบที่พัฒนาขึ้นสามารถตรวจจับเหตุการณ์ก่อนการหกล้มโดยใช้โมเดลการทำนายแบบการวิเคราะห์ถดถอยโลจิสติกสามารถทำงานได้ในเวลาที่กำหนดตามวัตถุประสงค์

คำสำคัญ : ตรวจจับหกล้ม, ไดนามิกเทรชโชลด์, การวิเคราะห์ถดถอยลอจิสติก, การวิเคราะห์รูปแบบ

Abstract The problem of falling among the elderly has significantly increased continuously. Researchers are trying to find a suitable way to monitor and alert before a fall to protect the body using an airbag, for example, to prevent the consequences of falls. In this paper, pre-fall surveillance and detection using three Kinnects installed at different angles enable detection without body tracking devices, which causes trouble. In addition, Kinnect detection uses only the head position, the center of gravity, and the position of the feet to calculate the base support area, so there are no privacy violations. The model used to predict the fall event was a logistic regression analysis that used predictive variables of head displacement versus dynamic threshold and body center of gravity versus base support area. From the pre-impact fall predictor experimental results, the accuracy was 98.17%, the sensitivity was 87.97%, and the specificity was 98.98%. Therefore, it can be concluded that the developed system can detect pre-impact fall events using the logistic regression model and can function at the specified time according to the objective.

***Keywords* :** Fall Detection, Dynamic Threshold, Logistic Regression, Posture analysis.

1. Introduction

Human gesture detection is one of the considerably challenging issues in the pre-impact fall detection system. According to [1] and [2, 3], the second foremost cause of incidental death comprehensive is unintended slips [4], which is a critical cause of individual damage, especially for the esteemed. Consequently, many investigations in healthcare are improving the pre-impact fall detection system to protect those who are possibly concerned. There are many methods used in human gesture detection and designation. These include vision markers and markerless and wearable devices for identifying pre-impact fall. Nonetheless, pre-impact fall detection often includes wearable devices such as an accelerometer and gyroscope [5, 6] to disclose fall incidents in the beginning scene. But the primary tribulation [6] of these technique varieties is that most individuals must remember to consume the devices during accidents. Thus, some researchers try to settle these obstacles by utilizing vision-based approaches such as omni-camera [7] and Kinect cameras [8, 9] that do not need the individual sample to wear any fabrics. Appropriately, the Kinect sensors proposed by Microsoft for human posture analysis and fall exposure are being recognized as relatively low-priced. The free Software Development Kit (SDK) is also convenient for improvement objectives. Vision-based methods still maintain their obstacles, such as overlay in some areas and surveillance within the camera viewpoint and the instance. The primary purposes of this investigation are to detect fall incidents in the initial scene, attend to the pre-impact fall stage and decrease the overlay issue by using multiple Kinect and logistic regression models for prediction.

2. Related work

2.1) Pre-impact fall detection approach: The pre-impact fall detection technique must confound many complications to improve a practical approach [10]. Some particular problems are occlusion, obtrusion, and overlapping in the vision-based method [2]. Further associated troubles are privacy interests, price, noise, calculation complexity, and definition of the threshold-based values [10]. Most pre-fall detection systems currently use both wearable sensors and external sensors that include vision-based or ambient-based systems. Wearable sensors [11] are low-priced, and small electronic devices, such as accelerometers and gyroscopes [5], are used to collect subjects' motion signs. External sensors transmit the subject's environmental signs and movement information for fall-event detection [12]. 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 [9]. Some fundamental problems with wearable devices are that many people need to remember to wear them. Therefore, a vision-based approach has been developed and used for collecting information on human activities of daily living. However, overlay, obtrusion, and occlusion in a vision-based approach [1] are some difficulties. A multi-Kinect-based system has also been improved to collect interaction signals near or surrounding the occurrence.

According to [13], Activities of Daily Living (ADL) monitor human walking, sitting down, picking up an object, rising from a chair, and lying on the bed. The body [13] or head [14] movement of velocities and accelerations has been measured vertically and horizontally. During a fall accident, the accelerations in both extent changing and timing of the magnitude changing will be increasingly higher than normal activities and will be triggered for fall alert. However, the only velocity of movement features needed more to classify ADL and falling events.

2.2) Velocity characteristics: The automatic detection of falls or slips using the velocity silhouette as a unique feature label has been suggested by Wu [13]. 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 lay down on the bed. Falling motions informed include slipping, forward, and backward falls from standing. The conclusions are based on vertical and horizontal velocities of the body motion. While falling transitions, the volume divergence and the timing of the magnitude assortment of both accelerations will be higher than usual movements, and the data will be involved to activate the caution.

2.3) A threshold-based approach: As a threshold-based algorithm suggested by Bourke et al. [5], it distinguishes between Activities of Daily Living (ADL) and fall events. Using a threshold- based algorithm, they operated a bi- axial gyroscope sensor attached to the individual body for fall appearance. It also calculates rise and yaw angular accelerations to divide among fall events and ADL conceived by young samples. Three thresholds are applied to predict fall occasions: angular accelerations, angular acceleration, and dissimilarity in trunk angle. Though there are cases regarding the threshold rates' dimensions, this affects other advancements.

2.4) Dynamic threshold and other related approaches: Dimou, Nemethova, & Rupp [15] and Youm & Kim [16] conducted a further view transition detection study. Their task specifies a computerized dynamic threshold ideal which is practical for ranking view transitions. Regularly, the velocity divergence of the mean speed for fall detection could be identified by applying a reasonable threshold. Although, the fixed threshold based on the average rate did work fine for all speed variations of the pre- fall event in this analysis.

According to the dynamic threshold method (DTM) by Dimou et al. [15] and Youm et al. [16], changeable parameters were claimed to adjust the threshold dynamically. The results shown that DTM had demonstrated low calculation demand and robustness to false alarms. Then again, a 3D bounding box technique was recommended by Mastorakis and Makris [1], which exhibited a different fall detection method based on Kinect sensors. The fall event was determined by acceleration and idleness assessment based on the width, height, and depth extension of 3D bounding boxes. Furthermore, their proposed method can be done without movement history to complete the fall detection process. Their real-time process [3] has improved accuracy and robustness against false positive movements. Moreover, a fall detection method assuming a single camera based on the 3D rotation of the head was proposed by Rougier et al. [10]. Their procedure could categorize fall activities from regular movements by measuring the velocity of the 3D head. Furthermore, Li et al. [32] introduced a data blending technique from various Kinects to calibrate the depth of the camera perspective with 3D areas of joints on a unique body. Kinect skeleton blending using a Kalman filter is required to evaluate the action detection based on the 3D parts of bony joints. Yang and Chuang [17] also used 3D human skeleton monitoring and ground plane detection based on depth visions obtained by a Kinect method. A shrunken centroid was defined as the mean of 3D body mass to estimate the gesture vector of 3D centroid accelerations within continuous frames. Several significant degrees of velocity were identified as most possible 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 procedure contends for the reasonable process of resolving efficiently suitable methods of thinking that are assessed rather than particular [18]. We can indicate correlating rules attending semantically practical variables rather than abundances within fuzzy logic. Feasting the definitions affords us the feasibility of exhibiting erroneous, anticipation, biased precision, and threshold [19]. In a while, fuzzy logic-based inference methods are experts in working actively and achieving a relationship with human-like conclusion arrangement in indefinite conditions.

2.5) Center of Gravity and Based Support Area : As the vertical projection [20, 21, 22] of the center-of-body onto the ground, it is usually called the center of gravity (COG)). Generally, a human would not slip when the projection of COG within the base of support is formed by both human feet on the ground [23]. Likewise, falling would be a high probability while the projection of COG exceeds the base of the support area. The threshold-based algorithm was submitted by Bourke et al. [24] to determine falls and activities of daily living. Regardless, a specified threshold value cannot perform well for all ADLs due to the distinction of their features. If it is defined too high, there is a high prospect that some falling misfortunes remain concealed. Vice versa, if it is deficient, the detection system induces false detections.

Again, logistic regression ideals the ability to simulate the reasoning habit of efficiently considering proper methods of reflection that are calculated rather than explicit [25]. The researcher can intimate mapping rules accompanying linguistically rational variables rather than quantities among logistic regression. The remarks' processing allows them to reveal imprecision, obscurity, partial truth, and threshold.

This study uses a dynamic threshold model for real-time scene change detection in various video arrangements. The head and chest position velocities were used for the first feature in the pre-impact fall detection method. Furthermore, the COG of the subject body was also used for the second feature. These features are combined and classified by logistic regression for pre-impact fall detection and prediction using Kinect sensors.

3. Materials and Methods

Aggarwal and Ryoo [26] revealed that 2-dimensional prototypes were compared to projecting 3-dimensional real-world views and spatial arrangements of humans and objects. A video was a series of 2-dimensional visions recorded in sequential order. Also, there were various transformations in the space-time explanation of the pure 3-dimensional portion.

Accordingly, a procedure could explain the movement as a path in space-time proportions instead of a quantity. Characteristic points specified by skeleton joints tracked by Kinect could be involved to represent motions of human body domains in features as a collection of revolutions. The quantity or the rotation could be derived from the attribute set of motion for additional processing.

3.1) Vision-based using Multiple Kinects: the Kinect sensor is offered worldwide, creating dense visions under low illumination. The depth data is then expropriated to specify a skeletal sample of any human body from Kinect's viewpoint, establishing each pixel as a human element or surroundings [27, 28, 29]. Self-occlusion occurs when the other portion of themselves hides any parts of a human body. When the expenditure of such a camera is low (e.g., the Kinect sensor) in the submitted procedure, multiple and triple Kinect sensors are used.

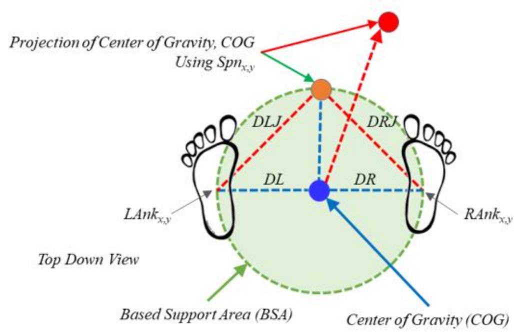

Fig 1. COG calculation

3.2) The Center of Gravity (COG) and Based Support Area (BSA): Whatever the essentials of falling are ifferent and complex, a significant characteristic is the capability to respond efficiently to 'loss of balance,' i.e., counterbalance interference [30]. The critical aspect that conclusively restricts whether or not a balance disorder leads to a fall is our incident, or failure, to recover balance. The calculation of the COG, as shown in figure 1, relates to the model of each skeletal joint offered by Kinect sensors. The Euclidean metric has been used to calculate straight-line distance between different feature skeletal joints. The *DL and DR* range among left and right ankle joint position as equation number (1), and *DRJ* and *DLJ* is the range on both sides of ankles and spine position as defined in equation number (2). Next, the circle region in figure 1 means for the BSA; meanwhile, COG is moving inside the BSA, people are safe, and vice versa, who is possibly unsecured or unstable while COG is running outside the BSA. The red dot is the top view of the COG projectile to BSA from the human spine position. However, in some instances, the COG may proceed outside the BSA, such as sitting and lying down; therefore, only the COG is inadequate for pre-impact fall detection.

$$COG = \frac{1}{2}\left(\sqrt{(Spn_x - LAnk_x)^2 + (Spn_z - LAnk_z)^2} + \sqrt{(Spn_x - RAnk_x)^2 + (Spn_z - RAnk_z)^2}\right) \quad (1)$$

$$BSA = \frac{1}{2}\left(\sqrt{(LAnk_x - RAnk_x)^2 + (LAnk_z - RAnk_z)^2}\right) \quad (2)$$

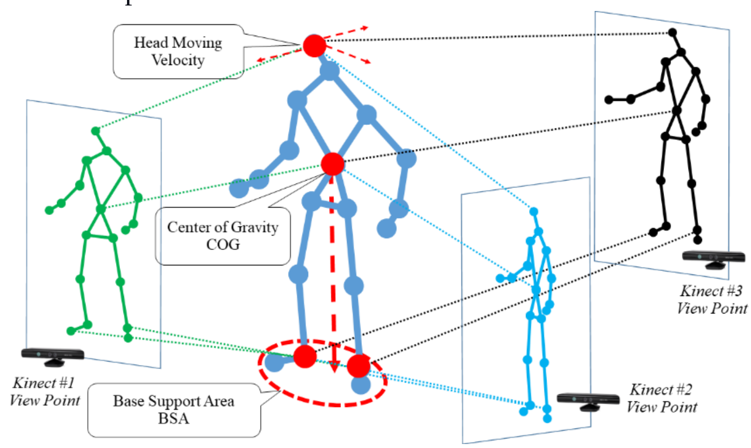

Fig 2. Multiple viewpoints from different Kinects

3.3) Velocity and Dynamic Threshold Approach. The fall event was described by Noury et al. [31] in four phases: pre-fall, critical, pre-impact, post-fall, impact, and recovery fall phases, respectively. Notably, the essential fall or pre-impact fall phase was movement during fall-down, a transient period and more accelerated gesture than normal lie-down. During the pre-impact fall phase, there was a brief free fall time that increases constant vertical and horizontal velocity increasingly. Aggarwal and Ryoo [26] revealed that 2-dimensional prototypes were compared to projecting 3-dimensional real-world views and spatial arrangements of humans and objects. A video was a series of 2-dimensional visions recorded in sequential order. Also, there were various transformations in the space-time explanation of the pure 3-dimensional portion. Accordingly, a procedure could explain the movement as a path in space-time proportions instead of a quantity. Characteristic points specified by skeleton joints tracked by Kinect could be involved to represent motions of human body domains in features as a collection of revolutions. The quantity or the rotation could be derived from the attribute set of motion for additional processing. The use of velocity features in both vertical and horizontal tendencies in a coordinate technique using wearable tags for different falls from normal activities was submitted by Wu [13]. However, wearable markers could be more suitable for actual life. In this study, 3D head poses determined from various skeleton arrangements of Kinect SDK are involved in measuring these properties without requesting markers. Previous research has proposed fixed threshold base techniques for approximating head velocity in various cases. Because the fixed threshold definition may be suitable for a unique only due to personal manners, it is not a stereotype. Therefore, a real-time dynamic threshold founded on the head post acceleration is proposed to classify fall happenings from daily life activity. The following equation can determine the head velocity among frame by frame.

$$RTVel, ADLVel = \left|\sqrt{(x_{i-1} - x_i)^2 + (y_{i-1} - y_i)^2 + (z_{i-1} - z_i)^2}\right| \quad (3)$$

with *RTVel* being the real-time velocity and *ADLVel* being the activities of 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 x_{i-1}, y_{i-1}, and z_{i-1} being the head position of the prior frame. Euclidean distance algorithm was applied as equation (3).

As the frame data provided by Kinect is 30 frames per second, fps is the time consumed per frame, roughly 33.33 msec. Thence, the mean value of acceleration in 1 second is calculated by involving

$$\bar{X}_{ADLVel} = \frac{1}{n}\sum_{i=1}^{n} ADLVel_i \quad (4)$$

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

$$\bar{X}_{RTVel} = \frac{1}{n}\sum_{i=1}^{n} RTVel_i \quad (5)$$

with $\bar{X}_{RTVel}$ being the mean value of head position accelerations while achieving real-time activities of representatives, and n is the number of 30 prior frames in 1 second kept in the buffer.

$$SD_{RT} = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}(RTVel_i - \bar{X}_{RTVel})^2} \quad (6)$$

Next, the standard deviation (SD_{RT}) of each series was processed as equation (4), then added by an average of $\bar{X}_{ADLVel}$ and $\bar{X}_{RTVel}$ as an outcome for specifying the dynamic threshold (*DT)* of individual frames was determined. In equation (7), let *DT* be the real-time dynamic threshold assessed by consolidating with a mean value of *ADL* acceleration and real-time detection value augmented by the standard deviation value of real-time detection.

$$DT = ((\bar{X}_{RTVel} + \bar{X}_{ADLVel})/2) + SD_{RT} \quad (7)$$

For head speed detection, the head position velocity of the present frame ($RTVel_i$) has been reached by dynamic threshold (*DT*), if

$RTVel_i$ value is more elevated than DT, it exhibits a hazardous motion determined. Then, the consequence of velocity comparison is passed to the comparison step in the logistic regression model between velocity and *COG* technique. However, only head velocity characteristics are insufficient for separate falls, and non-fall motions caused by some normal activities produce speed rising rapidly more elevated than the threshold, such as initiating to run or jumping.

3.4) Logistic Regression for classification between ADLs and fall occurrences: Logistic Regression Analysis was a multivariate analysis technique that aims to estimate or predict whether an event of interest will occur or not occur under the influence of a factor. The logistic model consists of dependent variables (or criteria variables) that must be binomial variables (Dichotomous Variables). There can be two values: happened and didn't happen or risk and no risk. Furthermore, independent variables (or predictive variables) may had one or more characters which can be either a Categorical Variable or a Continuous Variable. Logistic regression analysis was related to the binomial probability theory known as Binomial Logistic Regression. If the dependent variable was a polynomial, it was called Multinomial Logistic Regression. Logistic regression is a data analysis tool in research studies to predict events or assess risks. It had therefore been applied in research in various fields, including medicine, engineering, ecology, economics, and social sciences. Logistic regression analysis estimates the probability of occurrence of an event modeled after a logistic function. If there was only one independent variable, the logistic function (Figure 3) expresses the probability of the event shown in the figure below.

$$Prob(fall\ event) = \frac{1}{1+e^{-(\beta_0+\beta_1 X)}} \qquad (8)$$

when β_0 was a constant (when independent variables do not influence it), β_1 was the coefficient of the independent variable (estimated from observational data), X is the independent variable (predictive variable), and e is the natural logarithm (approximately 2.71828...). The logistic function is represented as follows in the case of multiple predictor variables (n).

$$Prob(fall\ event) = \frac{e^z}{1+e^z} \qquad (9)$$

or

$$Prob(fall\ event) = \frac{e^z}{1+e^{-z}} \qquad (10)$$

Where *Z* is a Linear Combination in the form

$$z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \qquad (11)$$

When the occurrence of an fall event is expressed as a probability, so the possibility of not happening is

$$Prob(no\ fall\ event) = 1 - Prob(fall\ event) \qquad (12)$$

If *Prob(fall event)* is substituted as P_y and the value of Z according to equation *(13)* is substituted into equation *(12)*, the function will be formed as follows:

$$Prob(fall\ event) = P_y = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_n X_n)}} \qquad (13)$$

$$\begin{gathered} P_y \geq 0.5 : fall\ events\ occurence \\ P_y < 0.5 : fall\ events\ inoccurence \end{gathered} \qquad (14)$$

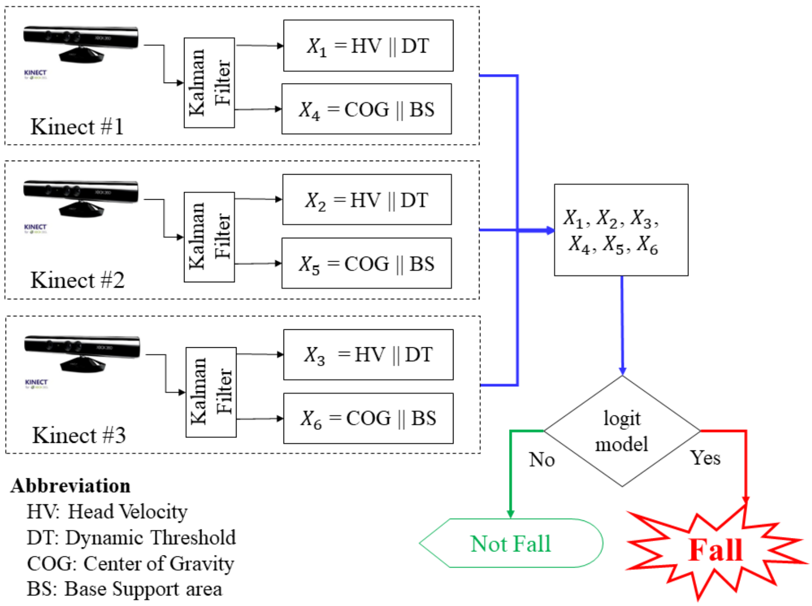

Fig 3. Pre-impact fall detection utilizing head velocity compared to a dynamic threshold and logistic regression.

In such a logistic regression analysis of two possible events of interest, odds are used instead of probabilities. As odds are the ratio of the likelihood of an event occurring and not occurring, that is 0 or greater. The ratio of such opportunities will be in the form of the following:

$$odds = \frac{P_y}{1-P_y} \qquad (15)$$

Equation *(15)* shows the relationship between the dependent and predictor variables, which is not linear. The function must be transformed into a linear form (logistic transformation). The log of odds is obtained, called logit, which is a logit model showing the relationship between the dependent variable and the predictor variable in the following form:

$$log(odds) = ln(\frac{P_y}{1-P_y}) \qquad (16)$$

Which can be expressed in the form of a linear regression equation as follows

$$\log(odds) = logit = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad (17)$$

Figure 3 shows the framework of the system consisting of inputs from the three Kinnects. The input data is filtered for noise by a Kalman filter. The system then compares the head movement speed with the dynamic threshold as X_1 *to* X_3 variables. Furthermore, it approximates the body's center of gravity (COG) with the base support area (BS) as X_4 *to* X_6 variables. The comparative results obtained from the three Kinnects, a total of 6 variables, were used to predict fall outcomes using the Logit Model. The probability ranges from 0 to 1. For example, when the center of gravity moves outside the support area and the head moves faster than the threshold, the probability of a fall is 0.25, meaning there is a fall probability of 25.

$$Logit(y) = 6.8341 - 1.2710\,X_1 - 0.4902\,X_2 - 0.3789\,X_3 - 0.0097\,X_4 - 0.0048\,X_5 + 0.0317\,X_6 \quad (18)$$

$$Prob(fall\ event) = \frac{e^{6.8341 - 1.2710\,X_1 - 0.4902\,X_2 - 0.3789\,X_3 - 0.0097\,X_4 - 0.0048\,X_5 + 0.0317\,X_6}}{1 + e^{6.8341 - 1.2710\,X_1 - 0.4902\,X_2 - 0.3789\,X_3 - 0.0097\,X_4 - 0.0048\,X_5 + 0.0317\,X_6}} \quad (19)$$

$$Prob(fall\ event) \geq 0.5 \quad Fall\ Occurence \quad (20)$$

$$Constant = \beta_0 = 6.8341 \quad (21)$$

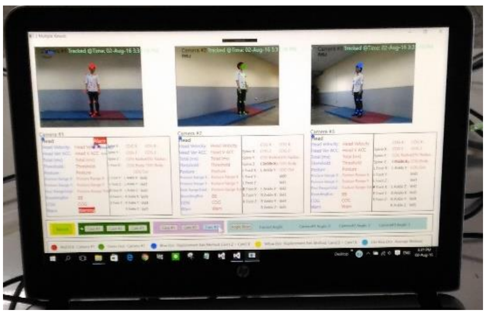

Fig 4. UI of application of multiple Kinect in diffrent view

Table 1 Confusion Matrix

<table>
<tr><td colspan="2" rowspan="2">Total = 5,317</td><td colspan="2">Predicted condition</td></tr>
<tr><td>Positive = 394</td><td>Negative = 4,923</td></tr>
<tr><td rowspan="2">Actual</td><td>Positive = 391</td><td>TP = 344</td><td>FN = 47</td></tr>
<tr><td>Negative = 4,926</td><td>FP = 50</td><td>TN = 4,876</td></tr>
</table>

4. Experimental results and Conclusions

The experiment was conducted by five male volunteers aged 20-25 years. They practiced activities of daily living postures, including falling from simulated situations on mats drenched with soapy water. They were protected from harm by wearing head and body protection. This experiment determined predictive parameters derived from processing head velocity and moving of center of gravity compared with the base of support area from three Kinnects. Using the data stored and processed from the above formula, 5,317 frames were divided into 391 actual falling incident frames and 4,926 actual non-falling frames.

Table 2 Experimental Results

Sensitivity	0.8797
Specificity	0.9898
Accuracy	0.9817
Positive Predict Value	0.8731
Negative Predict Value	0.9904
Positive Likelihood Ratio	86.6774
Negative Likelihood Ratio	0.1214

The values from the metrics can be used to calculate the sensitivity, specificity, accuracy, positive predictive value, negative predictive value, positive likelihood ratio, and negative likelihood ratio from the following formula. True positive (TP): A fall occurs in an actual trial, and the system correctly predicts a fall. True negative (TN): The actual trial did not cause a fall, and the system predicted that it did not occur. False positive (FP): The actual experiment had a fall, and the system predicted that it was wrong that there was no fall. False negative (FN): The experiment did not cause a fall, and the system incorrectly predicted a fall.

Evaluation of the logistic regression model using the confusion matrix found that. The sensitivity was 0.8797, indicating that the prediction result was correct when the fall event occurred at 87.97%, which exceeded 70%. The specificity was 0.9898, indicating that the prediction result was correct when no fall occurred at 98.98%. Accuracy is 0.9817, showing a total accuracy of 98.17%. The Positive Predict Value is 0.8730, representing a percentage of positive predictions of 87.30%, and Negative Predict Value is 0.9904, representing a negative prediction percentage of 99.04%. The positive Likelihood Ratio is 86.6774, and Negative Likelihood Ratio is 0.1214. Therefore, it can be concluded that the application of logistics regression to predict fall events caused by inputs 1) head velocity and 2) center of gravity and base of support area distance calculated from three Kinnects detection with different viewpoints was effective and satisfactory. However, to compare the prediction performance, the researcher must also compare it with other prediction methods, such as artificial neuron networks.

Conflicts of Interest

SAU Ethics Committee for Human Research has considered the Protocol Title of " Development of Pre-Impact Fall Detection System " as COA No. 009/2565, approved on 24/03/2023. The principal investigator is Nuth Otanasap. According to the ethical principles of human research, researchers respect human rights and honor, do not violate rights and safety, and do not harm the research participants.

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