บทความวิจัย

ระบบการตรวจจับก่อนการหกล้มกระแทกแบบอ้างอิงด้วยฟัซซี่เป็นฐานโดยเกณฑ์แบบไดนามิก

Fuzzy Inference Based Pre-impact Fall Detection System Using Dynamic Threshold

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บทคัดย่อ

ด้วยการหกล้มเป็นปัญหาสำคัญทางด้านความปลอดภัยในผู้สูงอายุ เพื่อลดผลสืบเนื่องจึงจำเป็นต้องหาวิธีการป้องกันการหกล้มแบบใหม่ๆ การวิจัยนี้จึงมุ่งเน้นพัฒนารูปแบบการกำหนดเกณฑ์แบบไดนามิกเพื่อตรวจจับก่อนการหกล้มแบบเวลาจริง โดยบูรณาการคุณสมบัติด้านความเร็วการเคลื่อนที่ของศรีษะและหน้าอก ร่วมกับจุดศูนย์ถ่วงของร่างกาย ด้วยกฎฟัซซี่ลอจิก 14 ข้อ แบบ Sugeno เพื่อการกำหนดท่าทางหกล้ม การเปลี่ยนแปลงท่าทาง และการเคลื่อนที่ รวมทั้งการเปรียบเทียบการใช้อุปกรณ์แบบผสมผสานแบบต่างๆ เพื่อการตัดสินใจขั้นสุดท้ายว่าเกิดการหกล้ม ด้วยวิธีนี้ทำให้สามารถตรวจจับก่อนการหกล้ม โดยอาสาสมัครใส่เซ็นเซอร์ที่มีขนาดเล็กเท่าเหรียญ ทำงานร่วมกับ คินเน็กท์ทำหน้าที่ตรวจจับด้วยภาพ โดยไม่บันทึกข้อมูลเพื่อความเป็นส่วนตัว การประยุกต์เกณฑ์แบบไดนามิกที่มีแบบแผนเหมาะกับปัจเจกบุคคล ทำให้ระยะเวลาการแยกแยะตรวจจับการล้มและไม่ล้มแบบเวลาจริงมากที่สุด และได้เปรียบเทียบผลบูรณาการอุปกรณ์หลากหลาย ทั้งคินเน็กท์ตัวเดียว สองและสามตัว ร่วมกับการใช้และไม่ใช้อุปกรณ์สวมใส่ ผลทดลองพบว่าระยะเวลาที่สามารถตรวจจับก่อนการหกล้มได้ คือ 549.83 มิลลิวินาที ด้วยบูรณาการแบบคินเน็กท์สองตัวร่วมกับอุปกรณ์สวมใส่สามารถลดปัญหาการทับซ้อนคลาดเคลื่อนของมุมกล้อง ด้วยความเม่นยำการตรวจจับ ร้อยละ 98.09 กลับกันการตรวจจับด้วยคินเน็กท์เพียงสองตัว ตรวจจับได้ด้วยอัตราความแม่นยำต่ำกว่าเพียง ร้อยละ 93.00

คำสำคัญ: การตรวจจับการหกล้ม การตรวจจับก่อนการหกล้ม เกณฑ์แบบไดนามิก ฟัซซี่ลอจิก การตรวจจับการหกล้มในผู้สูงวัย

Abstract

Problems of falling are particularly vital safety in seniors. For these reasons, increasing a useful fall prevention approach is necessary to relieve the infliction of falls. This study focuses on a dynamic threshold model for real-time pre-impact fall detection that enables the falls to be identified before the body crashes to the ground. The velocity of head and chest position and the center of gravity of the subject body used for the feature combination classified by fuzzy inference for pre-impact fall detection. It only needs subjects to wear some tiny coin-size sensors that combine with the Kinect sensor, vision-based, without recording any data due to privacy issue. The dynamic threshold-based model with stereotypes suitable for an individual one, is applied for real-time fall and non-fall classification for the longest lead time of pre-impact fall detection. Moreover, the various kinds of integration of single, multiple, and triple Kinect combined with and without the wearable device are evaluated. The 14 rules of Sugeno fuzzy set defining the falling posture, movement transitions, and comparison of the different combination of devices are inferred first, whereas the final decision is produced through thinking and trigger on such fuzzy sets. The experimentation result found that the highest lead-time of pre-impact fall detection is 549.83 ms. However, the integration method that combined multiple Kinect with the wearable device can reduce camera overlapping and obscurity with the highest accuracy about 98.09 percent. Vice versa, the method using only multiple Kinect without the wearable device provide lower accuracy than 93.00 percent.

Keywords: Fall Detection, Pre-Impact Fall Detection, Dynamic Threshold, Fuzzy Logic, Fall Detection in Elderly

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Introduction

Falls are a vital safety interest, particularly in seniors. Almost 28–35 % of seniors aged 65 and over fall at least once every year [1]. For the sake of minimizing the impacts of aging as the human constitutional failures, therapeutics are designated. Besides, seniors are likely to recurrent falls after a fall-related occurrence. Those frequently leads to the lack of movement and self-sufficiency [2]. For these reasons, increasing a useful fall prevention approach is necessary to relieve the infliction of falls, particularly in seniors. After fall movement detection is supposed to admit proper therapeutic support for fall patients, consequently avoid accidental injuries caused by long lie syndrome [3]. Dissimilarly after or post-fall movement detection, pre-impact fall detection is accomplished to defeat the conditions specified earlier. Pre-impact fall detection relates to the method that enables falls to be identified before the body crashes to the ground (i.e., the body-ground collision).

Related Work

Pre-impact fall detection method is a significant application that has been used to save a person who takes risks [4-7]. Not only those issues but cost, noise, privacy, the complexity of computation and the suitable threshold value for pre-impact fall detection also are concerned [8]. Currently, most fall detection methods are not only using wearable and ambient based devices but also vision based. Although wearable devices [9] are low cost and small size electronic devices that can be attached to clothing or wearing in body parts, such as gyroscope and accelerometer [10]. Some of the essential problems of wearable devices are most people usually forget wearing them. Therefore vision-based approach has been developed and used for collecting information on human activities of daily living. However overlay, obtrusion, and occlusion in vision-based approach [11] are some of the essential difficulties.

According to Wu, G. [12], Activities of Daily Living (ADL) is monitoring of human walking, sitting down, picking up an object, rising from a chair and lying down on the bed. The body [12] or head [8] movement have been measured in both of vertical and horizontal of velocities and accelerations. During fall accident, the velocities in both of magnitude 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 not enough to classify ADL and falling event more accurately.

As the vertical projection [13] of the center-of-body onto the ground, it has usually been called the center of gravity (COG). Generally human would not fall when the projection of COG within the base of support which is formed by both human feet on the ground [14]. Vice Versa, the falling would be the high possibility while the projection of COG is outside of the base of support. The threshold-based algorithm was proposed by Bourke *et al.* [15] to differentiate fall and activities of daily living. However, a fixed threshold value cannot accomplish well for all ADL due to the difference of their attributes. If it is determined too high, there is the high possibility that some falling accidents were still undetected. Vice versa, if it is too low, the detection system generates false detections.

Furthermore, fuzzy logic models the ability to emulate the rational way of thinking to efficiently appropriate methods of thinking that are estimated rather than specific [16]. Among fuzzy logic, we can intimate mapping rules attending linguistically logical variables rather than quantities. Processing the statements provides us the possibility to reveal imprecision, ambiguity, biased truth and threshold [17]. According to Takagi–Sugeno (TS) fuzzy inference system has been used to trigger a fall alarm utilizing the information about the person's motion and the distance of gravity center to the ground. The Sugeno method of fuzzy inference had been Introduced in 1985 [18], this technique is similar to the Mamdani approach in many regards. The first two components of the fuzzy inference method, fuzzifying the inputs and utilizing the fuzzy operator, are similar. The main contrast between them is that the Sugeno output membership purposes are either linear or constant.

In this study, we focus on a dynamic threshold model for real-time scene change detection in different video sequences. The velocity of head and chest position were used for the first feature in 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 fuzzy inference system for pre-impact fall detection and prediction using both wearable and Kinect sensors.

Materials and Methods

1) Vision-based using Multiple Kinects: the Kinect sensor is proposed for the worldwide market, which produces dense depth images under poor illumination conditions. The depth data is then appropriated to determine a skeletal model of any human body in Kinect's viewpoint, which specifies each pixel as being a human body part or environment [5, 19-20]. Self-occlusion occurs when the other portion of themselves hides any parts of a human body. Particularly, when the expense of such a camera is low (e.g., the Kinect sensor). In the proposed system, multiple and triple Kinects are used.

2) Wearable Device: Wearable sensor methods propose various benefits concerning size, weight, cost, power extermination, ease of use and portability [21]. They enable tracking without the constraints due to demands for ecosystem structuring and privacy attention. The MetaWearC [22] is a whole development and creation platform for wearable and connected device applications. It emphasizes the ultra-low power nRF51822 SoC, implementing energy efficient smartphone communication and central processing. We used MetaWearC [23] units, which include a tri-axial accelerometer and tri-axial gyroscope IMU from Bosch (BMI160). The inertial sensor time series estimated by the body mounted sensors were recorded together with data from the desktop applications. Body movement events for an individual were detected from these sensors processed by the dynamic threshold algorithm. All disadvantages are improved by our method, which is simple, inexpensive and quick.

3) Velocity Characteristics: According to the fall event was explained by [24] in four phases as pre-fall phase, critical fall or pre-impact fall phase, post-fall or impact phase and recovery fall phase respectively as shown in figure 2. Importantly, the critical fall or pre-impact fall phase is motion during fall-down that short period and very accelerated movement than normal lie-down. During the pre-impact fall phase, there is the free fall temporary time that constant vertical and horizontal velocity increasingly.

4) The Center of Gravity (COG) and Based Support Area (BSA): Whatever the conditions of falling are various and complicated, a significant factor is the ability to react efficiently to 'loss of balance,' i.e., balance interference [25]. The critical factor that conclusively defines whether or not a balance disturbance leads to a fall is our experience, or failure, to recover balance. For the calculation of the COG, as shown in figure 1, it relates to the model of each skeletal joint position offered by Kinect sensors. The Euclidean metric has been used for the straight-line distance calculation between difference feature skeletal joint positions.

The DK is range among left and right ankle joint position as equation number (9), and Dj_1 and Dj_2 is the range on both sides of ankles and spine joint position as defined in equation number (8). Next, the circle region in figure 1 means for the BSA, meanwhile COG is moving inside BSA people are safety, vice versa who possibly unsecured or unstable while COG is running outside the BSA. The black dot is presented as the top view of COG projectile to BSA from human spine position. However, in some instances, the COG may proceed outside the BSA such as sitting and lying-down, therefore only the COG inadequate for pre-impact fall detection.

$$\mathrm{DJ} = \frac{1}{2}\left(\sqrt{(\mathrm{Spine_x} - \mathrm{LAnkle_x})^2 + (\mathrm{Spine_z} - \mathrm{LAnkle_z})^2} + \sqrt{(\mathrm{Spine_x} - \mathrm{RAnkle_x})^2 + (\mathrm{Spine_z} - \mathrm{RAnkle_z})^2}\right) \quad (1)$$

$$\mathrm{DK} = \frac{1}{2}\left(\sqrt{(\mathrm{LAnkle_x} - \mathrm{RAnkle_x})^2 + (\mathrm{LAnkle_z} - \mathrm{RAnkle_z})^2}\right) \quad (2)$$

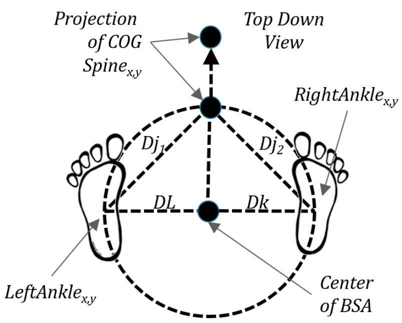

Figure 1 COG calculation

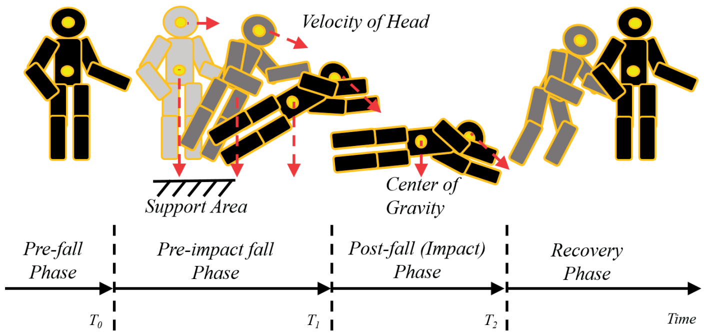

Figure 2 Four Phases of Falling Motion [24]

5) Spatiotemporal Dynamic Threshold Model: Though, a fixed threshold value cannot achieve appropriately for all activities of daily living due to the variety of their characteristics. The major problem is to reach the best estimation for each fixed threshold determination. If the fixed threshold has been set too high, it highly probable that some falling events are still undetected. Vice versa, if it is fixed too low, the detection system makes false detections as well. In this proposed method, not only using head position but also the center of gravity (COG) from various skeleton constructions provided by Kinect SDK also are used to compute without marker required. The dynamic threshold based using previous 30 frame value of the head position that provided by Kinect SDK. The simple mean value X and the standard deviation SD_n of X in the specified window are calculated as follows:

$$\mathrm{RTAcc}, \mathrm{ADLAcc} = \left|\sqrt{(x_{i-1} - x_i)^2 + (y_{i-1} - y_i)^2 + (z_{i-1} - z_i)^2}\ \right| \tag{3}$$

With Euclidean distance method [25] in (3), let the *Acc* being the acceleration of head position calculated by X_i, Yi and Z_i values provided by each Kinect sensor. This equation is defined as both acceleration calculation of *ADLAcc* movement and real-time pre-impact fall detection (RTAcc) also.

$$\overline{X}_{ADL} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{ADLAcc}_i \tag{4}$$

Then within equation number (4) let X_{ADL} being the mean value of head position velocities in each sliding window, let ADLAcc_i being the acceleration of head position in ADL in the dataset and let n being the number of the frame in ADLAcc dataset. The purpose of this equation is for defining the mean value of the head position in ADL for letting it be the based on dynamic threshold definition.

$$SD_{ADL} = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}(\mathrm{ADLAcc}_i - \overline{X}_{ADL})^2} \tag{5}$$

$$\mathrm{ADLth} = \overline{X}_{ADL} + SD_{ft} \tag{6}$$

$$\overline{X}_{rt} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{RTAcc}_i \tag{7}$$

In equation number (5), let SD_{ADL} being the standard deviation (SD) of each ADL series from the dataset have been calculated then combining it with ADL mean value (X_{ADL}) as the result of the threshold in ADL (ADLth) that defined in equation number (6). Within equation number (7), let X_{rt} being the mean value of head position velocities in real-time detection, and let n is the number of the previous frame in 1 second about 30 frames (33 millisecond per frame) or 30 sliding windows provided by Kinect or wearable device that calculated by equation (3) as Real Time Acceleration (RTAcc). The standard deviation (SD_{rt}) of each sliding window series can be calculated by equation number (8).

$$SD_{rt} = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}(\mathrm{RTAcc}_i - \overline{X}_{rt})^2} \tag{8}$$

$$DT = ((\overline{X}_{rt} + \overline{X}_{adl})/2) + SD_{rt} \tag{9}$$

In equation (9), let DT being the dynamic threshold, that calculated by combining with a mean value of ADL and real-time detection value added by the standard deviation value of real-time detection also. For head velocity detection, the head velocity of each current sliding window (RTAcc) has been compared by DT, if RTAcc_i is higher than DT that means an injured possibility. Then, the result of velocity comparison is passed to the step of comparison between velocity and COG using DT. However, only head velocity feature inadequate to separate fall and non-fall activities cause of some activities also make velocity increasing immediately higher than the threshold such as start to running and jumping.

The result of the previous experiment [5-7] of comparison in regular activity between the dynamic threshold and velocity of daily living. The moving of dynamic threshold was increased or decreased based on the last velocity in 1 second or 30 frames that provided by Kinect. Lead Time, Impact Time, and Pre-Impact Fall detection have also been presented also. In the fall phase, during the velocity of human body higher than the dynamic threshold that adaptive increasing based on previous normal velocity. It implied that falling accident happened. Furthermore, the time during first detected or pre-impact fall happening and peak time of human body velocity was defined as lead time. That means it valuable if lead time or fall recognized time was detected as long as possible.

6) Fuzzy Inference Based Techniques for Separation between ADLs and Fall Incidents: Since the number of fuzzy inputs and linguistic variables of any fuzzy set extensions, the amount of fuzzy rules increases exponentially. For n variables each of which can consider m values, the amount of rules is mn. The 14 rules of Sugeno fuzzy set, as Table 1 available online at http://bit.ly/fuzzyrule-otanasap, defining the falling posture, movement transitions, and comparison of the different combination of devices are inferred first, whereas the final decision is produced through thinking and trigger on such fuzzy sets. For the definition of each input variable for various methods, let x_i is the head velocity from Kinect number i. Then let y_i is COG of human body from Kinect number i, z is the velocity of wearable device, A_i is the dynamic threshold of velocity from Kinect number i, B_i is BSA of human body from Kinect number i, C is the dynamic threshold of velocity from wearable device, D_1 is fall is happening, and D_2 is ADL.

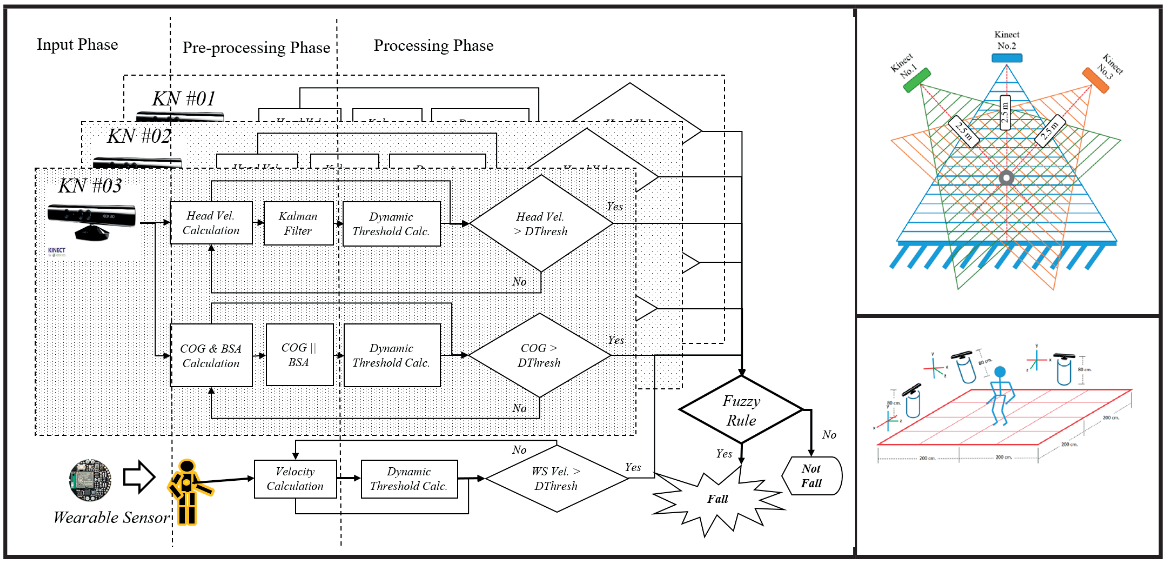

Figure 3 System Block Diagram of the proposed method, different Kinects viewpoint, set up installed on the stack

Procedure and Experimental

According to the literature review of pre-impact fall detection techniques based on computer vision based approach that has been developed and applied for obtaining data of human movements in ADL and fall accidents [1]. Therefore in this experiment, the multiple perspectives that implemented by various Kinect© sensors combined with the wearable device are proposed as shown in figure 3. The three Kinects were installed on the same height stack from the floor about 80 centimeters. The distance between them is 200 centimeters apart in 45 degrees of angle. Tracking spaces are about 400 by 800 centimeter. Each Kinect acquired 1024x1280 color images and 20 skeleton joint positions in 30 frames per second. The experimental performed by ten adolescents as volunteer age between 19 to 23 years, including 8 males and 2 females. They performed a sequence of regular ADL at a natural speed. ADL was recorded in 1100 videos. For realistic of experiments, they are performed on a 30 centimeters thick mat and 4 meters width by 8 meters long, poured soapy water on the top of the mat. As figure 4, the fall performing examples are captured for evaluation purpose that included sideward, frontward and backward falls. For realistic of the experiments, all volunteers are performed on 30 centimeters thick mat and 4 meters width by 8 meters long.

Results and Discussion

Experimental results for ADL included sitting down, standing up, object picking, walking, jogging, standing still, and jumping and simulate of falling events involved forward fall, backward fall, lateral fall left, lateral fall right. The result of experiments in various ADL activity types and the different methods of device combination present that method (n) with combined triple Kinect and wearable device, is the higher true-negative rate with correctly define as ADL in 691 times and only tiny false alarm with false positive rate in 19 times, as totally 700 times. That can be calculated specificity as 97.29 %. The second group of higher true-negative rate is the method (k), (l), and (m). They perform prediction correctly as ADL in 675 to 677 times and only little false alarm with the false positive rate in 23 to 25 times, 96.71 % to 97.43 % specificity. The third group of the true-negative rate higher than 95 percent is methods (e), (d), and (f). They operate prediction accurately as ADL in 666 to 670 times and only 30 to 34 times of false alarm, 96.71 % to 97.43 % specificity. The last group of the true-negative rate lower than 95 percent is methods (j), (g), (i), (b), (h), (a), and (c). They produce prediction precisely as ADL in 649 to 664 times and 36 to 51 times of false alarm, 92.71 % to 94.86 % specificity.

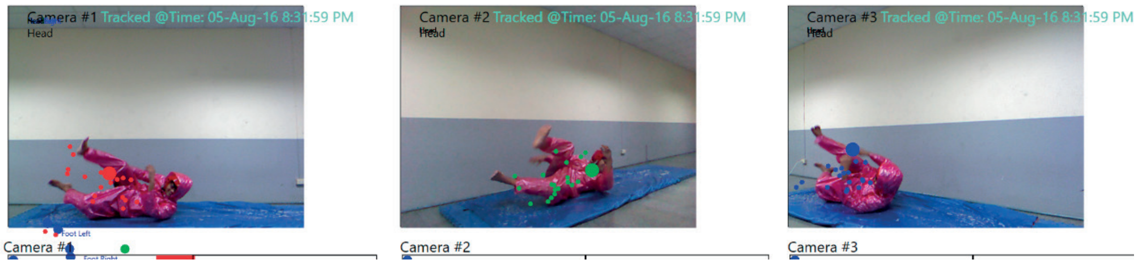

Figure 4 The fall performing examples are captured for evaluation purpose

According to the figure 5, the highest average pre-impact fall lead-time about 549.83 ± 129.46 ms detection time prior impact to the ground is the method (j) that integrated with triple Kinect viewpoint without the wearable device. The second highest average lead-time prior impact of 549.75 ± 129.79 ms is the method (h) that integrated with multiple Kinect numbers one and three without wearable device also. The third highest pre-impact fall detection lead-time with 538.92 ± 130.28 ms is the method (l) and (n) consecutively. Both of them consist of multiple and triple Kinect viewpoints combined with wearable sensor sequentially.

Refer to figure 6, the comparison for the result of accuracies, sensitivities, and specificities in various methods of both fall event and ADL have been presented. We found that the group of the technique only implemented single Kinect (a), (b), and (c) produce the lowest not only sensitivity and specificity but also accuracy and lead time. Furthermore, the group of the method that implemented only Kinect both single and multiple without the wearable device proceeds lower efficiencies and specificities than the method group of integrated both Kinect and wearable device together. However, the methods that combined both only multiple Kinect with and without the wearable device can provide higher lead time than only single Kinect with and without the wearable device. Commonly, the decision of airbag inflation is made within 15 to 30 milliseconds after the origin of the accident and fully inflated within 60-80 milliseconds approximately. According to the result of [26], the velocity and threshold-based features were used by implementing 3 markers placed on the posterior side of the trunk with 3 cameras. The average lead time before impact about 300 to 400 milliseconds approximately compare to our experimental about 538.92 milliseconds.

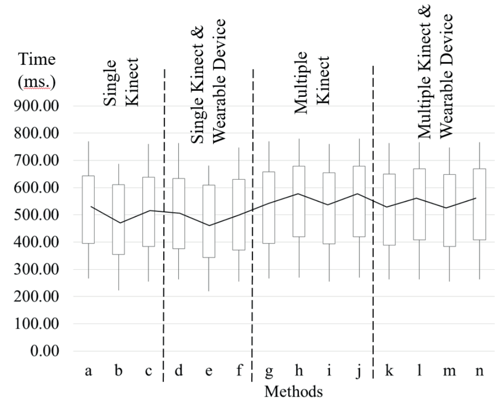

Figure 5 Pre-impact fall detection time in various methods

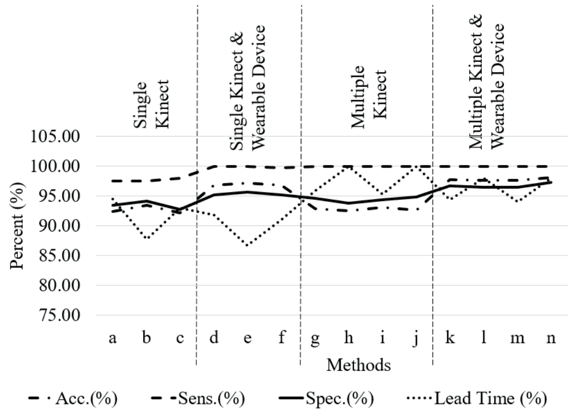

Figure 6 The comparison for accuracies, sensitivities, and specificities in various methods of fall and ADL

Conclusions

The dynamic threshold-based model that stereotypes and suitable for an individual one, are applied for real-time fall and non-fall classification for the longest lead time of pre-impact fall detection. Moreover, for selecting proper device combination techniques that differ from previous experimental [7] using only triple Kinect, various kinds of integration are evaluated that involved single, multiple, and triple Kinect combined with and without the wearable device.

The experimentation found that the highest average lead-time of pre-impact fall detection is 549.83 ± 129.46 ms prior impact. The next highest is 538.92 ± 130.28 ms that the method consists of multiple Kinect combined with wearable sensor sequentially. It shows that only using multiple Kinect without wearable device can produce longer lead time. Though, the method that combines multiple Kinect sensors with the wearable device can produce later lead time than the first one only in 10 ms approximately. However, the integration method that combined multiple Kinect with the wearable device can reduce camera overlapping and obscurity in vision-based with the highest accuracy about 98.09 percent. Vice versa, the method using only multiple Kinect without the wearable device provide lower accuracy than 93.00 percent. It does not affect the operation of peripherals such as airbag that require inflation time only 30 ms. Although with the integration method, it can reduce camera overlap and obscurity in vison-based.

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