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A NON-INVASIVE APPROACH FOR HUMAN FALL RISK ASSESSMENTS

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Abstract

Human fall risk assessments to predict an unintentional fall and strategies to reduce such events are major goals of every health care providers. Fall risk assessments were primarily conducted through questionnaires and clinical observations. They were also assessed using wearable devices by identifying the deviations in normal gait. This paper proposes a non-invasive approach using depth sensor to analyze the same parameters to measure the deviations in normal gait for fall risk assessments. The proposed method conducts an analysis on the lower body part using Kinect sensor. The experimental testing showed promising results in gathering the required information for computing the fall risk levels.

Keywords: Assistive living, Daily activities, Depth maps, Fall risk, Fall risk levels monitoring.

1. Introduction

Human falls, among elderly is a major health concern and a constant safety issue in every health care provider [1]. Therefore, protecting the patients from fall and providing a fall free environment is essential in ensuring quality health care. This requires the implementation of fall prevention programs and other strategies to decrease the risks of fall [2]. Human fall here is referred to as an unintentional physical fall of the body to the ground or to an object such as on to the bed. Fall risk assessments are basically assessed through questionnaires which includes information about the history of falls, physical condition, sensory deficit, age and many other risk factors of the targeted subject.

Apart from questionnaire-based tools, there are also devices designed to compute the common gait parameters to measure the fall risk levels. These devices require, the user to perform a predefined action and the data collected is used to identify the fall risk levels. The most commonly used protocol involves standing up from sitting on a chair, then walk for a certain distance, then turn and walk back to the chair and sit. The common parameters used are gait speed (walking speed), step length and height, step symmetry, step continuity and trunk sway.

As similar to fall detections [3-7] there is more than one approach used to identify the fall risk level of a user. The two basic approaches are either using a wearable device with sensors such as accelerometer and using non-invasive vision-based sensors such as depth sensor or normal cameras. Use of a wearable sensor is the simplest and the easiest method if the drawbacks of wearable devices are not considered. Similarly, like wearable based fall detection devices, systems designed for fall risk assessments are also worn at a different location on the body and data such as acceleration and angular velocity is used for the assessment. Non-invasive vision-based devices measure the same parameters, using vision sensors such as depth camera or RGB camera.

2. Related Works

This section briefly highlights the related fall risk assessment systems presented in different studies. Systems include studies that proposed or presented the development of a device-based tool. These include those that had proposed various devices or systems to perform fall risk assessments including wearable devices, wearable and non-invasive based devices and fully non-invasive devices.

A clinical tool for fall risk assessment based on a wearable device was proposed by Giansanti [8]. The wearable device consists of three mono-axial accelerometers and three rate gyroscopes which is worn at the trunk. The tests were based on a posturography protocol and statistical analysis of the parameters to assess fall risks. With the wearable device, the protocol was performed for training and validation configurations. Training configuration enables the design and construction of a statistical cluster space, whereas validation configuration is performed to validate the statistical cluster space and assess the test power. The test showed a high sensitivity and specificity. The percentage of a number of patterns correctly classified and the total number of patterns was also high.

In another study by Najafi et al. [9], a new method for evaluating the characteristics of postural transitions and their correlation with fall risk were described. The time is taken during sit-to-stand and stand-to-sit transitions were measured using a miniature gyroscope. The gyroscope is to be worn on the chest and a portable recorder on the wait. The three parameters measured from postural transitions were average, the standard deviation of transition duration and the existence any abnormal consecutive transitions. Trunk tilt was analyzed during sit-to-stand and stand-to-sit using a time-frequency analysis (wavelet) and a standard motion analysis system was used to validate. The tilt analysis gave significant parameters regarding the nature of transition and to compare them fall risk values. From the results of the estimated parameters and by monitoring the changes, the device could be used as a promising tool in home health care for the elderly.

Weiss et al. extended the method that they proposed previously to assess mobility in patients with Parkinson disease in daily life setting using a single body-fixed sensor. The aim of that study was to investigate whether accelerometer-based measures that could discriminate between Parkinson disease patients and healthy controls as they walk and simulate their daily activities of life [10]. The current study extends that method and demonstrates its potential use for assessing fall risks in the home setting using the accelerometer. The aim of this study was to evaluate the possibilities of using a wearable accelerometer continuously for 3 days to measure fall risks as the user carry out their daily activities of life. Seventy-one elderly living in a community setting were selected and classified as fallers and non-fallers based on their fall history. If they had at least 2 falls in the past year, then they were classified as fallers or else non-fallers. The protocol includes four parts, a clinical and traditional fall risk assessment, gait assessment in the laboratory, three-day activities of daily life assessment and a prospective assessment of falls.

Fall risk assessment in the laboratory was conducted using performance-based tests of mobility such as Time Up and Go. The three-day assessment was conducted using a body-worn tri-axial accelerometer on their lower back. Prospective assessment of falls was collected for six months from the self-report of any fall. The proposed sensor-based method provided valuable information on the quality and quantity of walking in the home setting [11].

An objective risk of falling assessment was proposed by Caby et al., which uses accelerometric data while walking on a 25meter distance. The novelty of the proposed approach includes the use of an accelerometer network to acquire 3D data from all the limbs and computation of new features in the field of application. They used 10 sensor networks where sensors are placed on each limb (left knee, left ankle, right knee, right ankle. Left elbow, left wrist, right elbow, right wrist left shoulder and right shoulder) and a data logger. The results from the developed tool showed significant differences between the group with the risk of falls and the group with no risk of falls [12].

There was only one study that presented a fall risk estimation and fall detection tool using a wearable and a vision-based sensor. This work was aimed to propose an integrated system to gain both the fall risk assessment and fall detection in the indoor home environment. They also provided a fall risk assessment tool with the Kinect sensor and an accelerometer placed at the chest in the same setup which can be switched when required [13]. The only study that investigated Microsoft Kinect sensor alone for fall risk assessment was conducted by Stone and Skubic [14]. They evaluated the use of Kinect sensor for obtaining measurements of temporal and spatial gait parameters as compared to existing web-camera based systems using Vicon. This work focuses on developing a system for assessing fall risks, detection of falls, detecting the early onset of illness and functional decline. Table 1 summarizes the studies in terms of the aim of the study, the parameters used, and the approaches employed.

Table 1. Summary of the related works.

Study	Approach	Parameters	Aim
[14]	Vision	Temporal and spatial	Fall detection and risk assessments
[13]	Vision and wearable	The inclination of torso angle, time required to stand up, steps, time required to perform the action, cadence	Fall detection and risk assessments
[12]	Wearable	Accelerometric data	Fall risk assessments
[10]	Wearable	Three-day accelerometric data	Fall risk assessments
[8]	Wearable	Kinematic parameters at trunk	Fall risk assessments
[9]	Wearable	Gyroscope-based	Fall risk assessments

3. Methodology

Fall risk assessment is an analysis of the physical strength or the ability to withstand from unintentional falls due to aging, weaker body, balancing problems, unsteadiness during walking, fears of fall or any other issues that may often lead to falls. The analysis is conducted on the lower body parts using the determinants of gait. Thus, the fall risk level is simply a measure of the deviation in normal gait.

Gait analysis is conducted to identify or assess the abnormalities in the normal gait cycle. The maintenance of a normal gait pattern depends on a variety of biomechanical features controlled by the nerves system [15] which has been defined as the determinants of gait. They are responsible for minimizing the displacement and maintaining the center of mass (COM) using body parts such as pelvic, knee and ankle. The six kinematics or determinants of gait established [16] are to ensure reasonable locomotion [15] by reducing the vertical center of mass (COM). The six determinants of gait are pelvic rotation, pelvic tilt/obliquity, knee flexion at stance phase, foot and ankle motions, knee motions and lateral pelvic displacement.

This study is concerned with the abnormalities in walking especially the way legs are placed and moved during walking for elderly people. Therefore, this study will analyze the spatial and temporal variables along with the positional data. Spatial refer to the distance variables such as step length and stride length. Temporal refer to the time variables including step time, stride duration, stance duration, swing duration, cadence and speed. Figure 1 illustrates all the foot measurements describing some common gait parameters [17].

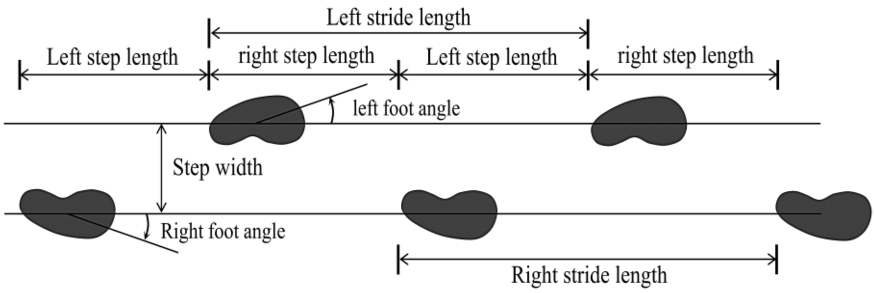

Fig. 1. Description of foot measurements for this study.

The fall risk assessment is conducted in a predefined direction with a protocol and it does not require to identify the direction of movements, but it required to identify different postures representing gait phases, in order to classify the parts of the phases. For this, four postures are chosen which will cover major parts of the gait cycle and points from where important information can be extracted. It will help to identify the percentage of time taken and accurately compute the gait parameters. The Posture shown in part (a) of Fig. 2, is when the right heel is striking the ground at the beginning of stance phase (initial contact) and part (b), of the same figure, represents the posture at mid-stance of right foot when the left foot is swinging. The posture formed when the left foot strikes the ground after swinging and the right foot toe gets off the ground for swinging is illustrated in Fig. 2 (c). The last part of the same figure shows the postures when the right foot is swinging, and weight is placed on left foot (left stance).

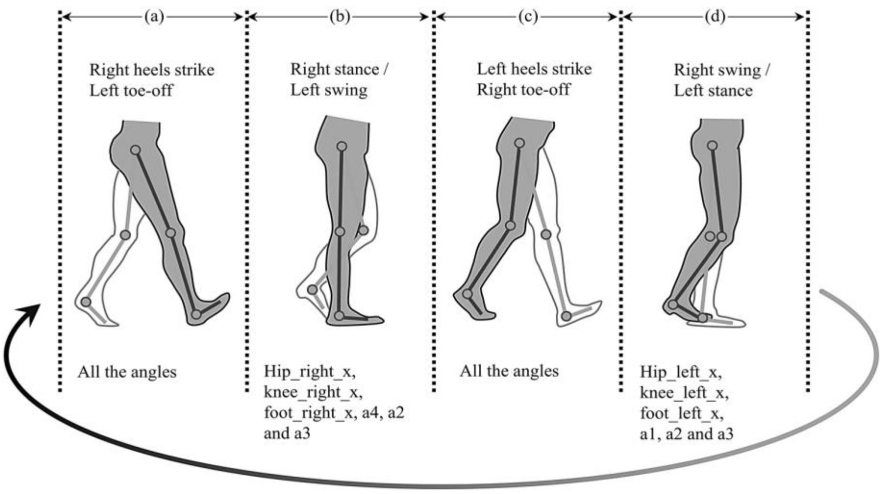

Fig. 2. Postures representing different parts of gait phases.

These postures are identified by considering the position and the angles between the joints. The angles and the position of the joints required to identify any posture are described just beneath it, in the Fig. 2. The four angles are described in the following Fig. 3. The angle (a1) is formed between the right knee and right ankle, where right knee is the center of rotation. The angle (a4) is the same angle formed between the left knee and the left ankle. The angle (a2) and (a3) is the angle formed between the hip center and right knee and hip center and left knee respectively, where the center of rotation is at the hip center. It was assumed that the two joints (the joint representing the center of rotation and the 'other' joint) will form a right-angled triangle. The angles mentioned are supposed to change as the 'other' joint moves by keeping the joint representing the center of rotation at stationary point. At a point, the angle will be zero and will again increase as the 'other' joint moves after crossing the center line. These angles will especially help to measure the amount of spread between the two limbs.

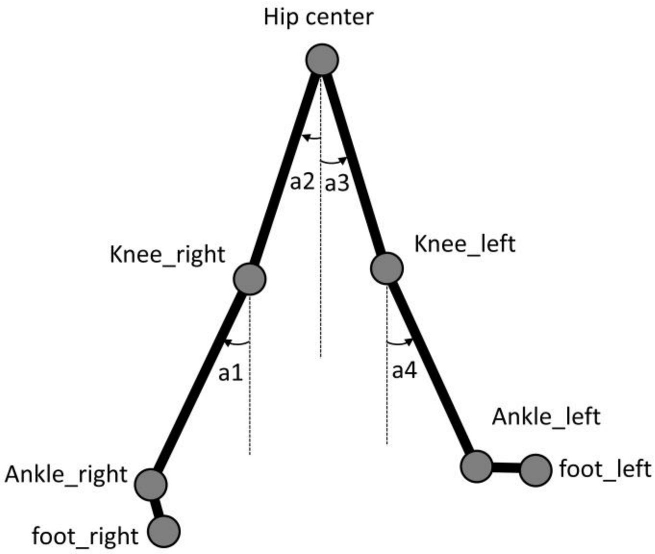

Fig. 3. Description of joint position while making a left step with the angles.

Since the direction of the movement for fall risk assessment is predefined, the following equation can be directly applied to calculate the four angles. For the calculation of the angles, adjacent and the opposite of the right-angled triangle is used. Adjacent is calculated by subtracting the y-value of the two joints forming the triangle and opposite is the difference of the x-value of the two joints. The tangent formula for a right-angled triangle is used where tangent of the angle is equal to the division of opposite and adjacent.

$$a1 = \tan^{-1}\left(\frac{R\_k_X - R\_a_X}{R\_k_y - R\_a_y}\right) \quad (1)$$

$$a2 = \tan^{-1}\left(\frac{H_X - R\_k_X}{H_y - R\_k_y}\right) \quad (2)$$

$$a3 = \tan^{-1}\left(\frac{H_X - L\_k_X}{H_y - L\_k_y}\right) \quad (3)$$

$$a4 = \tan^{-1}\left(\frac{L\_a_X - L\_k_X}{L\_a_y - L\_a_y}\right) \quad (4)$$

Here, R_k, R_a, H, L_k, and L_a are a right knee, right ankle, hip center, left knee and left ankle respectively. The subscript x and y refer to x coordinate value and y coordinate value respectively.

Once the posture is identified, the parameters required for the fall risk assessment can be computed, including parameters such as speed of walking, knee angles for daily movements, step frequency (cadence), step time and stride duration. The four angles and the identified posture of the gait phases are helpful in determining the step frequency (cadence), step time and stride duration [17]. Since considering the values of the four angles the system can decide if a step is placed on the floor and whether it is a left or right step. By this way, the system can count the number of steps (number of times right and left footsteps on the ground) for a minute to derive the step frequency in steps per minute. To ease the burden to the system, counting can also be reduced for 30 seconds for anyone feet and then it can be multiplied by 2 for one minute and again by 2 for two feet.

Step time is the time difference between any successive instance of the feet and floor contact of the opposite feet. This is calculated from the same loop used in step frequency calculation, except here the frame difference between two immediate step hits is multiplied by two to state the step time in second. Since the sensor generates 30 frames per second, the number of frames passed between the two opposite footsteps can be multiplied by 2 to get the time interval between those frames passed. Similarly, stride duration, which is the time difference between a successive instance of the foot and floor contact of the same foot can also be calculated. This was calculated in a different loop since stride duration can go beyond one second, but the concept used is same except that the frame gap between two successive left and right foot is extracted and multiplied by two for left stride and right stride duration respectively.

The stance duration is the time when the given foot is in contact with the floor and swing duration is the time while the foot is not in contact with the floor. These two parameters can be easily calculated by considering the postures in Fig. 2, as it shows the major parts of the gait cycle, the two phases can be separated, and the time duration calculated for each phase. In this way, stance duration can be simply calculated by measuring the time taken for the first three postures and the time taken for the last posture will be the swing duration. The time taken for each posture can be calculated by counting the number of frames passed to get new posture over the total number of frames per second. Walking speed is computed by considering the movement of the hip center with respective to time. More preferably, the gait speed can be easy calculated by multiplying the average step length and step time.

Step length is the horizontal distance along the plane of headway between two alternating steps. For an example, left foot step length is horizontal distance covered during a placement of left step, which is from right foot to the new left foot placed. Similarly, step length for the right foot is the horizontal distance covered while making the right foot move forward keeping the left foot at stationery. In other words, this is the horizontal distance along the plane of progression from previous left foot to the newly placed right foot step. The stride length is the horizontal distance along the plane of headway among two successive placements of the same foot. Simply it is the sum of a right and a left step length. Foot angle depends on how the foot is placed (orientation of the foot) on the floor with respect to the horizontal plane of progression.

For the analysis of fall risk assessment, the spatial variables are computed using the following equations by assuming that the direction of the movement is across the sensor.

Step width = $P\_R_z - C\_L_z$ (5)

Left step length = $C\_L_X - P\_R_X$ (6)

Right step length = $C\_R_X - P\_L_X$ (7)

Left Stride length = $C\_L_X - P\_L_X$ (8)

Right Stride length = $C\_R_X - P\_R_X$ (9)

Here R_z, L_z, L_x, and R_x are z value of right foot, z value of left foot, x value of left foot and x value of right foot respectively. The prefixes C and P mean the current frame value and previous frame value respectively.

4. The proposed protocol and the algorithm

The factors screened for fall risk assessments in the proposed algorithm are derived from different standardized fall risk assessment tools such as TINETTI Balance assessment tool and STRATIFY etc. The proposed fall risk assessment tool includes a questionnaire-based section and device-based assessment. The questionnaire-based section is used to identify the history of falls, physical and mental strength of the user. They include three main questions, to find information about the number of falls in the past six months, steadiness while standing or walking and fear of falls.

If the user had experienced a fall event in the past six months, the question will also be asked to know if it had caused any injury. Once this section of the fall risk assessment is filled, the remaining needs to be generated from the developed system using depth sensor. To generate the device-based assessment, the user needs to perform a predefined action. The screening procedure requires the user to sit on a chair at the beginning of the assessments and stand up from sitting on a chair, walk for 3 meters at normal speed, turn around and walk back to the chair, turn and sit down on the chair.

The data extracted from the user actions will be used to compute the parameters described in the last section and the results will be feed into the Table 2. In the end, all the scores will be summed up including questionnaire-based scores to produce a final score that will be matched with any one of the fall risk levels in Table 3.

Figure 4 illustrates the fall risk assessment described above. In the beginning, the questionnaires need to be answered first and the device (depth sensor) based assessment is conducted if the answers to any question are ‘Yes’.

If the answers to all the question were given as ‘No’ or device-based assessment could not identify any risk levels, then the system will consider the user as “normal’ or ‘low-risk patient or elderly’. If fall risk factors were found from both the questionnaire and device-based assessments, then the user will be identified as ‘moderate risk level’ or ‘high-risk level’ as discussed above.

Table 2. Overview of proposed fall risk assessment parameters.

Parameters screened	Risk level Normal = 0	Risk = 1	High Risk = 2	Score
1. Questionnaire				
a. History of fall in past six months?	No fall	One fall – no injury	>one fall or one fall with injury	
b. Feels unsteady when standing or walking?	No	Yes	Very unsteady	
c. Do you worry about falling?	No	Yes	-	
Questionnaire based score				/ 5
2. Gait temporal parameters				
a. Gait speed (m/s)	>1.10±0.30	<0.97	<0.58	
b. Step duration (sec)	0.55±0.04	<0.55	-	
c. Stride time Variability (ms)	=<50 ms ±4	=<105ms ±30	>105 ms	
d. Swing time variability (ms)	=<27 ms	=<39 ms	>39 ms	
3. Step length and height				
a. Right swing foot				
- Does not pass left stance foot with step		1		
- Passes left stance foot	0			
- Right foot does not clear floor completely with step		1		
- Right foot completely clears	0			
b. Left swing foot				
- Does not pass right stance foot with step		1		
- Passes right stance foot	0			
- left foot does not clear floor completely with step		1		
- Left foot completely clears	0			
4. Step symmetry				
- Right and left step length not equal		1		
- Right and left step appear equal	0			
5. Step continuity				
- Stopping and discontinuing between steps		1		
- Steps appear continues	0			
6. Trunk sway				
- Marked sway			2	
- No sway but flexion of knees or spreads arms out while walking		1		
- No sway, no flexion of knee and no use of arms	0			
Device based score				/ 14
Total Score = Questionnaire based score + device based score				/ 19

Table 3. fall risk level indicators.

Score	Fall Risk Level
Score ≤ 8	Normal or Low-Risk Level
9 ≤ Score ≥ 12	Moderate Risk Level
Score ≥ 13	High-Risk Level

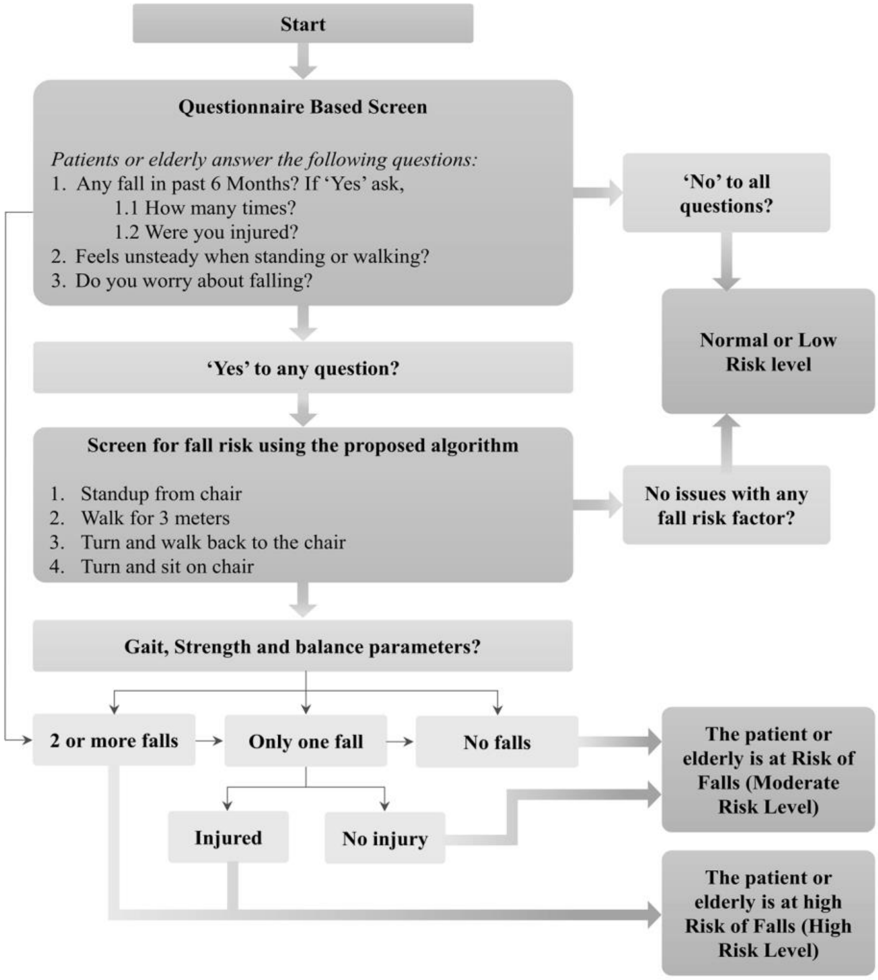

Fig. 4. The proposed fall risk assessment algorithm.

5. Results of preliminary testing

To measure the accuracy and robustness of the proposed algorithms, several testing's, were conducted with different walking speed across the sensor. This section will demonstrate the results gathered from testing's, to show the accuracy of different parameters used to assess fall risk levels. The step length and the time taken for the steps gives important information for the classification of fall risk levels. The step length is simply, one half of any of the stride length. Figures 5 and

6 show the number of steps with their step length and step time (duration) for the first three-meter walk after standing from a chair and the three-meter walk back to the chair respectively from a single simulation. The error bar in the black color shows the standard error for each of the step lengths. The step time or the duration of each of the step length is displayed inside the respective step length bar. The bars in dark blue is representing the left step lengths and the time taken for the step is displayed in transparent red bars. The bars in gray color is representing the right step lengths and their step time shown in transparent gold color bars.

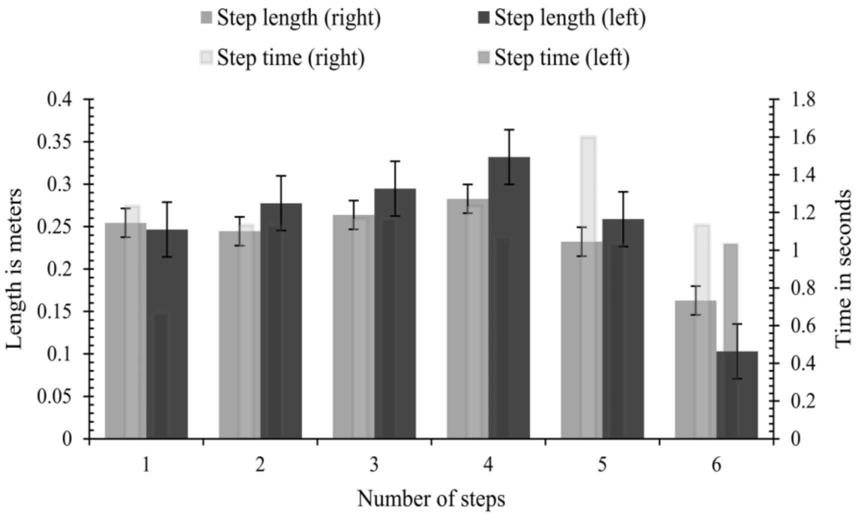

Fig. 5. Step length with step time for the first three-meter walk.

It was observed from Fig. 5, that the time taken for the right steps are more than the left steps. This is because the subject is more confident when the weight is loaded on the right leg if the subject was right-handed. The time taken to place the first step was also higher and it was then maintained at an equal amount between the two sides until the second last step, where the subject is preparing to stop and turn around to walk back to the chair. The step lengths are also shorter at the beginning then gradually increase and then decreases at the end. The shortest step length is observed at the end of the first three-meter walk.

The above Table 4 shows the sum of all step lengths and step time for the two foots with their standard deviation for the first three-meter walking segment of the same sample of data. The total distance covered by the left foot is more than the right foot with 1.4 seconds faster. The right foot steps covered 0.07214 meters, less than the left foot and it spends more time to place the right step. Because the subject is not very confident when the weight was loaded onto the left leg for right step placement. The standard deviation is low enough to prove that the error rate of the data computed from the sensor is negligible.

During the second segment of walking (the three-meter walk back to the chair), the time taken for the first two steps were significantly higher, because it included some of the time for turning. The generated data at the turning point is trimmed off to consider the actual number of steps for the two walking segments. The step length was shorter at the beginning and gradually increased until the end of the three-meter.

On average, six-step lengths (left and right) were observed for the sample of data displayed in Fig. 5, for the first three-meter walk after standing from a chair and the results of the last three-meter walk back to the chair is shown in Fig. 6.

Table 4. Overall details for the first three-meter walk.

	Step time (seconds)	Step length (meters)	Standard deviation
Left foot	6.1	1.51271	0.04154
Right foot	7.5	1.44057	0.07893
Total	13.6	2.95328	0.12047

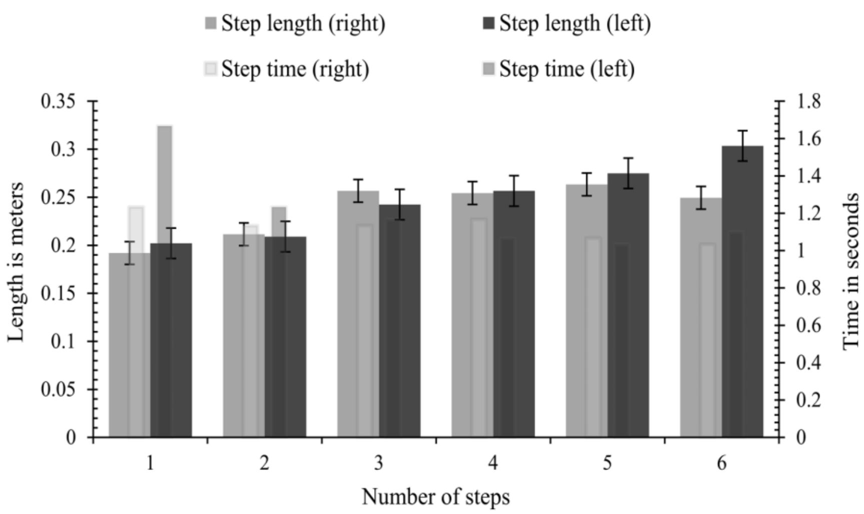

Fig. 6. Step length with a step time for the last three-meter walk (return).

Table 5 illustrates the total distance cover by the two feet with the total time taken and the standard deviation for each of the data for the second three-meter walking segment of the same sample of data. Similar like the first three-meter walking segment, the distance covered (total step length) by the left foot is more than the right foot but it took more time than the total duration of the right foot. The total time taken to cover 2.915646 meters, during this segment is 14.0333 seconds. The standard deviation of the computed data is even lower than the first three-meter walking segment.

Table 5. Overall details for the last three-meter walk.

	Step time (seconds)	Step length (meters)	Standard deviation
Left foot	7.266667	1.488386	0.038821271
Right foot	6.766666	1.42726	0.029034142
Total	14.033333	2.915646	0.067855413

The total distance covered for the two segments is 5.8689 meters and the time taken was 27.6333 seconds. It was found that the actual distance for the two segment is six meters and the reduction in the computed distance covered, is just due to the errors. The following Table 6, shows the summary of the two walking segments in the proposed fall risk assessment protocol. The distance covered, and the time is the average of the all steps generated for the whole walking segments. The total distance covered by this sample of data was 5.868926 meters in 27.63333 seconds. The overall contribution of the stance phase for all the steps was 62.65 percentage, while the swing phase was involved only in 37.35 percent of the time. The swing/stance ratio for an average of all the left and right steps was 5/8 and 4/7 respectively. The overall swing/stance ratio for the whole walking segment was 3/5, which means that there are five portions of stance phase for every three portions of swing duration.

Table 6. Overall summary of the two walking segments.

	Time (seconds)	Length (meters)	Swing time (seconds)	Stance time (seconds)	Swing/Stance ratio
Left step	13.367	3.001	5.141	8.225	5/8
Right step	14.267	2.868	5.179	9.088	4/7
Total	27.633	5.869	10.320	17.313	3/5

For the above-given sample of data from the simulated activities on the fall risk assessment protocol, the subject took 27.6333 seconds to complete the two walking segments. This results in 13.03 steps per minute and an average speed of 0.2124 meters per seconds.

6. Conclusions

This paper presented a non-invasive approach for fall risk assessment using a depth sensor. The proposed system performs a lower body analysis while the subject performs a predefined action. The protocol requires the user to stand up from sitting on a chair and walk for 3 meters and then turn back and walk to the chair and sit on a chair. The generated variables are feed into a table with fall risk assessment parameters, the result of which will point to the relevant fall risk level. The results showed that the depth sensor could accurately compute gait parameters to generate an appropriate fall risk level. The identification of postures before the computation of the gait parameters helped to count steps more precisely and thus improve the overall accuracy. On the other hand, the proposed system is subject to the limitations of the sensor such as inaccuracy due to losing clothing on the lower body and limbs with heavy muscles. Additional efforts are required to validate the effectiveness of the computed parameters and improve the identification of the postures.

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Abbreviations

C	Current frame
H	Hip centre
La	Left ankle
Lk	Left knee
Lx	x-coordinate of left foot
Lz	z-coordinate of left foot
P	Previous frame
Ra	Right ankle
Rk	Right knee
Rx	x-coordinate of right foot
Rz	z-coordinate of right foot

References

1. Oliver, D. (2006). Assessing the risk of falls in hospitals: time for a rethink? *CJNR (Canadian Journal of Nursing Research),* 38(2), 89-94.
2. Morse, J.M. (2006). The safety of safety research: the case of patient fall research. *CJNR (Canadian Journal of Nursing Research),* 38(2), 74-88.
3. Nizam, Y.; Jamil, M.M.A.; and Mohd, M.N. (2016). A depth image approach to classify daily activities of human life for fall detection based on height and velocity of the subject. *International Conference on Movement, Health and Exercise.*
4. Nizam, Y.; Mohd, M.N.H.; and Jamil, M.M.A. (2016a). Classification of human fall from activities of daily life using joint measurements. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC),* 8(4), 145-149.
5. Nizam, Y.; Mohd, M.N.H.; and Jamil, M.M.A. (2016). A study on human fall detection systems: daily activity classification and sensing techniques. *International Journal of Integrated Engineering*, 8(1), 35-43.
6. Mohd, M.N.H.; Kashima, M.; Sato, K.; and Watanabe, M. (2014). *A* non-invasive facial visual-infrared stereo vision based measurement as an alternative for physiological measurement. *Proceedings of the 2015 Lecture Notes in Computer Science* (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).
7. Mohd, M.N.H.; Kashima, M.; Sato, K.; and Watanabe, M. (2015). Internal state measurement from facial stereo thermal and visible sensors through SVM classification. *ARPN Journal of Engineering and Applied Sciences*, 10(18), 8363-8371.
8. Giansanti, D. (2006). Investigation of fall-risk using a wearable device with accelerometers and rate gyroscopes. *Physiological Measurement*, 27(11), 1081.
9. Najafi, B.; Aminian, K.; Loew, F.; Blanc, Y.; and Robert, P.A. (2002). Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly. *IEEE Transactions on biomedical Engineering*, 49(8), 843-851.

10. Weiss, A.; Sharifi, S.; Plotnik, M.; van Vugt; J.P., Giladi, N.; and Hausdorff, J. M. (2011). Toward automated, at-home assessment of mobility among patients with Parkinson disease, using a body-worn accelerometer. *Neurorehabilitation and neural repair*, 25(9), 810-818.
11. Weiss, A.; Brozgol, M.; Dorfman, M.; Herman, T.; Shema, S.; Giladi, N.; and Hausdorff, J. M. (2013). Does the evaluation of gait quality during daily life provide insight into fall risk? A novel approach using 3-day accelerometer recordings. *Neurorehabilitation and Neural Repair*, 27(8), 742-752.
12. Caby, B.; Kieffer, S.; de Saint Hubert, M.; Cremer, G.; and Macq, B. (2011). Feature extraction and selection for objective gait analysis and fall risk assessment by accelerometry. *Biomedical Engineering Online*, 10(1), 19 pages.
13. Cippitelli, E.; Gasparrini, S.; Gambi, E.; and Spinsante, S. (2016). An Integrated Approach to Fall Detection and Fall Risk Estimation Based on RGB-Depth and Inertial Sensors. *Paper presented at the Proceedings of the 7th International Conference on Software Development and Technologies for Enhancing Accessibility and Fighting Info-exclusion*.
14. Stone, E.E.; and Skubic, M. (2011). Evaluation of an inexpensive depth camera for passive in-home fall risk assessment. *Proceedings of the 5th* International Conference *on the Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, 2011.
15. Kuo, A.D.; and Donelan, J.M. (2010). Dynamic principles of gait and their clinical implications. *Physical Therapy*, 90(2), 157-174.
16. Inman, V.T.; and Eberhart, H.D. (1953). The major determinants in normal and pathological gait. *The Journal of Bone and Joint Surgery*, 35(3), 543-558.
17. Nizam, Y.; Mohd, M.N.; and Jamil, M.M.A. (2006). Biomechanical application: exploitation of kinect sensor for gait analysis. *ARPN Journal of Engineering and Applied Sciences*, 12(10), 3183-3188.