

A Real-time Pre-impact Fall Detection and Protection System

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Abstract—As the aging of the population aggravates, the problem of fall has aroused more attention. We have proposed a novel pre-impact fall detection algorithm and protection system. The real-time algorithm used the thresholds of vertical velocity and displacement profile to detect fall events in switching periods of fast motion. It can effectively solve the problem of false alarms of jump and jogging for daily-life applications. A second-order lag filtering algorithm method was utilized to reduce the drift of the vertical velocity with good performance. In addition, the vertical displacement profile was calculated by using the vertical velocity estimation. The algorithm got 93.6% sensitivity and 95.6% specificity, which was higher than the algorithm without displacement with 75.6% specificity. The results demonstrated the effectiveness of the proposed detection method, which were evaluated by subjects wearing fall detection and airbag system.

I. INTRODUCTION

It is estimated that nearly 30–40% of elders over the age of 65 and 50% of adults over the age of 80 fall at least once per year [1]. These falls become a primary cause of injury and death among the elders, which seriously threaten the health of the elderly and bring a heavy burden to the society [2]. Moreover, mortality rate increases as the waiting time for treatment increases [3], and elderly individuals are not always able to notify emergency personnel upon falling, due to injury or cognitive decline [4]. Methods for detecting the occurrence

This research was supported in part by the NSFC Grant No. - 51775485 and -61428304, and Zhejiang Provincial Natural Science Foundation of China under Grant No. LR15E050002. *Corresponding author.

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of a fall prior to impact have the potential to be life-saving by initiating protective actions such as airbag inflation or notifying medical aid [5].

Many researchers have focused on automatic fall detection methods over the last decade [6-8]. In general, fall detection can be categorized as post-impact fall detection and pre-impact fall detection [9]. Post-impact fall detection methods detect falls after the impact, and it could not be used to provide protection [10]. Thus researchers are more concerned about pre-impact fall detection. Pre-impact fall detection can be achieved by using inertial sensors (accelerometer and gyroscope) or video cameras [11]. However, video cameras have a lot of limits compared with inertial sensors which can be worn easily and comfortably without location restrictions [12]. For practical use, the number of sensors should be as small as possible, and the position of sensor is close to center of gravity in most literatures [13, 14].

Pre-impact fall detection typically includes signal analysis and feature classification [15]. There are four frequently-used features, namely acceleration, angular velocity, tilted angle [16-18] and vertical velocity [19-23]. Among them, vertical velocity is found to be effective in distinguishing falls with other Activities of Daily Living (ADL)[20]. To calculate the vertical velocity, certain algorithms are used to estimate the posture of the sensor such as the algorithm used by Lee et al. [19]. These algorithms typically involve direct integration from acceleration to obtain velocity, which results in an augmented drift. Wu et al. [21] first used inertial sensors to obtain the vertical acceleration without reducing this drift. Bourke et al. [22] used Butterworth band-pass filter to reduce the drift of the velocity, but this filtering method cannot run in real time. Kangas et al. [23] performed the integration only in a short period before the fall. Lee et al. [20] used a damping method to reduce the drift of velocity exponentially, but it may lead to inaccurate velocity estimations. In addition, using vertical velocity alone for pre-impact fall detection may trigger false alarms when the subject performs certain ADL such as jogging or jump.

In this paper, we developed a real-time fall detection algorithm using vertical velocity and another new feature, displacement. To reduce the drift of the integrated vertical velocity, a second-order lag filtering algorithm was utilized. The results estimated by our integration algorithm were compared with the ground truth from a human motion capture system, which confirmed its effectiveness. In addition, we

designed a fall detection and protection system to test the performance of our fall detection algorithm in actual daily lives.

II. MATERIALS AND METHODS

A. System Architecture

The detailed information of experiment set (ES) can be found in the Tab.1. We used the IMU to read acceleration to get parameters of our fall detection algorithm. The control experiment (CE) using Vicon recorded the movement of the IMU for a ground truth comparison. An Arduino UNO was used to synchronize the Vicon data with the IMU data which was sent through a pair of Bluetooth devices.

TABLE I

THE DESCRIPTION OF EXPERIMENT SET (ES) AND CONTROL EXPERIMENT (CE)

Detection unit	ES	IMU (JY61p, Wit-motion technology Co., Ltd)		range	resolution	stability
			Tri-axial accelerometer	±16 g	0.00 5g	0.000 1g
Location	CE	Optical motion system Vicon (Oxford Metrics Limited, T40S) with 6 cameras.	Tri-axial gyroscope	±20 00 °/s	0.61 °/s	0.02°/s
Sampling	Both	200Hz	one (front marker)	waist		
Sampling	Both	200Hz	three	back		

Four reflective markers were placed around the subject's belt, which represented the three-dimensional coordinate values of the sensor. When the front marker (FM) was hidden by the subject (for example, during squatting and fall activities), the left three markers were used to create a virtual front marker using methods described by Rahmatallaa et al [24], where we supposed that the relative positional relationship during rotating did not change. Comparing with the approach in [25], the advantage of our algorithm is that we can calculate the coordinate values of the FM more accurately.

B. Fall Detection Algorithm

The novel fall detection algorithm based on vertical velocity and displacement is shown in Fig.1. Using three Euler angles ($\gamma_r, \gamma_p, \gamma_y$) and tri-axial accelerations (a , 3x1 vector unit, g/s^2) relative to the sensor coordinate system from the IMU, the vertical acceleration (a) is calculated in the world coordinate system (Cw). Then resultant velocity (v) was obtained by subtracting the trend velocity (u_2) from the vertical velocity (u_0) obtained by direct integration. The resultant velocity was then integrated to obtain the vertical displacement profile (z). The criterion is that when both negative velocity ($-v$) and negative displacement ($-z$) exceed their corresponding thresholds ($v_{threshold}$ and $z_{threshold}$), a fall occurs. The thresholds of velocity and displacement were chosen by using the gradient descent method, and we used the

distance between the misclassification and the hyperplane as the loss function, which was similar to the way in perception.

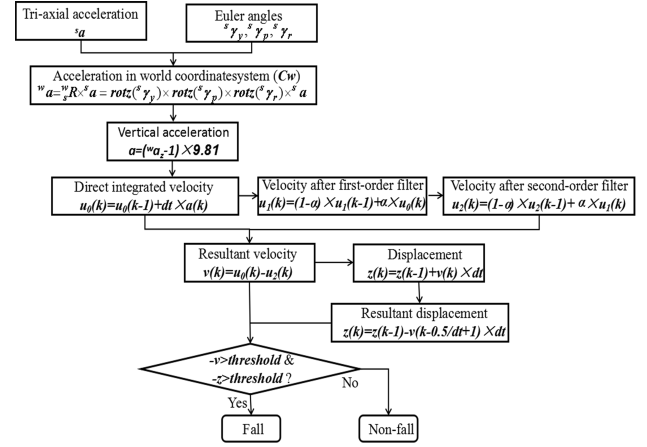


Figure 1. Flow chart of the fall detection algorithm. For presentation convenience, $rotz()$, $roty()$ and $rotx()$ are the rotation matrix around the z-axis, y-axis and x-axis respectively. a_z is the components of a along the z-axis of Cw . $u_i(k)$: the specified velocity at time step k , when parameter i is equal to 0, 1 and 2, u_i is the velocity after being direct integrated, the first-order and second-order inertial filter respectively. dt : the sampling period (in experiments, $dt=0.005s$). $z(k)$: the calculated vertical displacement profile at time step k .

The vertical velocity (v) is firstly calculated through integration of a . However, direct integration leads to drift due to the sensor's noise and integration error. The drift increases with time so that the estimation accuracy decreases as the subject continues moving, such as walking and jogging. Thus, a second-order lag filtering method is used to reduce the drift. Next, the velocity is calculated after the first-order and second-order lag filter, where α is the filter coefficient. The algorithm examines whether the sensor is in a static condition. If the magnitude of $|a|$ is smaller than the threshold in a period of time, the static condition is confirmed and the velocity and displacement are set to zero. Meanwhile, the static moment k_{static} is also recorded. When the lasting time is more than 1s from k_{static} , α is equal to 0 while equal to 0.015 on the contrary. By setting the velocity to zero in static condition, the drift of the velocity only occurs when the subject is moving. In order to capture the movement of a fall while limiting the drift error, the integration is corrected every 0.5s.

After getting displacement, we used vertical acceleration and velocity to judge whether people were jumping. In the case that a is less than $-0.4m/s^2$ and v is larger than $0.2m/s$, people is off the ground and moving upwards. Based on this characteristic, if an off-ground state is detected, the algorithm does not set the displacement to zero until the value of velocity changes from positive to negative. In other words, the displacement is integrated during both the ascending phase and the following descending phase. This method reduces magnitude of the negative displacement during jogging and jump, while maintaining an accurate displacement value during fall.

III. VALIDATION EXPERIMENTS

A. Subjects

Eight young healthy adults (6 males, 2 females; age: 23.2 ± 2.7 years; height: 171.4 ± 5.8 cm; mass: 63.5 ± 8.1 kg) from Zhejiang University volunteered to take part in the experiment. Subjects do not have a history of impaired balance, unexpected falls, neurological disease, or uncorrected visual deficit [14]. The study was approved by the Medical Ethics Committee of School of Medicine, Zhejiang University (Project identification code: 2016-007).

B. Experiment protocol

The experimental protocol included two categories of activities: ADL and falls. For the ADL category, subjects were instructed to walk, jog, sit and stand up, pick up an object from the ground, squat and stand up, make a small jump, and lie down onto a mattress respectively. The IMU was fastened to the anterior side of the subject's waist using a belt, positioned 0-5 cm above the iliac crest, as shown in Fig. 2. For the fall category, a total of eight types of simulated fall were included, which were selected based on the types of fall experienced often by the elderly [26]. Specifically, the included fall activities were: 1) Falling forward due to tripping while walking. 2) Falling backward while walking due to slipping. 3) Falling sideways while walking due to a cross-step. 4) Falling forward from a standing position. 5) Falling backward from a standing position. 6) Falling sideways from a standing position. 7) Sit-to-stand fall. 8) Stand-to-sit fall. These activities were performed at a comfortable speed and recorded three times. The order of activities was randomized. Due to communication errors in the recording system, 32 trials of ADL data and 4 trails of fall data were not usable. A total of 136 trials of ADL data and 188 trials of fall data were recorded and analyzed.

C. Results

Vicon markers trajectories were filtered using a Butterworth low-pass filter (10Hz cut-off frequency) and differentiated to determine the true vertical velocity of the sensor.

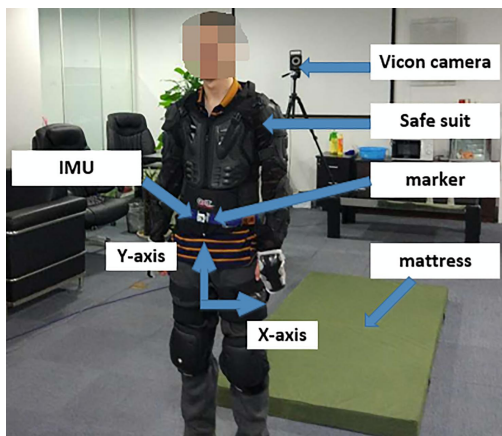


Figure 2. IMU is fastened to the subject's waist using a belt. The z-axis points forward, the x-axis points to the left, and the y-axis points to the sky.

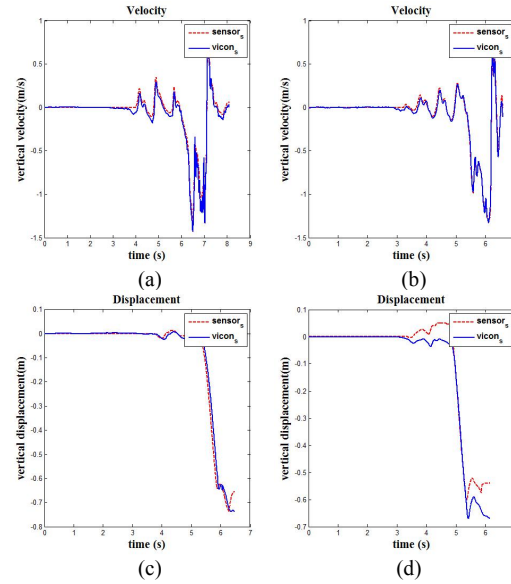


Figure 3. (a, b) A comparison of vertical velocity between the Vicon and sensor. (c,d) A comparison of displacement between the Vicon and sensor. *Vicon_s* in the legend (blue solid line) refers to the data measured from Vicon. *Sensor_s* (red dotted line) refers to the data of sensor calculated by our algorithm. Due to the limited space, only two activities containing (a, c) fall sideways when walking (FALL-WS), (b, d) walk and slip (FALL-WB) were listed.

Fig. 3 indicates that the estimate of vertical velocity from the IMU sensor shows a good correspondence with the ground truth (Vicon-based vertical velocity), which demonstrates that the algorithm provides an accurate measurement of vertical velocity. In the same way, the resulting vertical displacements are similar to the Vicon marker displacements, as shown in Fig. 3.

The maximum downward velocity and maximum displacement were plotted for each category, as shown in Fig. 4. For ADL, these values were calculated throughout the whole data range. For fall, the values were calculated only for the time range $[t_{\text{impact}}-1, t_{\text{impact}}-0.05]$. To use fall detection to trigger protective devices such as airbags, the detection must occur at least 25ms in advance of impact [21]. Thus, the endpoint time was set to 50ms before t_{impact} .

It can be seen from Fig. 4 that half of stand-to-sit falls have a maximal vertical velocity smaller than 1m/s. The vertical velocity-based detection method cannot effectively detect this type of fall and would generate an error signal in jumping. There is also a large negative vertical displacement ($-z$) during squatting and lying down. However, this feature can be used to detect jog and jump. We select velocity and displacement as features of our fall detection algorithm. The both features do not reach the maximum at the same time, and to get longer lead time and higher detection accuracy, thresholds were selected after testing, where $v_{\text{threshold}}=1\text{m/s}$,

and $z_{threshold}=0.12\text{m}$. The lead time can be obtained from t_{impact} (the time instant at which the acceleration reached its maximum magnitude) minus $t_{detected}$ (the moment when the values of v and z exceeded their respective thresholds). The lead time ranged from 65ms to 855ms ($363\pm174\text{ms}$). The minimum detection time of 65ms is considered to be sufficient as it is long enough to open the airbag.

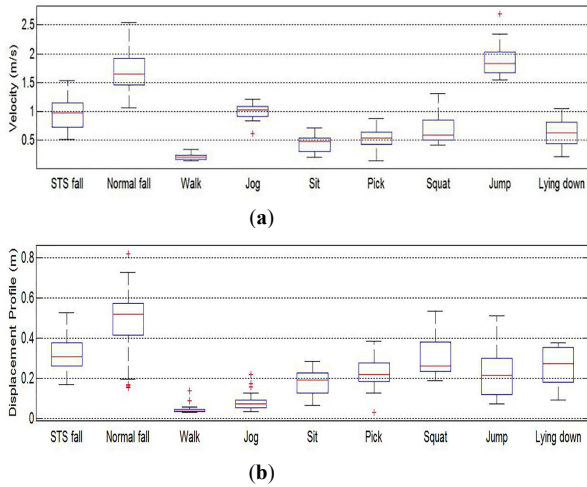


Figure 4. (a) Boxplot of the maximal downward velocity and (b) maximal downward displacement for each activity. Stand-to-sit fall is marked as “STS fall”. Other falls are grouped together and marked as “normal fall”.

IV. APPLICATION EXPERIMENTS

To test our algorithm in real environment, we designed a wearable fall detection and protection system. The system consisted of airbag and MCU (CC3200, ARM Cortex-M4 Core) which processed inertial data from the IMU. When a fall was detected, it would trigger to inflate to provide protection. The whole system weights about 1.2kg, which is placed inside the jacket. It can be reused as long as we replace the gas cylinder. The detection module tied to the belt is fixed 0-5 cm above the iliac crest. Fig. 5 shows a block diagram of the system.

Airbag folded on the back protects the hip which is vulnerable to elders [27]. When the movement parameters of people reach the thresholds of our algorithm, the MCU would send a signal to trigger the relay, then the driver circuit produces a 1.5A current to explode the gunpowder. It produces a force to push the needle, and then the needle punctures the opening of the gas cylinder. It will take 200ms for the compressed gas, which mainly contains carbon dioxide, to fill the airbag. The physical structure is shown in Fig. 6.

We conducted two groups of experiments. Firstly, we detected whether the airbag can inflate in time to provide protection as shown in Fig. 7. Two subjects simulated fall and we used high speed camera at 100 fps to record. The jacket was bounced up when airbag was full of gas. From the Fig. 7 (c), we could see that the airbag was filled in the process of fall. Secondly, we tested whether the system can

work well without producing error results. Two subjects wore the whole set for long-time tests including walking, running, sitting down and standing up slowly or fast, going upstairs and downstairs, picking up an object, across obstacle, lying, jump and doing bodybuilding exercise. The results were similar to the analysis before, only when sitting down fast and making a big jump would get wrong results. Though long-time integral easily produced error, the results confirmed that our algorithm can work effectively for a long time. Even if the airbag wrongly triggered, which never gave an impact on the subject. Thus, our system based on the proposed algorithm can be applied to use in daily life.

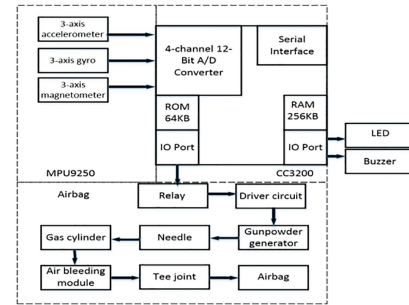


Figure 5. Block diagram of the wearable airbag system

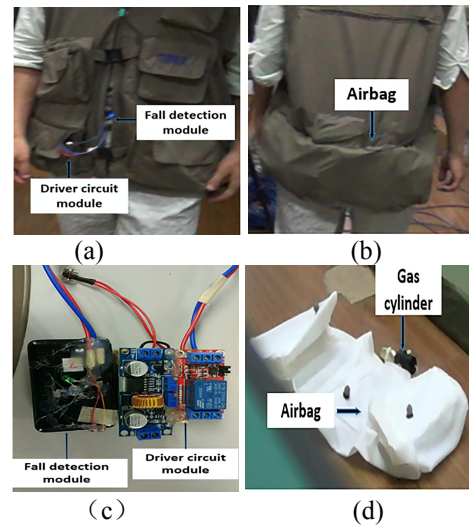


Figure 6. (a), (b) is the front and rear view of the whole system respectively; (c), (d) is the control module and protection module respectively.

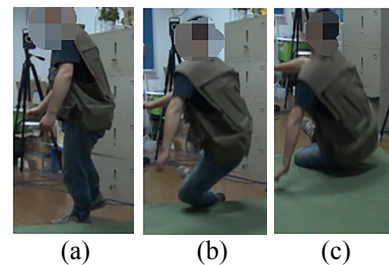


Figure7. The process of fall. (a) The moment when subject starts to fall; (b) The moment when the algorithm detects the state of fall; (c) The moment when airbag inflate completely;

V. DISCUSSION

Results of comparing the displacement and velocity obtained by the inertial sensor and Vicon are shown in Tab.2. It can be seen that the correlation coefficients of the displacement and velocity are high, and the root mean square errors of them are small for fall activities. All RMS values ($\sqrt{\sum_{i=1}^T (Vicon_v(i) - Sensor_v(i))^2 / T}$, where T is the total number) for displacement during fall are less than 0.1m. The RMS of velocity in fall activities are smaller than the results presented by Bourke et al. [7], where the integration drift is linearly accounted for in the re-integration.

Tab.3. lists the sensitivity (number of true predicted falls/number of actual falls $\times 100\%$) and specificity (number of true predicted nonfalls/number of actual nonfalls $\times 100\%$) of our algorithm (method 2), which are 93.6% and 95.6%, respectively. For comparison, we tested the detection algorithm using velocity only (method 1) reported by Lee et al. [20] with our data. The sensitivity and specificity of method 1 are 93.6% and 75.6% respectively. These results indicate that the vertical displacement profile is one useful feature for fall detection. For jump, although the negative maximum vertical velocity (-v) and displacement (-z) are both large, only 3 out of 18 trials are wrongly detected. This is due to the fact that the ascending period of jump is detected by using acceleration and velocity, and after the direction of the velocity changes, people fall back to the ground. Introducing the vertical displacement eliminated all false fall alarms during jogging, and reduced false fall detection from 18 to 3 trials for jump. In addition, additional false fall detection were not introduced, and average lead time was not shortened obviously. Wu and Xue [21], also used a vertical velocity threshold of -1m/s at the waist near the center of gravity, obtaining 100% sensitivity and 3 false detection during ADL. However, only simple fall types were considered and they did not cover the range of falls experienced by the elderly.

Most studies [20-23] evaluated the integration results in a particular time and a particular event. Their performance of fall detection algorithm was good in their short time experiment. However, in real daily lives, the motion of people is different and is always changing. Thus, using the data from a short time experiment to calculate the velocity is not suitable for long-term activities.

TABLE II
RESULTS FROM COMPARING THE SENSOR PROFILES AND THE PROFILES FROM THE VICON

Type	Par	Mean_CMC		Std_CMC		Mean_RMS		Std_RMS	
		M1	M2	M1	M2	M1	M2	M1	M2
Fall-SS	Dis	0.868	0.055	0.051	0.129				
	Vel	0.916	0.985	0.097	0.006	0.074	0.143	0.241	0.029
Fall-WF	Dis	0.718	0.275	0.094	0.174				

	Vel	0.851	0.984	0.124	0.007	0.085	0.131	0.202	0.027
Fall-WB	Dis	0.824	0.163	0.024	0.017				
	Vel	0.882	0.984	0.172	0.015	0.044	0.11	0.106	0.051
Fall-WS	Dis	0.81	0.2	0.042	0.112				
	Vel	0.829	0.978	0.113	0.022	0.06	0.149	0.129	0.088

The following terminology will be used:

Par: parameter, M1: our method, M2: the method used in [7]. Dis: displacement, Vel: velocity, Fall-SS: fall-standsidiways, Mean_CMC, Std_CMC, is the average and standard deviation of the absolute correlation coefficients respectively. Mean_RMS, Std_RMS, is the average and standard deviation of the root mean square error respectively.

TABLE III
FALL DETECTION RESULTS OF METHODS 1 AND 2

	Method	1	2	Total trials	
Thresh old	$-V(m/s)$	1	1		
	$-Z(m)$	N/A	0.12		
False number	Falls	normal	0	0	165
		stand-to-sit	12	12	23
	ADL	walk	0	0	19
		jog	12	0	19
		sit	0	0	20
		pick	0	0	20
		squat	2	2	19
		jump	18	3	19
		lie	1	1	20
		Results	Sensitivity	93.6%	93.6%
Specificity	75.6%	95.6%			
Average lead time(s)	0.378	0.363			

In this paper, we observed the performance of the real-time fall detection system in the long time tests. When people fell suddenly after moving for a long time, the MCU cannot detect this event due to the drift of integration which must have a large error in long-time integration. The velocity was a big positive number under such condition. However, in the usual limited experiment, this problem was ignored because the changes from ADL of subjects to simulated fall were slow. To eliminate this error, we must detect the static moment by setting static point artificially. When people was about to fall from movement states, the acceleration and velocity were not small. Here we fastened the determination of the supposed static time. Taking into account the frequency of human activities [28], we judged that the moment was static when the magnitude of $|a|$ was less than 0.01m/s^2 in 0.07s. The length of the time depended on the performance of fall detection algorithm, which meant that the sensitivity and specificity would not decrease due to this setting. In addition, the filter coefficient (α) may change in different states. When the movement of people tended to be static, the filter algorithm would not work. The two settings adapt to different movement states and can be adjusted according to different people. Thus, long-term experiments should be considered, and the usual performance of fall detection algorithm based on single event should be changed. Future researchers can consider more about the performance based on length of time.

VI. CONCLUSIONS

A second-order lag filtering method was used to calculate the vertical velocity for the application of fall detection. The

algorithm effectively reduced drift in the velocity signal when the subject was continuously walking and jogging. Based on this velocity, a novel feature with the vertical displacement profile, was proposed to improve fall detection methods. The results showed that introducing displacement can reduce false detection during all jogging trials and nearly all jump trials without triggering false detection. In fast motion switching, fall detection algorithm can still work well. Based on this algorithm, a fall detection and fall protection system was designed.

There is still a lot of work to do on this research. To eliminate the wrong results in ADL and avoid airbags triggered wrongly, we can add another parameter, pitch angles which would not change much in sitting down and jump. During experiments, an attempt was made by young individuals only to simulate the real living falls, even so, the data may be different from that of the elderly in real life fall scenarios.

ACKNOWLEDGMENT

We thank Fundação para a Ciência e a Tecnologia (FCT) and COMPETE 2020 program for the financial support to the project “Automatic Adaptation of an Humanoid Robot Gait to Different Floor-Robot Friction Coefficients” (PTDC/EEI-AUT/5141/2014).

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