Evaluation of a Low-complexity Fall Detection Algorithm on Wearable Sensor towards Falls and Fall-alike Activities

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Abstract*—Fall accidents cause severe damage to health, sometimes even mortality in older adults. With the increasing number of the elderly suffering from fall events, wearable products are in great demand. However, most of them for fall detection have difficulty in reducing false positive caused by fall-alike activities. In this study, we focus on evaluating the accuracy of fall detection among a set of fall-alike activities using a low-complexity fall detection algorithm and a 3-axis accelerometer. Quantitative evaluation in controlled study tunes the algorithm's parameters and provides us a 90% fall detection accuracy. The experiment result shows that jumping onto bed followed by a rest has the highest false positive rate of 45% and running followed by a sudden stop reaches 32%, while running upstairs or downstairs and standing quickly from sofa is less confusing with the false positive rates of 20% and 5%, respectively. The false positive rate is decided by the sensitivity of the threshold and the intensity of motions in the experiment. We also perform a 10-hour longitudinal study on real-life activities of one subject. In the longitudinal real-life pilot study, the low-complexity algorithm demonstrates the high accuracy, which indicates its effectiveness in real life.

I. Introduction

The fall accident is one of the major health risks, especially for the elderly (aged $65+$) [1]. Thirty three percent of the elderly are reported having experienced at least one fall per year [2]. As reported in [3], 68% hospitalization of the elderly are fall-related and the percentage with age above 85 rises to 86% [3]. In addition, the direct annual medical cost of elderly falls rises to about $20 billion dollars [4]. Even worse, fall has become one of leading causes of injurious death among the elderly, about $10,000$ deaths per year among people aged 65 years and older in the U.S. occur due to fall accidents [5].

As observed above, fall detection is urgently required. Wearable sensors such as inertial sensors play a key role in fall detection compared with other methods such as using camera [6]. In the past decade, there are a large number of research work [7]–[10] and commercial products [11] [12] in fall detection, all of which tend to employ a low-complexity algorithm. Considering the constraint of energy consumption and battery size, wearable fall detection products require a simple algorithm with less computational complexity.

Unfortunately, all the fall detection algorithms confront with the same challenge, false positive. The average accuracy is not the only standard to evaluate a fall detection algorithm. A fall detection solution without a low false positive rate will bother users for its frequent false alarm. We call those non-fall activities, which are likely to be detected as fall events by fall detection algorithms, as *fall-alike activities*. As a result, fall-alike activities introduce false positive. In [13], certain fall-alike situations, such as lying down on bed, are considered in evaluating the algorithm. However, this study is not specifically tailored to consider these fall-alike situations, and not much detail about these situations can be found in their research. Further more, other fall-alike situations are not mentioned. To the best of our knowledge, there is no study specially focusing on fall-alike activities.

In this study, our aim is to study the false positive rate of different fall-alike activities. We propose a low-complexity algorithm first, then tune the parameters for the algorithm in order to get the best performance. We perform an experiment including five typical fall-alike activities, the experimental result indicates above 90% fall detection accuracy in total 100 fall samples, evenly from ten subjects (four women and six men). The receiver operating characteristics (ROC) curve is also used to find a balance between fall detection accuracy and false positive rate. Surprisingly, some fall-alike activities we thought to be confusing can be distinguished easily, such as suddenly stopping a car before a red light and squatting quickly to pick up something. Another work we emphasize is the real-life activities study using this algorithm. The 10-hour consecutive acceleration data from one subject show the performance of the low-complexity algorithm in real life.

The remaining of this paper is organized as follows: Section II discusses some recent threshold-based fall detection algorithms. Section III describes the design of the low-complexity algorithm and its implementation. In section IV, a confusion table of fall-alike activities along with the ROC curves are presented to discuss the parameters in the algorithm. We also compare the threshold based algorithm with machine learning based fall detection method to figure out the difference between the two fields. With the suitable parameter combination, the low-complexity algorithm is applied to study the real-life performance. Finally, section V concludes the paper.

II. Related work

Fall detection aims at decreasing the damage caused by falls. As mentioned in Section I, to get a small, lightweight, and durable wearable fall detection product, people prefer low-complexity detection algorithms. Some researchers try to make their algorithm as simple as possible by using only one threshold. Bourke *et al.* place a 3-axis accelerometer on people's trunk and thigh separately to test their single-threshold algorithm [13]. However, relying on only one factor limits the detection effect. People start to combine multiple factors in their detection algorithms. As reported in [14], the value of a 3-axis accelerometer sensor placed at the height of waist during a falling event will surpass 2 g with frequency bandwidth of 20 Hz. Based on this, Daz *et al.* combine two factors to develop their algorithm by setting one amplitude and frequency flag separately: amplitude flag is related to the vertical acceleration and the other is associated with acceleration signal energy [15]. Another threshold-based algorithm estimates users' speed by integrating acceleration collected from wrist [16]. Similarly, Lindemann *et al.* put accelerometers into the hearing aid and setting three thresholds: sum of vectors of acceleration in vertical-lateral plane, velocity and acceleration of all spatial components [11]. In [17], vertical, lateral, and forward acceleration will be used separately in different detection periods to estimate people's gait speed for abnormal gait conditions. Chen *et al.* estimate human body's orientation change during a fall event by calculating the dot product of acceleration vectors before fall and after, which serves the second deciding factor along with impact detection [18]. Multiple factors-based algorithms are more specific and reliable in general.

The location of the accelerometer also can not be ignored when designing a fall detection algorithm. Kangas *et al.* evaluate three low-complexity fall detection algorithms with accelerometer placed on head, waist, and wrist, separately [19]. Result shows that head and waist are better than wrist. Considering the feasibility of wearing products on head, waist position is used more widely [18]. In addition, chest is another good choice for fall detection [20].

III. Low-complexity Fall Detection Algorithm

The low-complexity fall detection algorithm we use only needs acceleration from one 3-axis accelerometer fixed on chest. This section covers the state machine of the algorithm and the implementation.

A. Description of Algorithm

Considering some daily activities incur similar peaks in acceleration as falls such as running and jumping, we develop a algorithm combining multiple thresholds. In the algorithm, we assume that people losing consciousness have a relative stable acceleration compared to other situations, according to the conclusion from [21] and experiment result from [18]. There are five states as shown in Fig. 1: `Initial` state corresponds to the start of detection with time t to be 0. A reset button also leads to `Initial` for next use when the alarm is raised. `State0` waits for every 0.01 second (the accelerometer's sampling frequency is 100 Hz) to read acceleration and send to `State1`. `State1` compares the acceleration to the first threshold TH_1 for possible fall candidates, and then send those fall candidate moments to `State2`. `State2` monitors fall candidates for a certain period and reports body state as Inactive or Active. We regard active state as safe because the elderly can still move and the state goes back to `State1` for continuous detection. Otherwise, for inactive state, our algorithm regards it dangerous and goes to `State3` to raise an alarm. In `State2`, another threshold TH_2 is used.

B. Implementation of Algorithm

We first apply a median filter to the raw data from accelerometers, the overall acceleration is calculated like this:

$$A_{overall} = \sqrt{x^2 + y^2 + z^2}, \tag{1}$$

where x, y, z stand for acceleration along vertical, lateral, and anterior-posterior direction after median filter. The implementation of `State1` starts from comparing $A_{overall}$ to threshold TH_1. If under TH_1, the state goes back to `State0` waiting for next acceleration. Once $A_{overall}$ surpasses threshold TH_1, this moment will be sent to `State2` for further monitoring, as shown in $Algorithm 1$. The function *ProcessInState2(t)* describes how `State2` processes those fall candidate moments: We calculate the overall differential of the acceleration:

$$A_{diff} = \sqrt{diff(x)^2 + diff(y)^2 + diff(z)^2}, \tag{2}$$

where $diff(x)$, $diff(y)$ and $diff(z)$ represent differential of acceleration along x, y, z direction, which is suitable to represent older adult's active state. Even we consider people's breathing and heart rate, the differential is still at a low level when losing consciousness compared to other daily activities such as walking. In `State2`, a monitoring period is selected following the fall to report the body state. Considering slight movement of body may happen due to gravity after elderly falling and losing conscious, we divide the whole monitor period into n sub-periods evenly and introduce another threshold TH_3 to help decide body state. The maximum value of differential during a sub-period is compared with TH_2. If it is larger than TH_2, this sub-period is reported as $Active_{sub}$, otherwise is reported as $Inactive_{sub}$. TH_3 stands for the minimum percentage of inactive sub-periods to make the final report to be inactive. In the experiment, we choose n to be 100 and TH_3 as 95%. This improvement can effectively reduce the risk of being interrupted by other artifact motions.

C. Parameters Tuning

Besides the thresholds TH_1, TH_2, and TH_3 as mentioned above, there are another three time domain parameters used in the algorithm: t_1, t_2, and t_3. When to start the monitoring period after peak makes difference of the final result. As shown in the Fig. 2, the time $A_{overall}$ exceeds TH_1 is marked as t_{TH_1} and the time $A_{overall}$ reaches the peak is marked as t_{peak}. Obviously, figuring out t_{peak} helps us accurately locate the suitable start time of the monitoring period t_{start} because the time before t_{peak} can be ruled out. Parameter t_1 is used to figure out t_{peak}, to be precise, t_{peak} is the max value within

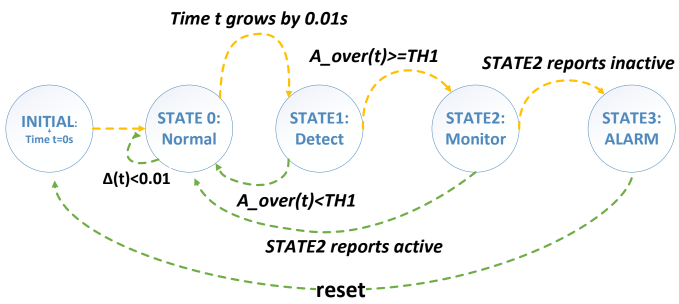


Fig. 1. State transition diagram in the fall detection algorithm.

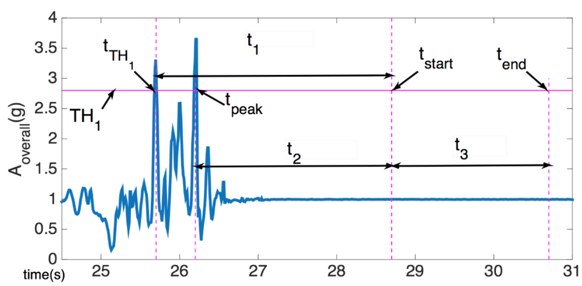


Fig. 2. Diagram of overall acceleration within a fall sample.

t_{TH_1} and $t_{TH_1}+t_1$. t_1 is set from $0.5s$ to $5s$ before evaluation. In Table II, t_2 is used to approach the end time of peak as well as t_{start} and is set from $0.5s$ to $5s$ before evaluation. t_3 determines how long the monitoring period should last. In the experiment, t_3 starts from $2s$ to $10s$.

Algorithm 1 Low-complexity multiple thresholds algorithm

```
Initial: time t = 0s;
In State0: wait 0.01s for State1;
Into State1;
while no alarm do
    if A_overall(t) > TH_1 then
        Into State2:
        status = ProcessInState2(t);
        if status = Inactive then
            Into State3, alarm;
        else
            t = t_start;
            Into State0;
        end if
    else
        Into State0;
    end if
end while

Function ProcessInState2(t)
Input: moment t
Initial: i = 1, n = 100, TH_3 = 95%;
Divide monitoring period into n sub-periods evenly from
    P_1 to P_n;
while i < (n + 1) do
    if max(A_diff(P_i)) < TH_2 then
        record P_i as Inactive_sub;
    else
        record P_i as Active_sub;
    end if
    i++;
end while
if number_{Inactive_sub} > TH_3 * n then
    return Inactive;
else
    return Active;
end if
```

IV. Evaluation

In this section, we conduct several experiments to evaluate the algorithm. First, we introduce the setup of the data collection and the experiment subjects. Then, the quantitative evaluation in the controlled study is presented with ROC curves and a confusion table of fall-alike activities. Finally, we perform a ten-hour pilot study to evaluate its real-life usability.

A. Data Collection

1) Experimental Setup: The 3-axis accelerometer with frequency of 100 Hz is placed on the subject's chest as shown in Fig. 3 (d). Subjects press a button to start and stop recording. In the experiment, the subject waits for extra three seconds to avoid interruption when starting and stopping recording. The data are collected from ten subjects including six men and four women. Since it is dangerous to invite the elderly to be our subjects, all the ten subjects are among their twenties. However, our subjects are very representational. Our male subjects' weights range from 67 kg to 93 kg and heights from 170 cm to 185 cm and female subjects' weights range from 48 kg to 65 kg and heights from 155 cm to 170 cm, which cover the most types of figures among people.

2) Experimental Scenarios: There are two parts of datasets: fall samples and fall-alike samples. For fall samples, every subject falls onto a mattress on the ground with three forward, three backward, two left-side, and two right-side, in total 100 fall samples. We recorded about 30 seconds for every fall sample to ensure the completeness of data and our subjects stay still after falling to simulate the situation of losing conscious. People fall and can still stand up soon are not regarded as dangerous in the study. For fall-alike part, samples include sitting and standing, walking, walking upstairs and downstairs, running and jumping with detailed description in Table I. For each fall-alike event in Table I, every subject contributes ten samples. In Fig. 3, sitting onto sofa and standing from sofa quickly (Fig. 3 (a), (b)), running downstairs and upstairs (Fig. 3 (c), (d)), jumping onto bed (Fig. 3 (e), (f)), and running then stopping to rest (Fig. 3 (g), (h)) are presented.

Fig. 3. Scenarios of fall-alike activities with the accelerometer located on subject's chest: (a) Sitting onto sofa, (b) Standing from sofa, (c) Running upstairs, (d) Running downstairs, (e) Jumping onto bed, (f) Rest lying on bed after jumping, (g) Running outsides, (h) Stop running and rest.

B. Quantitative Evaluation in a Controlled Study

1) Time Domain Parameters: as illustrated in Table II and Fig. 2, there are six parameters: TH_1 from 2.2 to 3.8, t_1 from 1 second to 5 seconds, t_2 from 1 second to 5 seconds, t_3 from 1 second to 5 seconds, TH_2 from 0 to 8, and TH_3 from 80% to 99%. These ranges of parameters come from the analysis of raw data. After analyzing $A_{overall}$ and A_{diff}, we first chose TH_1, TH_2 and TH_3 to be $2.8, 5, 95\%$, which is proved to be the maximal value point in Fig. 4. After comparing the effect of various combinations of the three time domain parameters, the final combination achieved the 90% accuracy: $t_1 = 4s, t_2 = 2.5s, t_3 = 2.5s$.

2) ROC Curve: We chose the three time domain parameters as $t_1 = 4s, t_2 = 2.5s, t_3 = 2.5s$ and started to tune thresholds. The ROC curve directly shows the relationship between false positive rate (FPR) and true positive rate (TPR), which helps tune thresholds of the algorithm for a balance of TPR and FPR. We first studied the third threshold TH_3 as shown in Fig. 5. We set TPR to be 70%, 80%, and 90%, respectively, to see the corresponding FPR at different TH_3 value. From the diagram, we found TH_3 as 95% is suitable with its 19% FPR at 90% TPR. In Fig. 6, the purple curve named *Combined* combines TH_1 and TH_2 with other parameters tuned. The yellow curve named $TH2$ shows the result of only changing TH_2 with TH_1 as 2.8 while the red curve named TH_1 only changes TH_1 with TH_2 as 5. As shown in the figure, neither red curve $TH1$ or yellow curve $TH2$ could detect all the fall events or perform better than the purple curve *Combined*, which showed the advantage of combining multiple thresholds. The blue curve named *SVM* is the ROC curve from support vector machine with the linear kernel function and 10 cross-validation. We changed the length of fall samples and fall-alike samples from 10 seconds to 2 seconds for the SVM classifier. In Fig. 6, point **A** $(FPR = 20\%, TPR = 80\%)$ and point **B** $(FPR = 15\%, TPR = 84\%)$ represent the balance of FPR and TPR for curves of *SVM* and *Combined*, respectively. From the ROC curve, we found that the low-complexity algorithm with parameters tuned performed better than SVM, which indicated the advantage of the multiple-threshold algorithm. We also studied the sensitivity of both TH_1 and TH_2. As shown in Fig. 4, the accuracy combines the fall detection rate and fall-alike events detection rate. The maximal point corresponds perfectly with the ROC curve.

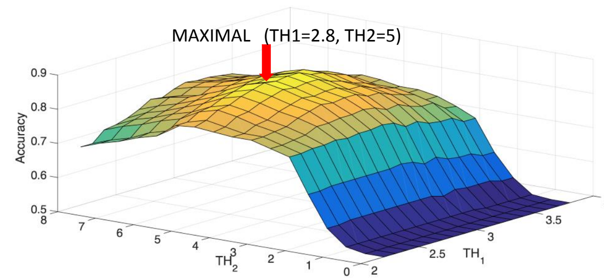


Fig. 4. Sensitivity of TH_1 and TH_2 in detection accuracy

3) Confusion Table of Fall-alike Activities: the confusion table is shown in Table III. We found that jumping onto bed followed by a rest is the most confusing, whose FPR reaches 45% with its acceleration and differential of acceleration shown in Fig. 7 (a), (b). Running followed by a sudden stop also reaches 32% FPR with its acceleration as well as the differential of acceleration shown in Fig. 7 (c), (d). On the other hand, standing from sofa and running downstairs quickly have FPR of 20% and 5%, respectively. Sitting quickly onto sofa is supposed to be confusing whose false positive is largely decided by the first threshold TH_1 and how quickly subjects sit. In the experiments, subjects are requested to sit more quickly than usual and FPR is 27%. Running with a stop and jumping onto bed are more related with the second threshold, most samples of them easily reach $TH_1 = 2.8$. Fig. 7 shows these two fall-alike activities in detail. Standing from sofa has low FPR for its low $A_{overall}$. Running upstairs or downstairs has high $A_{overall}$ but TH_2 can rule it out.

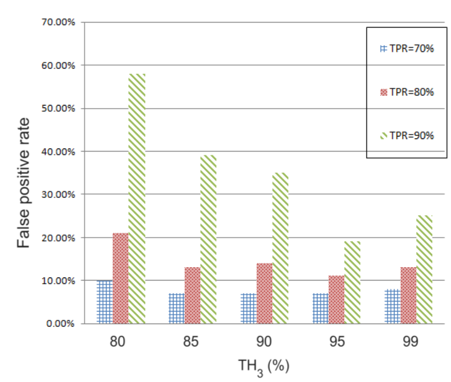


Fig. 5. Diagram of FPR at 70%, 80%, 90% TPR of different TH3

TABLE I
FALL AND FALL-ALIKE ACTIVITIES SCENARIOS IN THE EVALUATION

Scene	Action	Location	# of events	Description
1	Fall	Indoor	10	Fall includes forward, back and lateral direction, stay still after fall
2	Sit onto sofa	Indoor	10	After sitting onto sofa, use cell phone to browse some news
3	Stand from sofa	Indoor	10	After standing from sofa, holding on cell phone to view some news, but do not move
4	Jump onto bed	Indoor	10	Simulate people jump to bed for a rest, stay still after onto bed.
5	Run and rest	Outdoor	10	Run for about 10seconds and then quickly stop to rest, do not walk after stop
6	Run downstairs	Indoor	10	After running downstairs, walk softly

TABLE II
SUMMARY OF FALL DETECTION PARAMETERS

Parameters	Range	Description	Usage
$TH_1(g)$	$2.2-3.8$	First threshold to detect possible fall candidate	t_{TH_1} is the time when TH_1 is reached
$t_1(s)$	$1.0-5.0$	A range of time in which t_{peak} will be found	t_{peak} in t_{TH_1} to $t_{TH_1}+t_2$
$t_2(s)$	$1.0-5.0$	A range of time where t_{start} will be found	$t_{start}=t_{peak}+t_2$
$t_3(s)$	$1.0-5.0$	A range of time which is the length of monitor period	Monitor starts from t_{start} to $t_{start}+t_3$
$TH_2(g/s)$	$0-8.0$	Second threshold to determine if subject stays active	Max(sub-period) smaller than TH_2 is $Inactive_{sub}$
TH_3	$0\%-100\%$	A threshold to determine if subject stay active	Percentage of inactive sub-periods larger than TH_3 is Inactive

TABLE III
CONFUSION TABLE WITH PARAMETER COMBINATION: $TH_1=2.8g, t_1=4s, t_2=2.5s, t_3=2.5s, TH_2=3g/s, TH_3=95\%$

	Fall	Sit onto sofa	Stand from sofa	Jump onto bed	Run and stop	Run downstairs	total	Recall
Fall	90	non-fall 10					100	90%
Sit onto sofa	27	73	N/A	N/A	N/A	N/A	100	73%
Stand from sofa	5	N/A	95	N/A	N/A	N/A	100	95%
Jump onto bed	45	N/A	N/A	55	N/A	N/A	100	55%
Run and stop	32	N/A	N/A	N/A	68	N/A	100	68%
Run downstairs	20	N/A	N/A	N/A	N/A	80	100	80%

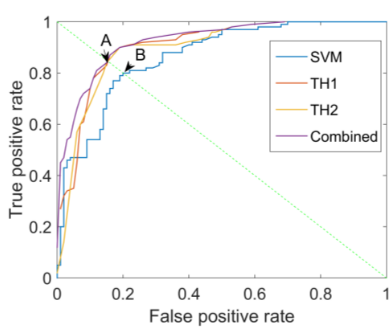


Fig. 6. ROC curves of TH_1, TH_2 combined, and from SVM

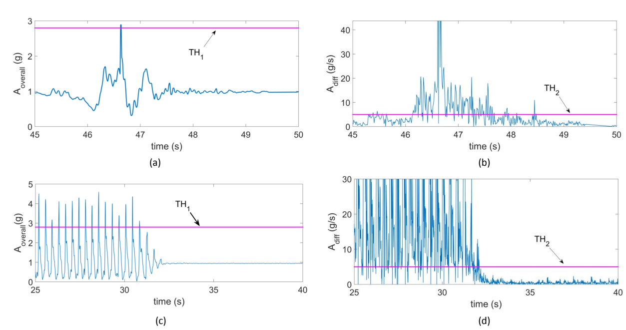
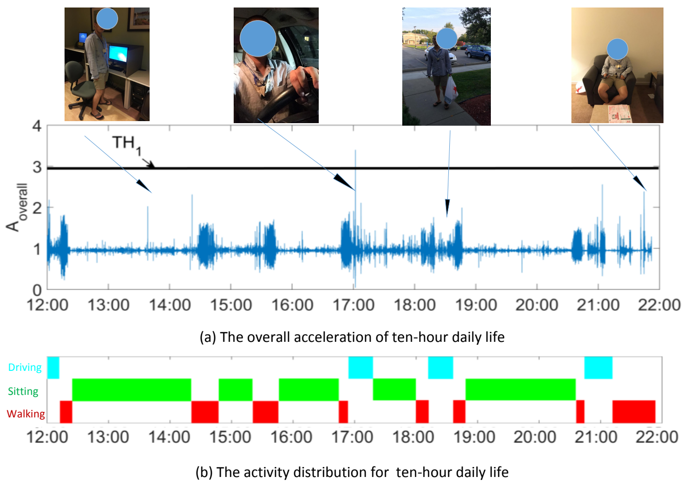


Fig. 7. Two samples of jumping onto bed and running and stop: (a) Overall acceleration of jumping onto bed, (b) Overall differential of acceleration of jumping onto bed, (c) Overall acceleration of running and stop, (d) Overall differential of acceleration of running and stop.

C. Evaluation of a Real-life Pilot Study

To investigate the effect of the low-complexity algorithm in real-life, we monitored the ten-hour daily life of one of our male subjects. Since the fall detection rate is already very high and are studied in the experiment, we want to test the false positive rate in real-life. Wearing the T-shirt with the sensor on his chest, the subject started to record data in the morning before he went to school and ended up the collection until he came back home and was ready to sleep at night. Recording starts from $12:15$pm to $10:30$pm, the total length is about ten hours. The overall acceleration and activity distribution during the ten hours can be obtained in Fig. $8(a)$ and in Fig. $8(b)$, respectively. Driving happened when the subject went to school and out for dinner, some acceleration peaks during driving period indicate sudden stops. Walking happened when subject went from parking lot to classroom, and classroom to classroom. In walking stage, taking elevator and walking upstairs and downstairs are also included because the duration of these activities are too short to be distinguished accurately. Sitting stage most happens in classroom and library. Standing up from chair incurs some small peaks in sitting stage. At around $5pm$, the subject went out for dinner and shopping. When the subject went back home at night, he sat onto sofa to watch TV, which incurred another peak. All these special situations are illustrated with pictures in Fig. $8(a)$. In the pilot study, most fall-alike activities are tested and our algorithm reports no fall during the consecutive ten hours.



(a) The overall acceleration of ten-hour daily life

(b) The activity distribution for ten-hour daily life

Fig. 8. Ten-hour daily life including running, driving a car, walking upstairs and downstairs, using elevator, sitting and standing.

V. Discussion and Conclusion

In this study, we present a low-complexity threshold based fall detection algorithm. The controlled study shows the algorithm reaches a balance of good fall detection accuracy and low false positive rate. Fall-alike activities are discussed in causing false positive. Machine learning method is used to compare with the threshold-based algorithm. We also conduct a ten-hour pilot study to test its usability in real-life. The result shows that our low-complexity algorithm can rule out most fall-alike activities in daily life. However, using only acceleration information, we have difficulty in distinguish between falls and jumping onto bed or run-and-stop. One possible improvement is that we can calculate the rough height change estimate using the vertical acceleration. The difference of height change may distinguish between falls onto ground and jumping onto bed, or run-and-stop. Considering its 90% fall detection accuracy,this algorithm can be applied into wearable products. In theory, only one accelerometer is needed for wearable products targeting fall detection using our algorithm, which is a strong guarantee for the size and energy consumption of products.

References

[1] A. A. Zecevic, A. W. Salmoni, M. Speechley, and A. A. Vandervoort, "Defining a fall and reasons for falling: comparisons among the views of seniors, health care providers, and the research literature," *The Gerontologist*, vol. 46, no. 3, pp. 367–376, 2006.

[2] N. Noury, "A smart sensor for the remote follow up of activity and fall detection of the elderly," in *Microtechnologies in Medicine & Biology 2nd Annual International IEEE-EMB Special Topic Conference on*. IEEE, 2002, pp. 314–317.

[3] D. L. Covington, J. G. Maxwell, and T. V. Clancy, "Hospital resources used to treat the injured elderly at north carolina trauma centers," *Journal of the American Geriatrics Society*, vol. 41, no. 8, pp. 847–852, 1993.

[4] J. Davis, M. Robertson, M. Ashe, T. Liu-Ambrose, K. Khan, and C. Marra, "International comparison of cost of falls in older adults living in the community: a systematic review," *Osteoporosis International*, vol. 21, no. 8, pp. 1295–1306, 2010.

[5] K. Doughty, R. Lewis, and A. McIntosh, "The design of a practical and reliable fall detector for community and institutional telecare," *Journal of Telemedicine and Telecare*, vol. 6, no. suppl 1, pp. 150–154, 2000.

[6] G. Wu, "Distinguishing fall activities from normal activities by velocity characteristics," *Journal of biomechanics*, vol. 33, no. 11, pp. 1497–1500, 2000.

[7] Z. Li, A. Huang, W. Xu, W. Hu, and L. Xie, "Fall perception for elderly care: A fall detection algorithm in smart wristlet mhealth system," in *IEEE International Conference on Communication (ICC'14)*, Sydney, Australia, June 2014, pp. 1 – 5.

[8] W. Xu, F. Gong, L. He, and M. Sarradzadeh, "Wearable assistive system design for fall prevention," in *Joint Workshop on High Confidence Medical Devices, Software, Systems & Medical Device Plug-and-Play Interoperability (HCMDSS/MDPnP'11)*, Chicago, USA, July 2011, pp. 1 – 8.

[9] H. Noshadi, N. Amini, J. Woodbridge, W. Xu, M. Lan, H. Hapopian, N. Terrafranca, and M. Sarrafzadeh, "Lightweight context-aware smart insole for gait analysis, research and rehabilitation," in *3rd International Congress on Gait & Mental Function (Parkinsonism & Related Disorders) (PRD'10)*, Seattle, USA, February 2010, p. 29.

[10] W. Xu, M.-C. Huang, N. Amini, J. Liu, L. He, and M. Sarrafzadeh, "Smart insole: A wearable system for gait analysis," in *International Conference on Pervasive Technologies Related to Assistive Environments (PETRA'12)*, Crete Island, Greece, June 2012, pp. 69 – 72.

[11] U. Lindemann, A. Hock, M. Stuber, W. Keck, and C. Becker, "Evaluation of a fall detector based on accelerometers: A pilot study," *Medical and Biological Engineering and Computing*, vol. 43, no. 5, pp. 548–551, 2005.

[12] Q. Li, J. Stankovic, M. Hanson, A. T. Barth, J. Lach, G. Zhou *et al.*, "Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information," in *Wearable and Implantable Body Sensor Networks, 2009. BSN 2009. Sixth International Workshop on*. IEEE, 2009, pp. 138–143.

[13] A. Bourke, J. Obrien, and G. Lyons, "Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm," *Gait & posture*, vol. 26, no. 2, pp. 194–199, 2007.

[14] C. V. Bouten, K. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen, "A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity," *Biomedical Engineering, IEEE Transactions on*, vol. 44, no. 3, pp. 136–147, 1997.

[15] M. Prado, L. Roa, J. Reina-Tosina, G. Sánchez *et al.*, "Preliminary evaluation of a full-time falling monitor for the elderly," in *Engineering in Medicine and Biology Society, 2004. IEMBS'04. 26th Annual International Conference of the IEEE*, vol. 1. IEEE, 2004, pp. 2180–2183.

[16] T. Degen, H. Jaeckel, M. Rufer, and S. Wyss, "Speedy: A fall detector in a wrist watch." in *ISWC*, 2003, pp. 184–189.

[17] B. Najafi, A. Vaziri, and A.-R. Boloori, "Ambulatory system for measuring and monitoring physical activity and risk of falling and for automatic fall detection," Jun. 26 2012, uS Patent 8,206,325.

[18] J. Chen, K. Kwong, D. Chang, J. Luk, and R. Bajcsy, "Wearable sensors for reliable fall detection," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*. IEEE, 2006, pp. 3551–3554.

[19] M. Kangas, A. Konttila, P. Lindgren, I. Winblad, and T. Jämsä, "Comparison of low-complexity fall detection algorithms for body attached accelerometers," *Gait & posture*, vol. 28, no. 2, pp. 285–291, 2008.

[20] B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C. J. Büla, and P. Robert, "Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly," *Biomedical Engineering, IEEE Transactions on*, vol. 50, no. 6, pp. 711–723, 2003.

[21] L. Quagliarella, N. Sasanelli, and B. Belgiovine, "A fall and loss of consciousness wearable detector," *Gerontechnology*, vol. 7, no. 2, p. 191, 2008.