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Fall Detection for Mobile Phone based on Movement Pattern

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요 약

인간의 동작 인식은 건강관리, 상황기반 응용 등 실제적인 삶의 여러 부분에서 이용할 수 있기 때문에 중요한 주제이다. 건강관리를 위한 조언을 제공하는데 사용될 수 있기 때문에 동작인식 중 일상생활 동작인식이 주로 연구되고 있다. 특별히 넘어짐은 심장문제로 발생할 수 있기 때문에 넘어짐 인식은 독거 노인의 건강한 삶에 중요한 역할을 할 수 있다. 넘어짐 인식은 여전히 어려운 연구과제이다. 넘어짐 인식을 위해 몸에 여러 종류의 센서를 부착하는 시스템이 제안되었지만 이는 사용자가 센서를 부착하는 것을 잊어버리거나 이런 시스템에 익숙하지 않기 때문에 유용성에 문제가 있다. 본 연구에서는 사용자가 휴대하고 있는 스마트 폰 내의 가속도 및 자이로센서 값의 변화를 분석하여 알려진 넘어짐 패턴과 유사성을 분석하여 넘어짐을 판단하는 방법을 제안한다. 이 연구를 위해 5명의 자원자를 모집하여 다양한 종류의 넘어짐을 실험하였다. 실험결과는 본 연구를 통해서 넘어짐 인식을 위한 제안한 방식이 유효하다는 것을 보여준다. 실험 알고리즘은 많이 사용되고 있는 G1 스마트 폰 위에 구현하였다.

ABSTRACT

Nowadays, recognizing human activities is an important subject; it is exploited widely and applied to many fields in real-life, especially in health care and context aware application. Research achievements are mainly focused on activities of daily living which are useful for suggesting advises to health care applications. Falling event is one of the biggest risks to the health and well-being of the elderly especially in independent living because falling accidents may be caused from heart attack. Recognizing this activity still remains in difficult research area. Many systems equipped wearable sensors have been proposed but they are not useful if users forget to wear the clothes or lack ability to adapt themselves to mobile systems without specific wearable sensors. In this paper, we develop a novel method based on analyzing the change of acceleration, orientation when the fall occurs and measure their similarity to featured fall patterns. In this study, we recruit five volunteers in our experiment including various fall categories. The results are effective for recognizing fall activity. Our system is implemented on G1 smart phone which are already plugged accelerometer and orientation sensors. The popular phone is used to get data from accelerometer and results showthe feasibility of our method and significant contribution to fall detection.

☞ keyword : 동작인식(activity recognition), 넘어짐 사건(falling event), 상황기반(context aware), 가속도센서(accelerometer sensor), 오리엔테이션센서(orientation sensor)

1. INTRODUCTION

Activity recognition is researched to determine the action or states of the user by analyzing sensor data. With simple human activities such as walking, running, a large number of classification methods have been investigated. Users use wearable accelerometer or bring mobile phone equipped with accelerometer. In this way by exploiting X, Y and Z value of accelerometer we can infer physical activities of users. Many studies are based on this method to contribute classifiers.

Specially, the fall is a very risky factor in the elderly people's daily living, especially in the independent living, since it often causes serious physical injury such as bleeding, and center nervous system damages. A rate of 1/3 the persons aged over 65 has been reported to occur at least once per year [1]. If the emergency treatments were not on

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time, these injuries could result in disability, paralysis, even death. The current fall detection methods can be basically classified into three types based on data [1]:

- Video data: The video based system captures the images of human movement, then determines whether there is a fall event or not based on the variations of some image features and using machine learning algorithms [2].
- Acoustic data: Detecting a fall via audio signal analysis.
- Wearable sensor data: Embedding some micro sensors into clothes, or girdle, shoes, plug on foot, etc. to monitor the human activities in real-time, and find the occurrence of a fall based on the changes of some movement parameters [3].

However, these approaches have some weak points asnarrow scope of video system, poor accuracy of audio system, and inconvenience of wearing sensors system. Recent smart phones are well equipped with useful sensors including accelerometers and orientation. With maturation of Internet and rapid development in mobile communication, device could bring enhanced services to the person especially in health care center. Therefore, we focus on developing a fall detector based on mobile handset. Recent reports on posture tell that people have popular habit using mobile phone by putting the phone next to their ears for listening or calling, holding it by hand for typing short message service (SMS) or playing game, and putting mobile phone in bags, pants or chest pocket [4]. A fall event can happen in those cases. Therefore, we separate them into categories to easily observe the change of acceleration andorientation as in Table 1.

(Table 1) THE POSTURES OF USING PHONE

Mobile position	Description
Category 1	Hold by hand while typing SMS
Category 2	Hold by hand while listening
Category 3	In chest pocket
Category 4	In pants pocket

Accelerometer has been proposed being suitable for falls detection, but there still remains basic restrictions. The basic approach was published in [5]. In that approach, a change in orientation that occurs immediately when user have bumped into something while walking is indicative of a fall event. The common and simple methodology for fall detection is using a tri-axial accelerometer with threshold algorithms [6]. Such algorithms simply raise the alarm when the threshold value of acceleration is reached. Zhang et al. [7] designed a fall detector based on SVM algorithm. The detector used one waist-worn accelerometer fixed on human body. The features for machine learning were the accelerations in each direction, changes in acceleration, etc. Their method detected falls with 96.7 % accuracy. Recently, researchers [8], Roehampton University, make an experiment using motion signals while participants is equipped G1 phone to observe acceleration's change in different falling directions and propose corresponding thresholds to distinguish the falls from some specific activities (walking, picking, getting up). The fall is suspected when acceleration's amplitude crosses fixed thresholds. In other ADLs, their acceleration can exceed the falling thresholds; therefore, improving the accuracy of fall detection need be investigated more including phone usage habit and orientation.

In this paper, we use an easy way with popular Google Nexus phone included built-in accelerometer and orientation sensor to observe the changes of acceleration and orientation based on characteristics of fall event and then propose a novel method based on acceleration thresholds and orientation and then measure similarity of new sample with typical collected falling sample to detect a fall event. The result from proposed algorithm shows the method can detect the falls effectively.

2. THE PROPOSED METHOD

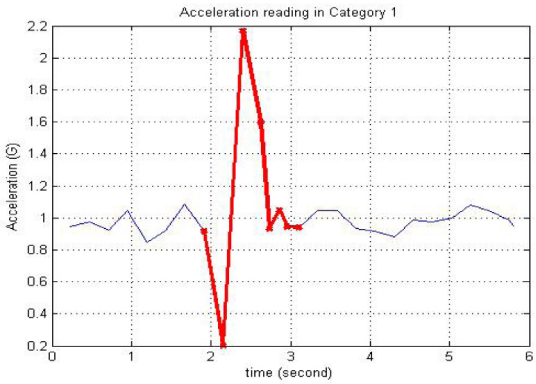
2.1 OBSERVING ACCELERATION

The fall will cause acutely varieties in acceleration and generally occurs in a short time period with a typical range of 0.4~0.8 second [9]. We can separate the fall event into 3 steps as following:

-First step: While the normal activity is happening, the fall occurs suddenly. The human body loses balance and moves from upright standing to falling state. This causes the acceleration's amplitude to be dropped significantly. The actual fall is taken place in this step.

- Second step: When the body hit onto the ground, the actual fall ended. At this moment, the ground affects to the human body immediately as a force. It causes the acceleration raise significantly.
- Third step: Human can return to normal activity or be lying down on the ground.

The typical fall is performed as following graph:



(Figure 1) Change of acceleration in Category 1

As Figure 1 indicates, while a human is holding phone to compose SMS, the fall occurs suddenly as Category 1, acceleration decrease from 1.15G to 0.2G. In 2^{nd} step, acceleration increase to 2.18G. After the human lying down on the ground, it causes acceleration return around 1G in 3^{rd} step. The 4 young volunteers, (age 22-30) with height from 1.6m to 1.75m are selected to attend experiment while bringing Google Nexus One phone. We collect data from the proposed categories to observe variation of acceleration in the steps.

(Table 2) SAMPLE TO OBSERVE ACCELERATION

Category	Description		
	Forward	Backward	Aside
Category 1	80	40	20
Category 2	90	35	20
Category 3	75	30	20
Category 4	85	35	30

Table 2 shows total sample of each category correspond to fall orientations. The volunteers stand upright and perform the fall down activity while the phone is brought in specific position. We obtained acceleration in above 3 steps to find the thresholds in negative peak (NP) of first step and positive peak (PP) of second step.

Algorithm to compute thresholds in NP - PP

Step1:
Initialize samples for each Category and corresponding orientation.
S_{ij} = set of samples in Orientation j of Category i with $i \in [1, 4]$, $j \in [1, 3]$

Step2:
Find a,b of each sample $s_{kij} \in S_{ij}$; $k \in [1, \text{size of } S_{ij}]$ with:
a = marginal value of acceleration in NP of 1^{st} step at t_0
b = marginal value of acceleration in PP of 2^{nd} step at t_1
Where $[t_0, t_1] \leq 1$ *second*
Initialize value for LT_{ij}, UT_{ij} from a,b of 1^{st} sample in S_{ij}

Step3:
Update thresholds in S_{ij} from a,b of each sample s_{kij}

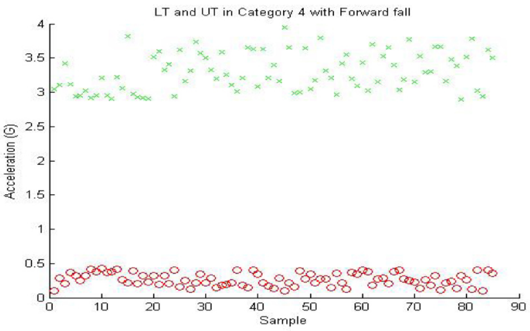
$$update(LT_{ij}) = \begin{cases} LT_{ij} = a & if\ LT_{ij} \leq a \\ kept & otherwise \end{cases}$$

$$update(UT_{ij}) = \begin{cases} UT_{ij} = b & if\ UT_{ij} \geq b \\ kept & otherwise \end{cases}$$

In fall orientations of each corresponding category, the highest value of NP in 1^{st} step is elected. It ensures a safe threshold for all remaining falls like in experiment of first step. In this step if acceleration exceeds the threshold, it becomes a good condition to review an actual fall event. We also choose the lowest value of PP in 2^{nd} step as safe threshold. These thresholds are respectively called as Lower Threshold (LT) and Upper Threshold (UT). After following three above steps, if the amplitude crosses the LT and UT, the fall down event is suspected. These thresholds are summarized in Table 3.

(Table 3) THE THRESHOLDS IN EACH CATEGORY Max Value in NP-Min Value in PP (Unit: G)

Category	Description		
	Forward	Backward	Aside
Category 1	0.6-1.9	0.59-1.86	0.57-1.92
Category 2	0.38-1.95	0.43-1.93	0.35-1.94
Category 3	0.32-2.07	0.36-1.84	0.4-1.84
Category 4	0.42-2.94	0.44-1.87	0.3-2.84

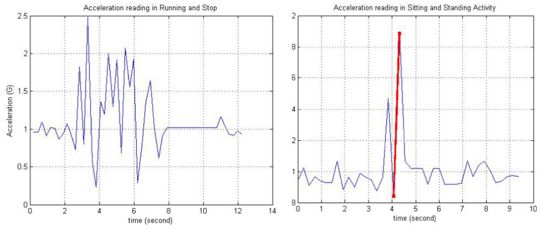


(Figure 2) Marginal values of acceleration in 1st, 2nd step of 85 falls in Category 4-Forward

As Figure 2 indicates, the marginal values in negative peak of 1st step over [0.1, 0.42], and [2,94, 3.81] is determined for 2nd step in Category 4 and Forward Orientation. Therefore (0.42- 2.94) range is used for LT-UT in this case.

In some jumping, running activities, they can break LT and UT in Category 4. After that, if the user suddenly stops, it can cause an extended period of 1G acceleration. These events together suggest a fall. With moving from sitting to standing activity in Category 4, sitting and standing's acceleration do not usually break the LT and UT. However, it can change the orientation.

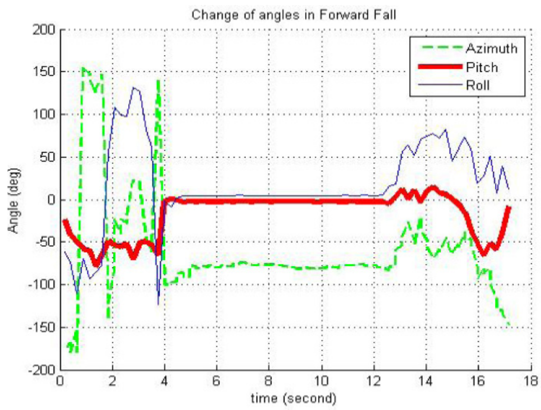
Besides the change of acceleration, orientation of human also changes for instance upright to horizontal direction in actual fall event. Because orientation sensor is already plugged on smart phone, we need to observe it in proposed falling categories.



(Figure 3) Change of acceleration in Running-Stop exceeds Backward Thresholds, Sitting -Standing activities in Category 4

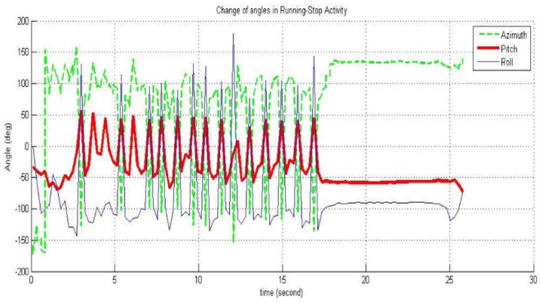
2.2 OBSERVING ORIENTATION

A study by Lord et al. [10] found that 82% of falls occurred when people were in upright stance. The fall can only end in a horizontal direction when human lying down on the ground, thus the difference between orientation before and after the fall is close to 90 degree. In this study we observed the change of orientation in each category with forward falls, backward falls, and aside. Orientation sensor in Google Nexus proposes 3 angles; Azimuth rotating around the Z axis, Pitch and Roll angle respectively rotating around X, Y axis respectively. The typical change of angles in forward fall event is represented as following graph:

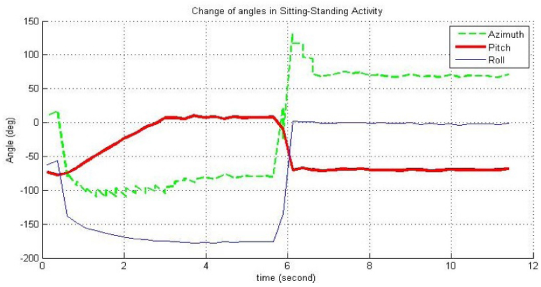


(Figure 4) Change in angles of forward fall

Figure 4 shows change of angles in which case the fall occurs suddenly while the phone is put in pants pocket making human moves from upright state to horizontal state and liedown on the ground. This causes Pitch angle change significantly from near -90 degree to 0 degree. Roll angle rotates around Y axis and illustrates the tilt of the phone. In case of horizontality and flat, the Roll changes to near 0 degree. In normal activities such as running, jogging or walking, the angles always change based on characteristics of body part's movement. Activity of the thigh makes the angles change cyclically when the phone is put in pant pocket. In running-stop activities, the Pitch angles before and after the stop activitiy keep intact when acceleration cross LT and UT. They do not have the difference including near 90 degrees before and after the acceleration exceeds the thresholds or Pitch angle keeps 0 degree within extended period after the fall event.



(Figure 5) Angles of running-stop activities in Category 4

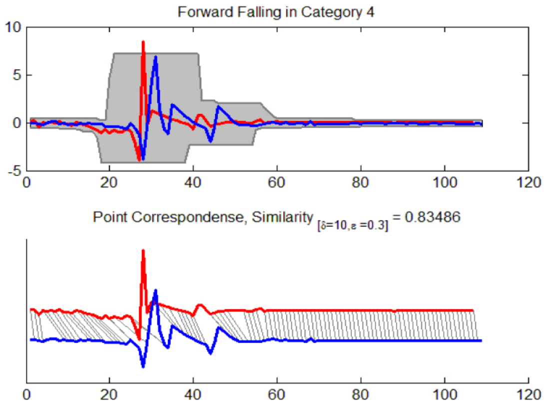


(Figure 6) Angles of sitting-standing activities in Category 4

In sitting-standing activities, the Pitch angles before and after standing have near 90 degree difference. When human stands upright stably, three angles keep stable value. The actual change in orientation depends on the initial and final position of the person, but in any case, there usually has a change.

2.3 FALL PATTERN MATCHING

In sample collection phase in order to observe the changes of acceleration and orientation when fall events occur, we also consider these changes as templates of user's falling pattern. Similarity score is measured from the templates in each category to guarantee for actual fall events. Wherefore, from a new unknown sample in testing phase, we could match its featured changes with the templates which have stored in the system to compute its lowest similarity score. When this value is lower than the threshold we computed before, non-fall result can be labeled to this sample. Since dynamic time warping (DTW) was developed for spoken-word recognition [11] and has used to temporally align various types of biometric data [12], we apply it to measure the similarity of real fall events with a new sample. The similarity of two templates in our collecting phase is performed as figure 7. Similarity score is measured as the ratio of longest common subsequent among two sequences and maximum size value between them.



(Figure 7) Matching 2 templates in Forward of Category 4

As showing of Figure 7, above graph shows changes of two templates in the same one scale, and below graph shows pairs of each two corresponding points on them.

3. FALL DETECTION SCHEME

Based analyzing fall event, if the amplitude crosses the LT and UT, the fall down event is suspected. If the amplitude exceeds LT value, we observe this change. In some activities, they can decrease to the value which is lower than LT. Letting t_o be the time as amplitude reaches the lowest value in 1st step before it begin to increase.

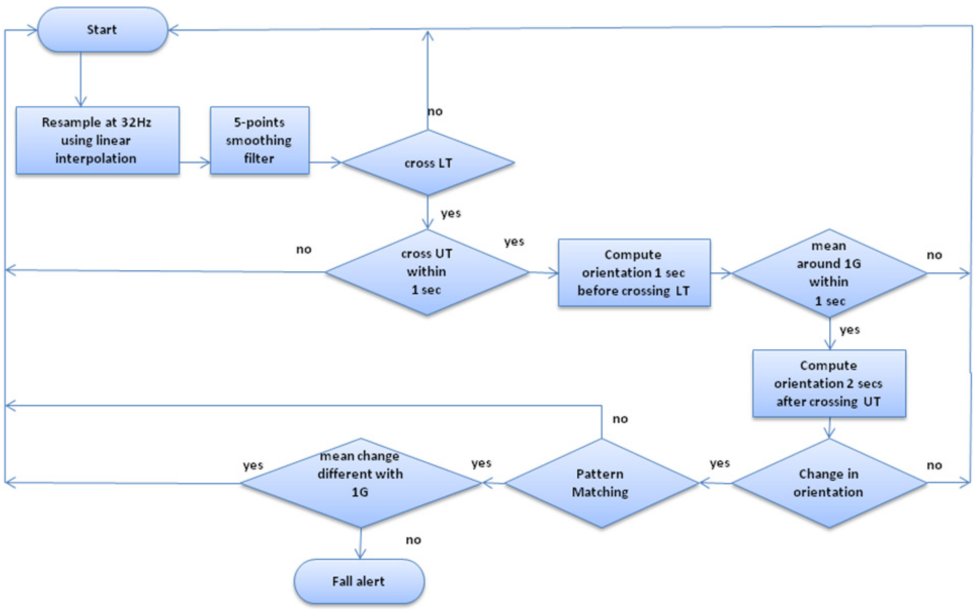
If the amplitude exceeds UT value in the 2nd step over $[t_0, t_0 + 1]$, we estimate the average of the three angles over $[t_0 - 1, t_0]$ in the 1st step of fall event. In the 3rd step, if there exists a period which has the average of acceleration is around 1G within 1 second; we assume that the human can be paralyzed. In this case, we estimate the average of the Pitch angles within 2 seconds after the acceleration exceed UT. When the Pitch value keeps around 0 degree in a period or has the difference before and after the fall close to 90 degree, the 3 angles do not change in a period, the fall down event is suspected. These cases correspond to the phone lying flatly on the plane, or it is kept vertically in Category 1, 3 and 4 before the fall happened, or people lie motionlessly on the ground. For final checking an actual fall event, we match this acceleration's change to given templates to measure the similarity.

If a fall is suspected when reaching the similarity threshold of known category in experiment is not available, we allow a short time for a fallen user to regain an upright state or pick dropped phone when it is thrown away in Category 1, 2. The scheme in Figure 8 summarizes fall detection algorithm.

4. EXPERIMENTS AND EVALUATION

4.1 SIGNAL PROCESSING

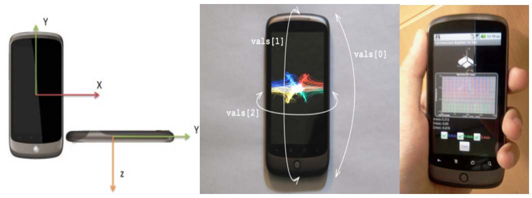
Many of these smart phones nowadays are equipped with location; motion, light, audio, video sensors. We have chosen Android-based cell phones as the platform for our study because the Android operating system is free, open-source, easy to program. It is expected to become a dominant one in the cell phone marketplace. We perform all experiments on a Google Android HTC Nexus One with the following specifications:



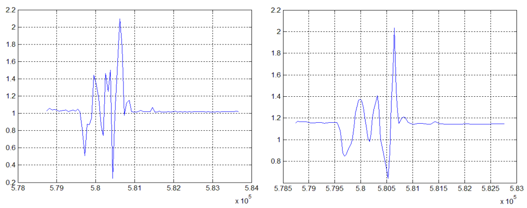
(Figure 8) Fall detection scheme

1. Android™ 2.1 (Eclair) OS, 512MB ROM and 512MB RAM.
2. Bosch Sensortec's 3-axis BMA 150 accelerometer with 24.45Hz average frequency in FASTEST mode in our experiment
3. AK8973 orientation sensor

We implemented general software architecture for the purpose of data collection. A snapshot of the data collection is shown in Figure 9.



(Figure 9) Tri-axial Accelerometer, angles of orientation sensor in Google Nexus One and our prototype



(Figure 10) Original acceleration and filtered data after interpolating at 32Hz in Forward Category 3

Since these built-in sensors are wrapped by Android OS, it only allows acquistion of an acceleration sample on an "onSensorChange()" event generating irregularly sampled values , we need to regularize sampled values via linear interpolation at an expected frequency as 32Hz in our experiment. The linearized value is computed by findingthe closest sampled data point before and after the desired sampling time, and then interpolating a new value at a desired sample time. The linearized signal was then filtered through 5-point smooth to reduce additional noises. Figure 10 shows acceleration before and after linearization and noise reduction.

4.2 EVALUATION OF FALL DETECTION

Fall detection experiments were done on 4 proposed categories. Five people aged over 23 years were recruited to evaluate our developed system. There have better experiments if we study on elderly people, but it is not easy because the risk of our experiment can harm to their health. Each experiment was repeated 20 times for each category. The experiment in daily life activity was performed five times including walking, running, and climbing up/down stair. The result is summarized in Table 4.

Table 4 shows the result of our experiment, it is success when the actual fall is detected with forward, backward and aside orientation. In sitting and standing, ADL, it is success when the algorithm does not detect successfully a fall event. In total data, the system detects successfully in 296 times and 44 times corresponding to correct and incorrect cases. The accuracy is 87 %.

Sensitivity is the capacity to detect a fall

$$Sensitivity = \frac{TP}{TP + FN} \tag{1}$$

(Table 4) THE RESULT OF EXPERIMENT IN 4 CATEGORIES SUCCESS(S), FAIL (F)

Category	Fall Detection									
	Forward		Backward		Aside		Sitting and Standing		ADL	
	S	F	S	F	S	F	S	F	S	F
Category 1	17	3	16	4	15	5	20	0	4	1
Category 2	18	2	15	5	15	5	20	0	4	1
Category 3	18	2	17	3	16	4	20	0	5	0
Category 4	19	1	18	2	15	5	20	0	4	1

Specificity is the capacity to detect only a fall

$$Specificity = \frac{TN}{TN + FP} \tag{2}$$

where TP = true positives (detected fall), FN = false negatives (undetected fall), TN = true negatives (normal movement, not alert), FP = false positives (normal activity, alert).

Sensitivity = 0.829, Specificity = 0.97.

5. CONCLUSION & FUTURE WORKS

In this paper we propose a novel method applied on an independent mobile phone to extract changes from built-in accelerometer, orientation sensor and detect fall activity. Ourproposed approach ensures simplicity and high efficiency because the algorithm can be implemented easily on popular phones and the fall activity is detected on time. Based on the proposed thresholds of using phone, we believe it is a good preliminary work for further approaches. With the importance of human activity recognition, especially in health care to elderly, the proposed method makes human activity recognition in smart phone is easier like fall detection in daily life. For future study, we need to implement real time classifier on mobile phone to enhance accuracy. Falling detection based on wearable sensors or specific device has gained maturely, but popular device such as mobile phone is still a challenge.

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