Fall Detection with Orientation Calibration Using a Single Motion Sensor

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Abstract. Falls are a major threat for senior citizens living independently. Sensor technologies and fall detection algorithms have emerged as a reliable, low-cost solution for this issue. We proposed a sensor orientation calibration algorithm to better address the uncertainty issue faced by fall detection algorithms in real world applications. We conducted controlled experiments of simulated fall events and non-fall activities on student subjects. We evaluated our proposed algorithm using sequence matching based machine learning approaches on five different body positions. The algorithm achieved an F-measure of 90 to 95% in detecting falls. Sensors worn as necklace pendants or in chest pockets performed best.

Keywords: Fall detection · Sensor orientation calibration · Machine learning

1 Introduction

People are enjoying longer lives due to advances in medicine and technology. Senior citizens are facing challenges to their independent living, e.g., chronic health conditions that compromise their ability to maintain their independence. Among those conditions, falls have been a major cause of fatal injury and create a serious obstruction to independent living. According to a report from the World Health Organization [1], approximately 28 to 35% of people aged 65 and over fall each year, and this proportion increases to 32 to 42% for those over 70 years of age. Falls threaten senior citizens' autonomous living both physically and psychologically. On one hand, in addition to the direct injuries from the fall, many who fall are unable to get up again without assistance, which can lead to hypothermia, dehydration, bronchopneumonia and pressure sores, which increases the severity of consequences [2]. On the other hand, senior citizens with a history of falling live in fear of future falls, which has been shown to be associated with negative consequences such as avoiding or reducing physical activity, falling, depression, decreased social contact, and lower quality of life [3].

The consequences of falling can be severe. Nevertheless, obtaining quick assistance after a fall reduces the risk of hospitalization by 26% and the risk of death by 80% [4]. For senior citizens living alone, automatic fall detection systems with motion sensors are necessary for requesting prompt care after falls. Those mini-sized sensors are placed on the body and track the activities performed by the sensor wearer. When the sensor

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detects a fall, caregivers will be dispatched accordingly, even if the wearer becomes unconscious after the fall.

The effectiveness of an automatic fall detection system depends in large part on the fall detection algorithms as well as sensor positions. In this paper, we propose an approach using a single accelerometer for detecting falls in home settings to deal with the sensor orientation issue, which has been little addressed by former fall detection researchers.

This paper is organized as follows. The next section reviews the literature in acceleration signal processing. Section 3 presents our research design for applying sensor orientation calibration. Section 4 provides evaluations and discussions of experiment results. The final section concludes the study and suggests future directions.

2 Literature Review and Research Gaps

The data collected by the wearable motion sensors, or accelerometers, are acceleration signals. Therefore, we reviewed past studies related to acceleration signal processing, specifically, sensor orientation calibration and fall detection.

2.1 Sensor Orientation Calibration

Three-axial accelerometers are typically used for tracking the motion of the human body. The acceleration signals are described by tuples of three orthogonal acceleration components (x, y, z) in the sensor reference system. However, the sensor reference system is not always well-aligned with the body reference system denoted by the vertical (VT), medio-lateral (ML) and antero-posterior (AP) directions. This inconsistency provides much complexity in data processing, in that two series of signals may not be directly comparable without prior knowledge of sensor orientation, common in real world scenarios. Kale et al. [5] concluded that the classification algorithm can only achieve an accuracy of less than 50% if the sensor is misoriented for more than 15° on any axis.

According to Henpraserttae et al. [6], we can calibrate the signals to a unified reference system before feature extraction to solve this issue. A transformation matrix is applied on the raw acceleration signals for calibration. This approach can provide acceptable consistency across the signal sequences without losing direction information. We further investigated studies in sensor orientation calibration.

Mizell [7] proposed an approach to calibrate the acceleration signals implicitly, without extra device support or human effort. Since the accelerometer is constantly measuring the gravity, it acts as a clue for the direction of VT axis in the body reference system. By taking the average of acceleration signals over a reasonable time period, the approach produces a good estimate of the gravity (i.e., the VT axis) in the sensor reference system, and then the vertical components can be isolated. Yang [8] estimated the horizontal components of the acceleration signals after removing the vertical components from the raw signals. They utilized the magnitude of horizontal components to avoid identifying AP and ML axes. Henpraserttae et al. [6] further estimated the AP axis from the horizontal components by performing eigen-decomposition on the covariance matrix, assuming that most of the activities were done along a certain direction (e.g., the AP axis). Morales et al. [9] directly applied principal component analysis (PCA) on the acceleration signals without estimating the gravity. Features were extracted from the PCA-transformed signals for classification algorithms. Those studies mainly focused on activity recognition. Although none of them were conducted in the context of fall detection, they provide a solid foundation of techniques for addressing the sensor orientation issue.

2.2 Fall Detection

A fall is an event which results in a person inadvertently coming to rest on the ground or floor or other lower level [10]. The goal of fall detection algorithms is to distinguish fall events from non-fall activities with high precision and recall rates, since false alarms can be noisy, and failing to capture a fall event will be very costly and potentially dangerous. Compared to regular activities of daily living, fall events contain multiple special characteristics. Three phases occur sequentially during a fall event, which are collapse, impact, and inactivity. In the collapse phase, the faller accelerates towards the floor. Various rule-based thresholds were proposed to identify the three phases, including impact detection, vertical velocity detection, and posture monitoring [11, 12], among which impact detection is the most prevalent approach. When the faller approaches the floor, a very large magnitude of acceleration would be recorded by the accelerometer, which can be used as an identifier for a fall. Subjects were asked to wear the sensors on the upper body in fixed initial sensor orientations, and performed simulated fall events and non-fall daily activities. Past studies reported 85 to 100% of fall detection accuracies based on simulated falls. However, Bagalà et al. [13] applied several rule-based algorithms on a real world dataset with real falls, reporting that the detection accuracies were considerably lower (57 to 83%), and the number of false alarms generated by the algorithms during one-day monitoring of three representative fallers ranged from 3 to 85. Rule-based methods also suffer from the ad hoc nature of setting the thresholds, in that researchers set the thresholds to best fit their own datasets, with a concern of generalizability.

Machine learning approaches are also applied for fall detection. They can be further categorized as feature based and sequence matching based algorithms. Özdemir and Barshan [14] investigated fall detection with wearable sensors using various machine feature based learning techniques. Sequence matching based methods do not extract features from signal sequences. Instead, sequence matching directly compares the similarity between two signal sequences using certain metrics. Two popular metrics include Euclidean distance [15], and dynamic time warping [16]. A k-Nearest Neighbor (k-NN) classifier is applied on the distance metrics, with k typically set to 1. Unfortunately, most of the machine learning approaches did not discuss the sensor orientation issue explicitly, assuming the sensor orientation is given and fixed. It remains to be studied how the sensor orientation calibration would affect the accuracies of fall detection.

2.3 Research Gaps

As is discussed above, most prior studies on machine learning based activity recognition and fall detection assumed that the sensor orientations were given and fixed across different acceleration signal sequences. However, this assumption can hardly be held in real world applications. Each time the sensor is unequipped and re-equipped, a new arbitrary orientation will be set for the sensor, which cannot be predicted. Furthermore, failing to align the sensor orientation will lead to a decrease in activity recognition and fall detection accuracies. The sensor orientation issue needs to be addressed properly. Hence, we propose the following research question:

- Can sensor orientation calibration techniques be leveraged to improve the precision, recall rates for sensor-based fall detection?

3 Research Design

3.1 Data Collection

Five student subjects (aged 23 to 29) participated in our controlled experiments. We used MetaWear C sensors, measuring between $\pm$4G at a sampling frequency of 12.5 Hz. The goal for this relatively low sampling rate is to save the battery power as much as possible without losing necessary information for classification. Although we aim to detect falls using a single motion sensor, we attached five sensors simultaneously on subjects' bodies to investigate the influence of different positions. The five positions we attached sensors to were neck, waist keychain, left chest pocket, right pants pocket, and right shoe. The necklace sensor was set in the pendant. The keychain sensor was clipped on the belt on the waist. The right shoe sensor was clipped on the shoe. Note that none of the sensors were attached firmly to subjects' body. Pocket sensors may be rolling, and keychain sensors may be dangling throughout the experiment. The initial sensor orientations were arbitrarily chosen by the subjects without our control. This setting is very unique compared to prior studies where the sensor orientations were pre-set and fixed by researchers, as we would like to mimic the real usage scenarios as much as possible.

Four simulated fall events were performed by each subject. The subject intentionally falls onto a large mattress from a static upright posture in four directions (once for each), namely, forward, backward, left laterally, and right laterally. Eight non-fall activities of daily living were performed, including quiet sitting, quiet standing, 10-meter walk, timed up and go, 5-time sit-to-stand, sit-stand-walk mixture, collapsing onto a chair (sit down on a soft armchair with a certain acceleration), and collapsing onto a mattress (sit down and then lie down on a mattress with a certain acceleration). The last two events were introduced because they tend to be misclassified by traditional threshold-based impact detection algorithms. Overall, 20 fall samples and 40 non-fall samples were collected for each sensor. The samples are transmitted to a desktop computer via Bluetooth Low Energy (BLE) for further processing.

3.2 Signal Preprocessing

Each signal sample, S, is an $n \times 3$ matrix, consisting of n acceleration vectors. Since we focus on fall detection, we extracted the acceleration signals around a potential shock or impact [14]. The potential shock is identified by the maximum magnitude of acceleration.

After the potential shock is identified, 2-second intervals both before it and after it (included) are extracted, generating 4-second time windows with signal samples of 50 data points (12.5×4). This 4-second time window is considered to be sufficient to cover the entire fall procedure, including the collapse, impact and inactivity phases, and also simplifies the comparison across signal samples.

3.3 Sensor Orientation Calibration

To completely transform the sensor reference system (x, y, z) to the human reference system (VT, AP, ML), we need to express two orthogonal axes in the sensor reference system. The third axis can be delivered by a cross product of the two known axes. Taking the average of acceleration signals over a reasonable time period (e.g., t_0 to t_1) can produce a good estimate of the gravity, and thus the VT axis, $\boldsymbol{a}_V$ [7, 8]. The amplitude of vertical component, v, in the acceleration vector, $\boldsymbol{a}$, is extracted by:

$$v = |\boldsymbol{a}| cos\theta = \boldsymbol{a} \frac{\boldsymbol{a}_V^T}{|\boldsymbol{a}_V|}$$

Note that v can be negative. The horizontal acceleration component, $\boldsymbol{c}$, is orthogonal to the direction of vertical component, which is given by:

$$\boldsymbol{c} = \boldsymbol{a} - v \frac{\boldsymbol{a}_V}{|\boldsymbol{a}_V|}$$

Now, if it is known that most of the activity is in a particular direction, e.g., AP direction in walking scenarios, the AP axis, $\boldsymbol{a}_P$, may also be estimated by proper operations on $\boldsymbol{c}$. However, in our case that deals with static activities, the estimation of $\boldsymbol{a}_P$ may be less meaningful. Instead, Yang [8] suggested to extract the features from the magnitude of the horizontal component, $|\boldsymbol{c}|$. By this approach, the acceleration vectors are expressed in a combination of vertical amplitude and horizontal magnitude. Each calibrated signal sample, S', is then expressed in a 50×2 matrix.

3.4 Fall Classification

We implemented sequence matching based machine learning approaches on our sensor orientation calibration algorithm (CAL). Euclidean distance (EUC) and dynamic time warping (DTW) were chosen to be used as distance metrics. Given two time series, $\boldsymbol{X} = (\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_n)$, $\boldsymbol{Y} = (\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_n)$,

$$\mathrm{EUC}(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{i=1}^{n} ||\boldsymbol{x}_i - \boldsymbol{y}_i||$$

Dynamic time warping is a method that calculates an optimal match between two given sequences (e.g., time series) with certain restrictions. The sequences are "warped" non-linearly in the time dimension to determine a measure of their similarity independent of certain non-linear variations in the time dimension. Further discussion can be found in [16].

A k-NN classifier was applied on the distances. k was set to 1 as in prior studies [15, 16]. The leave-one-out cross-validation method was applied to avoid over-fitting. We compared our approach with two benchmarks, which are raw tri-axial acceleration signals (RAW), S_1, and acceleration magnitude (MAG), S_2. Both benchmarks have been widely used by prior fall detection and activity recognition studies. All 5 sensor positions were evaluated separately.

4 Evaluation and Discussion

Figure 1 plots the precision, recall and F-measure for the sequence matching based algorithms. In terms of precision, all three algorithms performed reasonably well. The MAG benchmark outperformed the others by achieving 100% precision for all sensor positions. However, MAG performed relatively poorly in the recall rates. All three tests with recall rates greater than or equal to 85% were achieved by CAL. Similarly, all three tests with F-measures greater than or equal to 90% were achieved by CAL. Although MAG seems to reduce the false alarm rate, the poor recall rates led to the more severe consequence of fall events not being recognized properly. CAL with EUC metric at the position of chest pocket achieved an F-measure of 95%, outperforming all the other experiments conducted in this study.

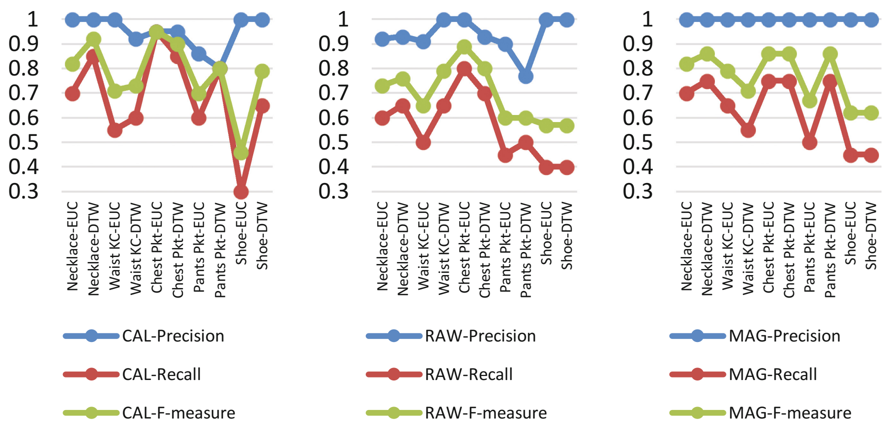

Fig. 1. Precision and recall and F-measure for sequence matching based algorithms

The sensor positions on the human body seem to influence the precision and recall rates of fall detection for sequence matching based algorithms. Consistent with the literature, the sensors set on the upper body (necklace and chest pocket) achieved relatively satisfactory results. Although the waist is typically regarded as a legitimate position to place the sensor, one potential issue for waist keychain sensors is that the dangling sensors may produce more random and complex patterns across experiment trials, increasing the difficulty of sequence matching. Pants pocket sensors and shoe sensors may encounter the issue that they are set on the lateral side of body and/or are too far away from the center of mass, which cannot properly reflect the body movement.

5 Conclusion

In this study, we proposed an orientation calibration algorithm to improve the precision and recall rates for fall detection. This algorithm aims to eliminate the influence of arbitrary sensor orientation issue in real world scenarios, improving the effectiveness and robustness of fall detection. F-measures of 90 to 95% have been achieved for sensors positioned in necklace pendants and chest pockets using a sequence matching based machine learning approach, which seems promising for real life applications.

We need to address several related directions in future works. First, we need to study feature based machine learning approaches to assess the proposed sensor orientation calibration algorithm more extensively. Feature based approaches may be able to provide high level abstraction from acceleration signals, and may perform differently from sequence matching approaches. Second, we may consider combining multiple approaches in practice. For instance, we can construct a classifier that first filters out stationary activities, and then applies a trained classifier to detect falls. This approach may consume fewer computational resources for large-scale applications.

One limitation to this study is that the data samples were collected from young healthy student subjects in a small sample size, as experiments of simulated falls by senior citizens may be improper and dangerous. Although conventional in literature, this setting may not necessarily reflect senior citizens' activities. Data samples from senior citizens in real life scenarios need to be investigated in the future to identify any potential discrepancies.

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References

1. World Health Organization: Ageing and Life Course Unit, "WHO Global Report on Falls Prevention in Older Age", World Health Organization (2008)
2. Tinetti, M.: Predictors and prognosis of inability to get up after falls among elderly persons. JAMA **269**(1), 65 (1993)

3. Scheffer, A., Schuurmans, M., van Dijk, N., van der Hooft, T., de Rooij, S.: Fear of falling: measurement strategy, prevalence, risk factors and consequences among older persons. Age Ageing **37**(1), 19–24 (2007)
4. Stevens, J.: Falls among older adults—risk factors and prevention strategies. J. Saf. Res. **36**(4), 409–411 (2005)
5. Kale, N., Lee, J., Lotfian, R., Jafari, R.: Impact of sensor misplacement on dynamic time warping based human activity recognition using wearable computers. In: Proceedings of the Conference on Wireless Health. ACM (2012)
6. Henpraserttae, A., Thiemjarus, S., Marukatat, S.: Accurate activity recognition using a mobile phone regardless of device orientation and location. In: 2011 International Conference on Body Sensor Networks (2011)
7. Mizell, D.: Using gravity to estimate accelerometer orientation. In: Proceedings of the 7th IEEE International Symposium on Wearable Computers, ISWC 2003. IEEE Computer Society (2003)
8. Yang, J.: Toward physical activity diary. In: Proceedings of the 1st International Workshop on Interactive Multimedia for Consumer Electronics - IMCE 2009 (2009)
9. Morales, J., Akopian, D., Agaian, S.: Human activity recognition by smartphones regardless of device orientation. In: Mobile Devices and Multimedia: Enabling Technologies, Algorithms, and Applications 2014 (2014)
10. "WHO|Falls", Who.int. http://www.who.int/violence_injury_prevention/other_injury/falls/en/. Accessed 11 May 2016
11. Bourke, A., O'Brien, J., Lyons, G.: Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. Gait Posture **26**(2), 194–199 (2007)
12. Lee, J., Robinovitch, S., Park, E.: Inertial sensing-based pre-impact detection of falls involving near-fall scenarios. IEEE Trans. Neural Syst. Rehabil. Eng. **23**(2), 258–266 (2015)
13. Bagalà, F., Becker, C., Cappello, A., Chiari, L., Aminian, K., Hausdorff, J., Zijlstra, W., Klenk, J.: Evaluation of accelerometer-based fall detection algorithms on real-world falls. PLoS ONE **7**(5), e37062 (2012)
14. Özdemir, A., Barshan, B.: Detecting falls with wearable sensors using machine learning techniques. Sensors **14**(6), 10691–10708 (2014)
15. Lan, M., Nahapetian, A., Vahdatpour, A., Au, L., Kaiser, W., Sarrafzadeh, M.: SmartFall: an automatic fall detection system based on subsequence matching for the smartcane. In: Proceedings of the 4th International ICST Conference on Body Area Networks (2009)
16. Paiyarom, S., Tangamchit, P., Keinprasit, R., Kayasith, P.: Fall detection and activity monitoring system using dynamic time warping for elderly and disabled people. In: Proceedings of the 3rd International Convention on Rehabilitation Engineering & Assistive Technology - ICREATE 2009 (2009)