Wearable Fall Detection System Using Barometric Pressure Sensors and Machine Learning

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***Abstract*—As the global population is aging, healthcare systems in developed countries are facing many new challenges, such as insufficient human resources for quality patient monitoring and elderly care. One of the major health threats to elderly patients is falling, which could cause severe injuries and the associated complications can lead to mortality. To reduce the potential damage caused by falling, there are many wearable-based monitoring systems commercially available, but they often suffer from high false alarm rates and high costs. Most of the available solutions are based on embedded Inertial Measurement Units (IMUs), which can easily detect a sudden slip fall or a sudden trip fall from standing, but often fail to detect short falls, such as falling from a bed or a chair when an elderly is trying to get up. In this paper, a wearable fall detection system using barometric pressure sensors is proposed. The system is capable of detecting falls from high and low positions with high accuracy, and it was tested using a dataset collected from 10 healthy subjects and validated using a 5-fold inter-subject cross-validation.**

Keywords-Fall detection; Body Sensor Network; Healthcare; Barometric pressure sensor.

I. INTRODUCTION

Due to declining fertility rates and rising life expectancy in many countries, the world elderly population is expected to continue to increase rapidly. According to the World Health Organization (WHO), the proportion of the world population who is over 60 years old will rise from 12% in 2015 to 22% by the end of 2050 [1]. Elderly population is often at risks of falling, which is one of the most consequential events leading to severe injuries. According to the Centers for Disease Control and Prevention (CDC), one in every four elderly people living in the United States report one or several falls each year [2]. When elderly people fall down, they are often immobilized due to joint dislocations, bone fractures or head trauma. Therefore, fall detection systems are of vital importance for elderly people who live alone, as a study of 125 elderly people who fell shows that half of the elderly fallers who remain laying on the ground for more than an hour after falls died within 6 months after the incidents [3]. If the injuries caused by falls are not fatal, it still leads to a significant burden to the public healthcare service, as elderly fallers require longer time to heal, and they often have a higher chance of falling again. In 2012, 30.3 billion dollars were spent in medical treatments related to non-fatal falls in the U.S. [4].

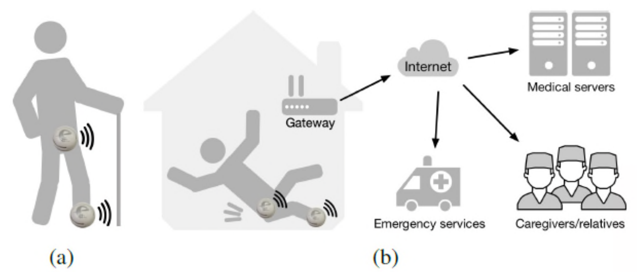

Figure 1. (a) Sensor positions and (b) System architecture

Although it is difficult to prevent elderly people from falling, fall detection systems can significantly reduce the time between falls and medical treatments by informing emergency services automatically and promptly after the incidents [5]. Extensive research has been proposed for fall detection, which can be categorized into two basic types of systems: vision-based and wearable sensor-based. Vision-based systems, such as [6], are less intrusive and can detect multiple fall events simultaneously [7]. However, such systems have very limited range of usage, as fall events will not be detected outside the sight of cameras or are occluded by other people or objects. On the other hand, wearable fall detection systems are effective almost anywhere, and less expensive than vision-based systems. With recent advancement in sensing technologies, many wearable sensors have been developed for fall detection, such as those based on Inertial Measurement Units (IMUs). IMUs often consist of accelerometers, gyroscopes, and magnetometers, and they can measure the acceleration, angular velocity, direction, and tilt of a device in three dimensions [8].

The research on IMU-based fall detection systems is mature, and the majority of such systems are based on the algorithms that can detect sudden sharp changes in the magnitude of acceleration signals, such as [9][10]. To avoid false alarms on other activities, such as squat and sit on a chair, the threshold value for detecting falls of these algorithms must be set very accurately for different individuals, as they might have different muscle reflection

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and strength, causing difference in acceleration signals [11]. Another disadvantage of using IMUs for fall detection is that the IMUs must have very high sampling rates to detect sudden changes in magnitude. As fall detection devices are ought to be worn by elderly people 24/7, the battery of the devices will drain very quickly. In addition, if the fall detection is not processed on node, the data collected by IMUs needs to be transmitted over wireless channels constantly, which can cause congestions of the wireless network. Instead of measuring the sudden changes in magnitude of acceleration signals, barometric pressure sensors can measure actual drop in altitude of the body mass of the elderly people. It has three advantages over IMUs, first, pressure sensors can operate at much lower sampling rates than IMUs; second, elderly people's initial falling positions, such as standing and sitting, can be determined by air pressure signals, which is useful for assessing the severity of the falls; third, the orientation of devices will not affect the fall detection algorithms using air pressure signals.

In this paper, we propose a wearable fall detection system using only barometric pressure sensors and machine learning algorithms, to detect the actual drop in altitude of the body using air pressure signals. The proposed wearable fall detection system has low power consumption, and it can be worn in any orientation in the waist or just be attached to the top of the trousers. The rest of the paper is organized as follows. Detailed experimental setup, feature extraction, and fall detection algorithms are presented in Section II. The experimental results on the performance of the proposed system are shown in Section III, and the conclusion is presented in the final section.

TABLE I. FALL DETECTION PROTOCOL

	Incidents	Fall	Initial Positions	Final Positions
1	Fall forward slowly	Y	Standing	Lying
2	Fall forward fast	Y	Standing	Lying
3	Fall backward slowly	Y	Standing	Lying
4	Fall from a chair slowly	Y	Sitting	Lying
5	Fall from a bed slowly	Y	Lying	Lying
6	Walking	N	Standing	Standing
7	Standing	N	Standing	Standing
8	Sitting on a chair	N	Sitting	Sitting
9	Lying on a bed	N	Lying	Lying
10	Pick up an item on the floor	N	Standing	Standing

II. METHODOLOGY

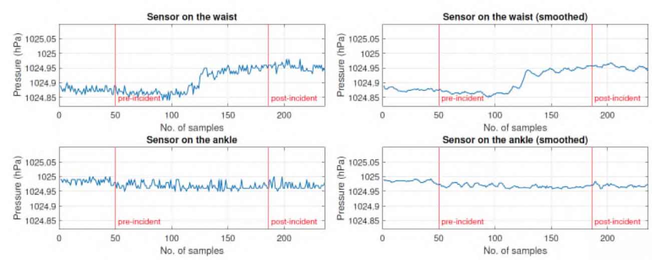
Figure 1 shows the system architecture of our proposed solution. The pressure signal captured by the sensors is transmitted to the gateway, where the fall detection algorithms are executed. If a fall occurs, the gateway will inform caregivers and relatives.

A. Experimental Setup

The barometric pressure sensors used in the study were Infineon DPS310 Pressure Shield2Go [12], which has a relative accuracy of ±0.06Pa, a sampling rate of 128Hz, and a precision of ±0.005hPa (or ±5cm in altitude). The pressure sensors were used with an Infineon XMC2go development board during data collection, then integrated with a Body Sensor Network (BSN) wireless sensor node [13], as shown in Figure 2. 10 healthy subjects (8 males and 2 females) were recruited in the experiments, and the participants were asked to perform the incidents as listed in Table I for 3 times per incident in one session. The participants simulated falls from standing, sitting, and lying positions onto a mattress, and also performed non-fall incidents, such as walking and standing. There were two pressure sensors used in the experiments, the first sensor was attached to participants' trousers at waist positions or on the belts, and the second sensor was attached to the shoes of the participants. The second pressure sensor is used as a reference, and it can also be fixed on a wall or placed on the floor in a room. The proposed system can potentially work without a reference sensor, but the accuracy will drop and could lead to higher false alarm rates.

(a) DPS310 sensor (b) Case

Figure 2. The proposed fall detection sensor node, which consists of a a BSN node, a battery, and a casing of the sensor (with a quarter US dollar coin on the side)



(a) Raw signals (b) Smoothed signals

Figure 3. Raw and smoothed air pressure sensor signals

B. Feature Extraction

The feature extraction process can be done either on the sensor node or on the network gateway. Before feature extraction, the barometric pressure signals with high frequency noises are smoothed, as shown in Figure 3, using a moving average algorithm, which can be generalized as.

$$\bar{x}_i = \frac{1}{2K+1}\sum_{n=i-K}^{i+K} x_n \qquad (1)$$

where x_i is the moving averaged signal at time instant i, which is also at the center of moving window with a window size of $2K$+1. Then, the entire sample S, which contains only one repetition of an incident, is normalized by subtracting its mean, which ensures the overall signal energy of the sample is zero for different incidents. Then, the sample is partitioned equally into M parts and feature extraction is conducted for each part individually. This is to extract features for different stages of incidents. For example, if M is set to 3, the sample will roughly be divided into 3 parts: pre-incident, incident, and post-incident. For each part of the sample, 6 features are extracted for each sensor. Therefore, if M is set to 3 and 2 sensors are used, there will be 36 features per sample. Assuming there are N data points in the m^{th} part of the sample S, the first feature is the standard deviation, which can be expressed as

$$\sigma_m = \sqrt{\frac{\sum_{n=1}^{N}(x_{mn} - \bar{x}_m)^2}{N-1}} \tag{2}$$

where x_{mn} is the mn^{th} moving averaged signal point $\bar{x}_i$, and $\bar{x}_m$ is the mean of the m^{th} part of the sample. Then, the minimum and maximum of the m^{th} part of the sample are extracted using $min(x_{mn})$ and $max(x_{mn})$ where $mn = m_1, m_2, \ldots, m_N$. The root mean square deviation r_m is also calculated using

$$r_m = \sqrt{\frac{1}{N}\left(\sum_{n=1}^{N} x_{mn}^2\right)} \tag{3}$$

and Shannon entropy E_m is calculated as

$$E_m = -\sum_{n=1}^{N} x_{mn}^2 log(x_{mn}^2) \tag{4}$$

These features are selected as they can present the status of the pressure signals. Finally, all the features R_m extracted for different parts of the sample are concatenated together to form a final feature maps for the sample, which can be expressed as

$$\mathbb{R} = [R_1, R_2, \ldots, R_M] \tag{5}$$

Algorithm 1 Pseudo code for fall detection with k-fold inter-subject cross validation

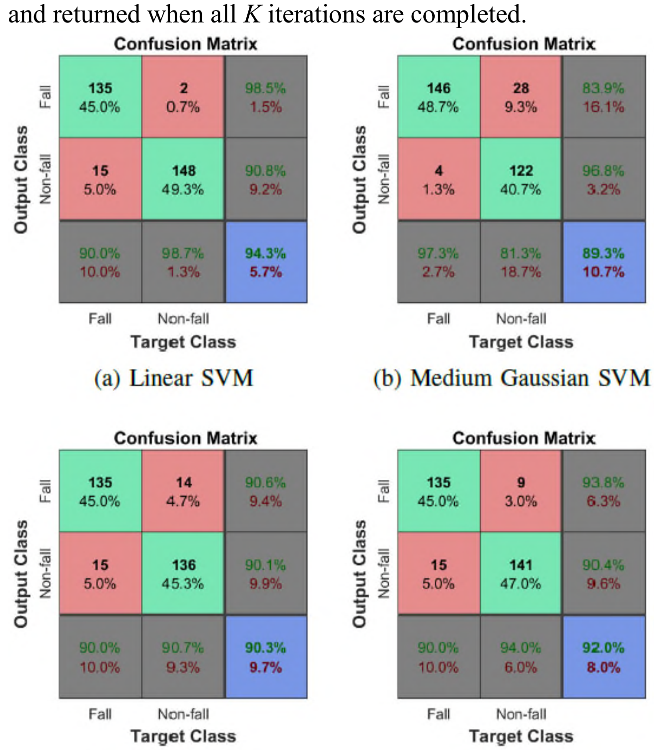
```
Require:
    dataset ← Samples from 10 subjects
    label ← Label of incidents
    M ← 3 (3 parts per sample) K ← 5 (5-fold)
    learner ← supervised machine learning algorithms
function CROSSVALIDATION(learner,dataset,label,M,K)
    results ← empty array
    for k=1 to K do
        feature ← FEATUREEXTRACTION(dataset)
        trainSet,testSet ← PARTITION(feature,label,M)
        model ← TRAINMODEL(learner,trainSet)
        performance ← TESTMODEL(model,testSet)
        results[k] ← performance
    end for
    return results
end function
```

Figure 4. Pseudo code for the fall detection algorithm

C. Experiments

To evaluate the performance of the proposed fall detection system, a series of experiments were conducted to classify fall and non-fall incidents under various conditions. The performance evaluation followed pseudo codes presented in Figure 4, where a k-fold inter-subject cross validation is presented to demonstrate the robustness and effectiveness of the proposed fall detection system. The cross validation function requires 5 inputs: the dataset which contains barometric pressure readings from participants while emulating different incidents, the labels of these incidents, which are in numeral orders listed in Table I, M, which is set from 2 to 5, K, which represents the number of partitions for cross validation and is set to 5, and learner, which is the type of classifier used for the machine learning process. There are 4 types of classifiers used in the experiments: Decision Tree, k-Nearest Neighbor (kNN), linear Support Vector Machine (SVM), and medium Gaussian SVM.

The algorithm will iterate K times and will return a metric called *results*, which contains matrices, such as True Positive (TP) rates and True Negative (TN) rates. In each iteration, first of all, feature maps $\mathbb{R}$ are extracted from the dataset using the equations presented in feature extraction subsection, which are then partitioned into training and testing sets with a ratio of $(1-\frac{1}{K})/\frac{1}{K}$. The training set is then fed to the model training function with one of the 4 classifiers to produce the trained model, which is then tested using the testing set and compared with testing labels to produce classification metrics, which are stored in results and returned when all K iterations are completed.



(a) Linear SVM (b) Medium Gaussian SVM

(c) Decision Tree (d) kNN

Figure 5. Confusion matrices of the proposed system (M=4) when using linear SVM (a), medium Gaussian SVM (b), decision tree (c), and kNN (d) of 300 samples

III. EXPERIMENTAL RESULTS

The first experiment is fall detection, which contains only two classes: fall and non-fall. Figure 5 shows the confusion matrices of the proposed system using 4 different machine

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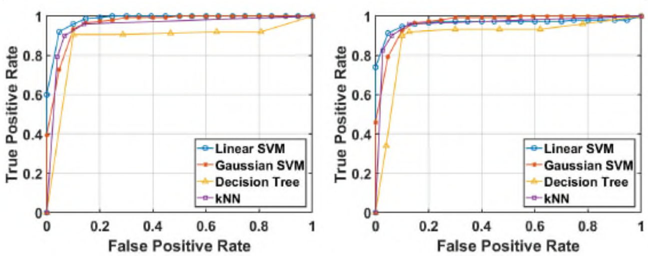
learning classifiers, and Table II presents the performance of the proposed fall detection system using different machine learning classifiers. There are totally 300 samples and all of them were tested using 5-fold inter-subject cross validations with M set to 4. Among these classifiers, linear SVM has the best accuracy of 94.3% and medium Gaussian SVM performs the worst in terms of overall accuracy. However, medium Gaussian SVM has an accuracy of 97.3% when detecting falls, but also has the worst false alarm rate at 18.7%. Decision tree and kNN have similar performance on detecting falls, but both have slightly worse false alarm rates than linear SVM. Similarly, linear SVM has the best fall detection performance in terms of accuracy, specificity, and F1 score at 94.3%, 98.7% and 93.5% respectively, whereas medium Gaussian SVM has the best sensitivity of 97.3% for detecting falls. In addition, Figure 6 shows Receiver Operating Characteristic (ROC) curves of the proposed fall detection systems when M was set to 3 and 4, respectively.

TABLE II. PERFORMANCE OF THE PROPOSED SYSTEM ON CLASSIFYING FALL AND NON-FALL INCIDENTS

	Accuracy	Sensitivity	Specificity	F1 score
Linear SVM	**0.943±0.064**	0.900±0.135	**0.987±0.016**	**0.935±0.080**
Gaussian SVM	0.893±0.056	**0.973±0.025**	0.813±0.107	0.903±0.050
Decision Tree	0.903±0.031	0.900±0.106	0.907±0.057	0.900±0.041
kNN	0.920±0.053	0.900±0.092	0.940±0.044	0.916±0.059



(a) $M = 3$ (b) $M = 4$

Figure 6. ROC curves of the proposed system using different machine learning classifiers when (a) $M = 3$ and (b) $M = 4$

In the second experiment, initial falling positions were also taken into consideration. As indicated in the confusion matrix in Figure 7, there are 6 classes instead of only fall and non-fall. Experiment participants are falling from standing (F_{stand}), which includes action 1, 2, and 3 in the fall detection protocol in Table I, falling from sitting ($F_{sitting}$), falling from lying (F_{lying}), walking (Walk), staying still (Still), which correspond to actions 7, 8, and 9 in Table, and pick up items on the floor (Pickup). The proposed system has an averaged accuracy of 81.7% for all classes. The system distinguishes falling from standing at sensitivity of 93.3%, but can only distinguish falling from sitting and lying at 63.3% and 66.7% respectively. This is because, as presented in Figure 7, many falling from sitting and lying samples were detected as falling from standing by the proposed system.

IV. CONCLUSIONS

In this paper, a novel wearable fall detection system using only barometric pressure sensors and machine learning algorithms is proposed. This paper demonstrates the feasibility and accuracy of using only barometric pressure for fall detection, especially for slow fall situations. In addition, this study shows that the barometer can complement IMU sensors in a wearable fall detector to provide better accuracy in detecting different types of falls and optimize the energy consumption. Future work can include more types of incidents of falling, analyze the power consumption and the processing time of the system, conduct an in-depth comparative study with IMU-based fall detection systems, recruit more subjects for the experiments, and test the system in more practical and natural settings, such as in nursing home and hospitals.

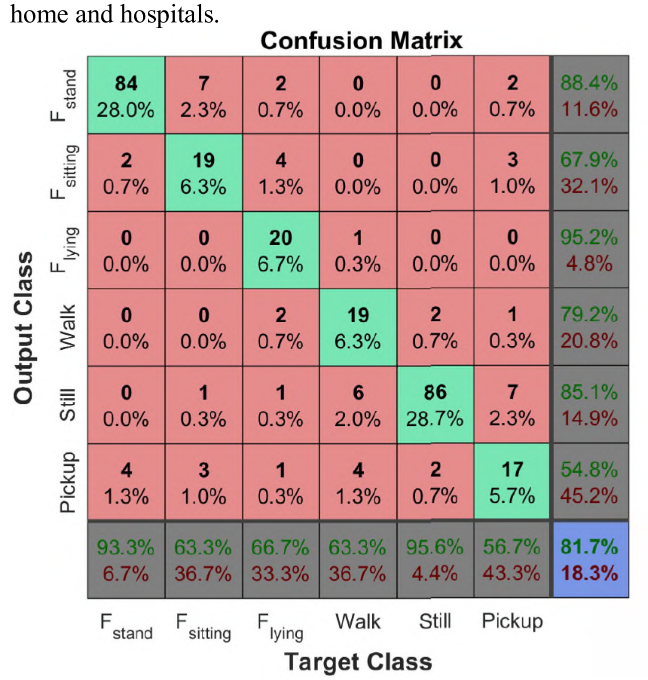


Figure 7. Confusion matrix for classifying initial falling positions and non-fall events $M = 4$), F=Fall

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