Subject-Independent Slow Fall Detection with Wearable Sensors via Deep Learning

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Abstract—**One of the major healthcare challenges is elderly fallers. A fall can lead to disabilities and even mortality. With the current Covid-19 pandemic, insufficient resources could be provided for the care of elderlies, and care workers often may not be able to visit them. Therefore, a fall may get undetected or delayed leading to serious harm or consequences. Automatic fall detection systems could provide the necessary detection and warnings for timely intervention. Although many sensor-based fall detection systems have been proposed, most systems focus on the sudden fall and have not considered the slow fall scenario, a typical fall instance for elderly fallers. In this paper, a robust activity (RA) and slow fall detection system is proposed. The system consists of a waist-worn wearable sensor embedded with an inertial measurement unit (IMU) and a barometer, and a reference ambient barometer. A deep neural network (DNN) is developed for fusing the sensor data and classifying fall events. The results have shown that the IMU-barometer design yield better detection of fall events and the DNN approach (90.33% accuracy) outperforms traditional machine learning algorithms.**

Keywords—Covid-19 pandemic, Healthcare monitoring, Elderly, Robust activity, Slow fall, Wearable, Deep learning

I. Introduction

During the current pandemic of Coronavirus disease 2019 (Covid-19), social distancing is the main mitigation to contain the spread of the virus [1]. Due to the effects of aging, the musculoskeletal systems of the elderlies are often weakened. Thus, they are prone to fall. A fall could often lead to severe injuries and long recovery time. It could lead to bone fractures or muscle injuries restricting mobility. In some cases, the elderly fallers could not be able to get up after fall and seek for help, and in some instances the elderly fallers have died due to late response. Fall detection is an essential element of elderly care. Especially for those elderly or impaired who live alone, constant monitoring is required to detect fall instances. However, in the current Covid-19 pandemic, physical contact is being avoided which may lead to late intervention and threaten the health of the elderly population. An automatic fall detection system is needed to provide timely care for elderly fallers. In this paper, we propose a wearable sensing system with a deep learning algorithm for accurate fall detection.

With recent advances in computer vision, the camera-based system could provide accurate detection of falls. However, as Google Smart City project suggested: "Our society seeks to create a smart city of privacy instead of a smart city of surveillance." Therefore, the privacy problem has become the main disadvantage of camera-based systems, especially for fall detection in the user's home [2]. Thus, wearable sensors with accelerometer, gyroscope or barometers have been widely used to detect falls. However, previous research mainly focused on sudden falls, which includes slipping or tumbling. Nevertheless, many instances of the elderly falls are slow falls, where the fall happens slowly as the elderly tries to rebalance themselves during a fall.

Accelerometers have been commonly used to detect body motion and recognize postures for fall detection. For instance, an accelerometer was used to detect falls and monitor activities. The Care-Net system applied a mercury tilt switch for detecting orientation information (i.e. from upright to lying), and a piezoelectric sensor for capturing impact information such as large negative acceleration (i.e. fall) [3]. An e-AR (Ear-worn Activity Recognition) sensor based on the Body Sensor Network (BSN) [4] was proposed for pervasive monitoring of gait and activities. Baek et al. [5] proposed a fall detection system based on a necklace sensor for posture and behavior detection. Kang et al. [6] proposed a wrist-worn device for health monitoring and fall detection. This device involved a custom-made posture sensor which included a photo-interrupter with a pendulum. Kerdjidjet al. [7] investigated three approaches for detecting: the absence of the fall, static or dynamic state, fall and six activities of daily living (ADL). Sun et al. [8] developed a waist-worn based fall detection system using barometric sensors. An additional reference barometer on the wall was also utilized to reduce the noise. Although most studies have shown promising results of using wearable sensors for detecting falls, previous studies mainly followed limited protocols where the targeted activities were distinctively different from fall events. The proposed approaches could mainly be applied for recognizing simple activities. Therefore, in real-life scenarios, such methods would fail due to false triggering of various confusing ADLs. Indeed, most prior works have not considered slow fall, a typical fall instance for elderly fallers. As slow falls often have similar sensing profiles as per normal ADL and especially for noised activities, conventional methods would fail to detect slow falls. Such limitations have hindered the practical use of fall detection systems to date.

II. Methods

A. Protocol Design and Human Experimental Trial

In planning a robust fall detection system, an extensive ADL protocol is designed. More variety of activities with confusing ADLs such as sitting on the floor, squatting down, low impact fall with fast recovery, and noised ADLs have been considered in the design of this protocol. These activities are common in ADL and are similar to fall, especially slow fall, which will cause false alarms. This system also has added sudden falls and slow falls caused by muscle weakness, leg fatigue, etc. 11 subjects (seven males, four females, Table. 1) were recruited and consented in our study. Each subject was required to perform two groups: ADL group and fall group (each group contains 15 events) shown in Table 2.

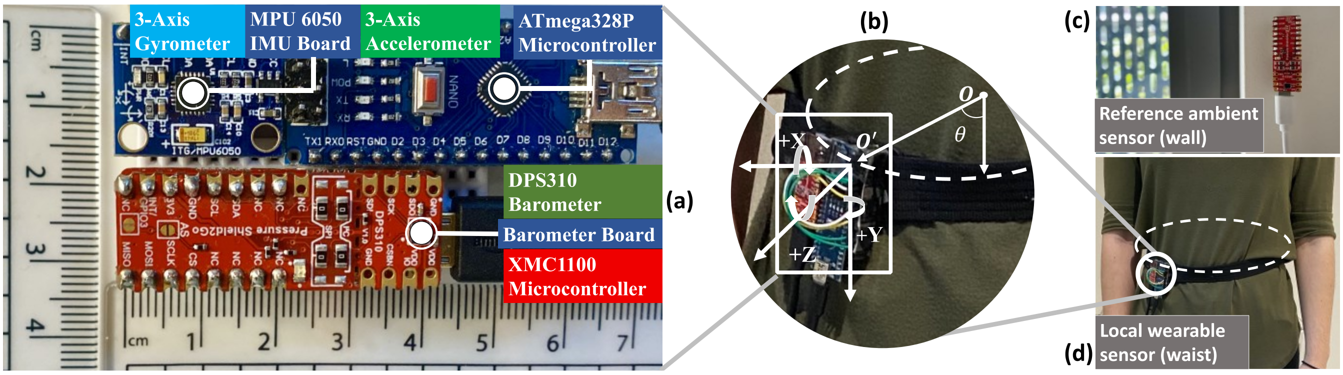

Fig. 1. Experimental configuration: (a) shows the details of the waist-worn sensors. (b) shows the coordinates of IMU and its relative location to the center of the body (a flexible angle of θ between 20-70 degrees from front and right side) which is adjustable to improve the wearability of the device. (c) shows the reference sensor on the wall. (d) shows the general location and orientation of the waist-worn sensor.

TABLE I. STUDY PARTICIPANTS CHARACTERASTICS

Characteristics	Training set (n=600)	Testing set (n=300)
No. Subjects	1	10
Age (years)[a]	23	24 ± 2
Sex, No. (%)	M	M (6), F (4)
Height (cm)[a]	178	172 ± 9
Weight (kg)[a]	72	65 ± 12

[a] Data are expressed as mean ± std, dev

TABLE II. TYPES OF FALLS AND ADLS IN THE PROPOSED EXPERIMENTAL PROTOCOL DATASET

Types of ADLs		Trials[b]
Basic ADLs		**240**
E1	Sitting down on a chair	30
E2	Standing up from a chair	30
E3	Lying down on the bed	30
E4	Getting up from the bed	30
E5	Picking up items from the floor	30
E6	Standing (lower bunk is stable)	30
E7	Walking (forward, backward, lateral, turning)	30
E8	Jumping (1-4 times)	30
Confusing ADLs (RA)		**120**
E9	Low impact fall with fast recovery	30
E10	Squatting down to tie the shoelaces	30
E11	Kneeling down to find items on the floor	30
E12	Sitting down on a floor	30
Noised ADLs (RA)		**90**
E13	Sitting down on a chair when opening the window	30
E14	Sitting down when using the hairdryer	30
E15	Lying down on the bed with tapping on sensors	30
Type of falls		**Trials[b]**
Basic Falls		**240**
E16	Forward fall, end with kneeling	30
E17	Forward fall, end with lying down	30
E18	Forward fall, end with attempting to get up	30
E19	Backward fall, end with sitting	30
E20	Backward fall, end with lying down	30
E21	Backward fall, end with attempting to get up	30
E22	Lateral fall, end with lying (left/right)	30
E23	Lateral fall, end with sitting (left/right)	30
Transitional Falls		**120**
E24	Fall from the bed when getting up	30
E25	Fall from jumping (1-4 times)	30
E26	Fall from turning (1-2 turning circles)	30
E27	Failed to stand up from the chair or toilet (fast fall)	30
Slow Falls		**90**
E28	Failed to stand up from the chair or toilet (slow fall)	30
E29	Failed to stand up from squatting (slow fall)	30
E30	Fall from squatting down (slow fall)	30

[b] Trained and test trials (2:1)

B. A Wearable System Design

Our wearable sensor system was designed on an IMU with two barometric pressure sensors. The sensor prototype is of size 7 cm × 3.4 cm and it is designed as waist-worn device, and it mainly consists of a 6-axis motion tracking IMU (MPU6050, InvenSense, U.S.A.) with a digital barometric air pressure sensor, and another barometric air pressure sensor can be placed on a desk or mounted onto a wall as a reference (as shown in Fig. 1). One barometric sensor on the body can detect the bodily movement and a sensor on the wall/desk will be used as a global reference to help eliminate environmental noises which can be caused by opening doors/windows, etc. [8]. The barometric sensor has a pressure precision of ± 0.002hPa and an operation range of 300-1200 hPa.

C. Classification

To detect fall events, a DNN approach was designed. The DNN approach has four main stages in Fig. 2. The first and second stages contain two convolutional neural network (CNN) layers. Each CNN has a convolutional layer for feature detection with a pooling layer for down-sampling [9]. As sensor signals are time-series signals where the signal features are temporally correlated. The third stage contains a bidirectional long short-term memory (bi-LSTM) layer. Bi-LSTM duplicates the raw inputs side by side in two ways. Information gains from the past (backward) and future (forward); thus, the future input information can be reached from the current states [10]. The last stage has a Softmax layer which infers the probability of the result classes. Hence, the Softmax layer outputs the likelihood of the detected event belonging to either fall or no fall event.

For detecting falls, eight features from the wearable sensors are chosen empirically, including acceleration with X, Y, Z directions, angular velocity along X, Y, Z directions and two barometer pressure recordings. These sensor signals are fed directly to the DNN for classification.

To optimize the training of the DNN, Adam is used as an adaptive learning rate (LR) optimizer where the squared gradients are used to scale the learning rate and momentum [11]. The training based on the subject-independent dataset is sensitive to the initial choice of learning rate. Instead of monotonically decreasing the learning rate, cyclical learning rate (CLR) [12] is introduced in our DNN. Results show that CLR can improve classification accuracy without a need to tune, and reduce iterations, saddle points and local minima.

To validated the proposed DNN approach, we compared our method with traditional threshold methods [13] and conventional machine learning algorithms [14, 15], including K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Tree (DT), Logistic Regression (LR), and Random Forest (RF).

III. Results and Dissusion

Fig. 3. shows the results of applying the proposed DNN approach with different sensor combinations (i.e. a single IMU, a single barometer, and a hybrid of IMU with barometer). While a single sensor system results shows low accuracy in subject-independent testing based on challenging protocols, IMU-Barometer combinations improved accuracy significantly with minor errors increasing in some confusing and noised ADLs such as hairdryer effects. As we expected, the results have shown that confusing ADLs, noised ADLs, transitional falls and slow falls induced most errors which is the most challenging part of current research. Thus, it has further proved that the proposed protocols are practical and can be used to build a robust fall detection system. Fig.4. shows the performance of different classification algorithms based on the IMU-Barometer sensor system. Although machine learning algorithms like decision tree and gradient boosting have generally improved threshold algorithms performance, errors are still high for fall detection. The proposed deep neural network outperformed other algorithms. More advanced learning algorithms can be applied to reduce training loss and increase accuracy in the future. This detection system can be considered as a node in a health monitoring internet of things system, and which can be deployed to retirement homes, hospitals and residential homes to provide the needed monitoring for elderlies.

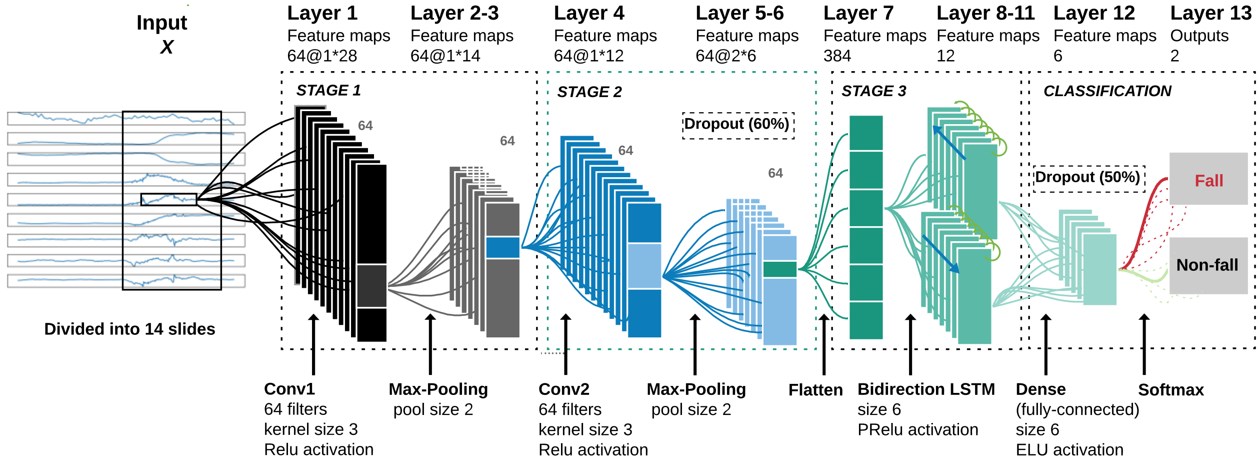

Fig. 2. Schematic of the proposed deep neural network approach. With an 8-dimensional raw sensor signal as the input vector, we first used two stages of 1D CNN to extract its activity-related features and then effective features were flattened and transferred to a bi-LSTM layer which then was used to find the hidden correlations both from past and future events. Finally, Softmax was used to compute the likelihood of fall/non-fall.

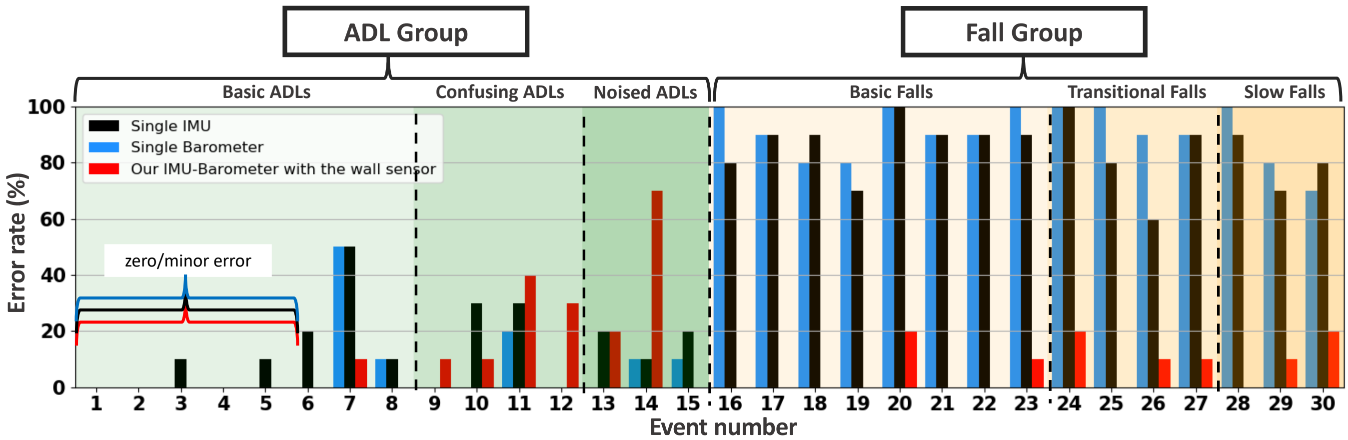

Fig. 3. Comparative study with different sensors. Using the proposed DNN method, the signals from a single IMU, a single Barometer and a hybrid IMU with a barometer system were processed, and the respective results are shown as black, green and red bars. The left diagram shows the detection result of ADLs and the right figure shows the detection results of fall events.

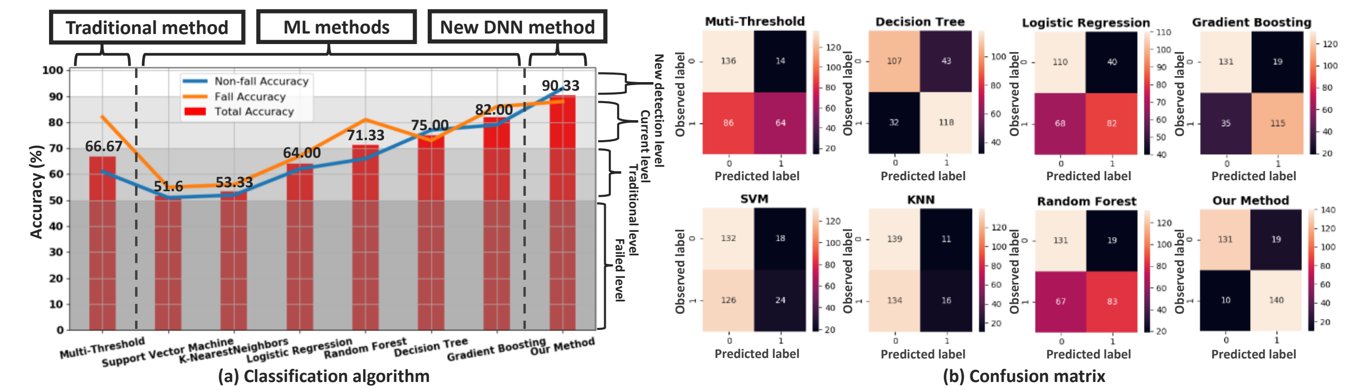

Fig. 4. (a) shows the accuracy of applying different classification algorithms to the IMU-Barometer sensor system. (b) shows the confusion matrix of different classification algorithms (label 0 represents a non-fall event and label 1 represents a fall event).

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