Fall Detection Algorithm Based on MPU6050 and Long-Term Short-Term Memory network

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***Abstract*—Fall is the second cause of accidental death in the world and is the main cause of physical injuries, especially older. Development of fall detection systems can re-duce the injuries by falling. In this study, three-axis acceleration, three-axis angular acceleration, and Euler parameters that are obtained by MPU6050 sensor are adopted to collect standing, walking, and falling data. Two nrf52832 Bluetooth modules are the receiver and transmitter individual. One reads the data and calcu-lates behavior's information from MPU6050, then transmits data to another on the development board (Nordic nRF52832). Then the development board trans-mits data to the computer through UART. Long-Term Short-Term Memory net-work (LSTM) is used to identify the three movements and then distinguish the difference between falling and normal activities. The results show that this meth-od has 97% rate to determine when fall has occurred.**

Keywords*—Fall, MPU6050, nrf52832, Long-Term Short-Term Memory network (LSTM)

I. INTRODUCTION

The aging of the population is an issue of concern through world. According to the report in the United Nations World Population Prospects, there are an estimated 962 million elderly people in the world in 2017. It is expected to reach 1.4 billion in 2030 and will meet in 2050. It reached 2.1 billion or even 3.1 billion [1]. For the elderly people, fall is a serious problem that causes serious injury or even death.

In the past, elderly person required to take care of them at time which wasted time, money and energy and then caused a burden on the family. Therefore, devel-opment of electronic monitoring device at home can help the family to monitor the situation of the elderly person. In previous studies, several methods were adopted to detect falls. The most common method is to define a threshold algorithm to detect an abnormal data. When data exceeds the defined threshold [2], it is judged to be a fall. The k-nearest neighbors (KNN) algorithm [3, 4], support vector machine (SVM) [5, 6] are also common methods, but the accuracy of these methods are not satisfactory.

In this study, the wearable fall detection device is developed using the MPU6050 and Nordic nRF52832. The fall detection algorithm develops by a sequence-to-sequence classification [7] using LSTM network to classify the motion of elderly at home. According the fall detection algorithm, the recorded data can be used to de-termine whether the user has fallen. The devices proposed in the future can be com-bined with smart homes to monitor the elderly to reduce the damage after falling.

II. METHODS

This study develops the fall detection device using MPU6050 and Nordic nRF52832. The device can be placed at the user's waist and produce the data of 12 series of actions from MPU6050. The data transmitted to the computer through Bluetooth. The fall detection algorithm develops by a sequence-to-sequence classification with LSTM network. This study asks eight subjects (male, mean age =22) to produce the 30-second normal data and fall data, which is, can't climb for about 30 seconds after falling. Those data can be as the training and testing data to verify the accuracy of fall detection algorithm.

A. Fall detection device

The development of fall detection device is based on MPU6050 and Nordic nRF52832, as shown in Fig.1a. Nordic nRf52832 has ultra-low power wireless system on chip (SOC), powerful computing power and floating point-computing capability. MPU6050 can produce three-axis acceleration, three-axis angular acceleration using accelerometer and gyroscope. In MPU6050, accelerometer is available in 4 scales (2g, 4g, 8g and 16g) and gyroscope is available in 4 scales (250 deg / sec, 500 deg / sec, 1000 deg / sec, 2000 deg / sec). In this study, the value of accelerometer is 4g and the value of gyroscope is 16g. By combining the three-axis acceleration and three-axis angular acceleration, the quaternion parameter can be obtained and then the parameters of the Euler angle can be calculated through the quaternion.

Two nrf52832 Bluetooth modules are the receiver and transmitter individual. One reads the data and calculates behaviour's information from MPU6050, then transmits data to another on the development board (Nordic nRF52832). Then this study place the development board near the computer and it can transmit data to the computer through UART. In order to wear the device on the user's waist using belt (Fig. 1b), this study places the RF52832 with MPU60650 in the small box. There is a rechargeable battery in the box.

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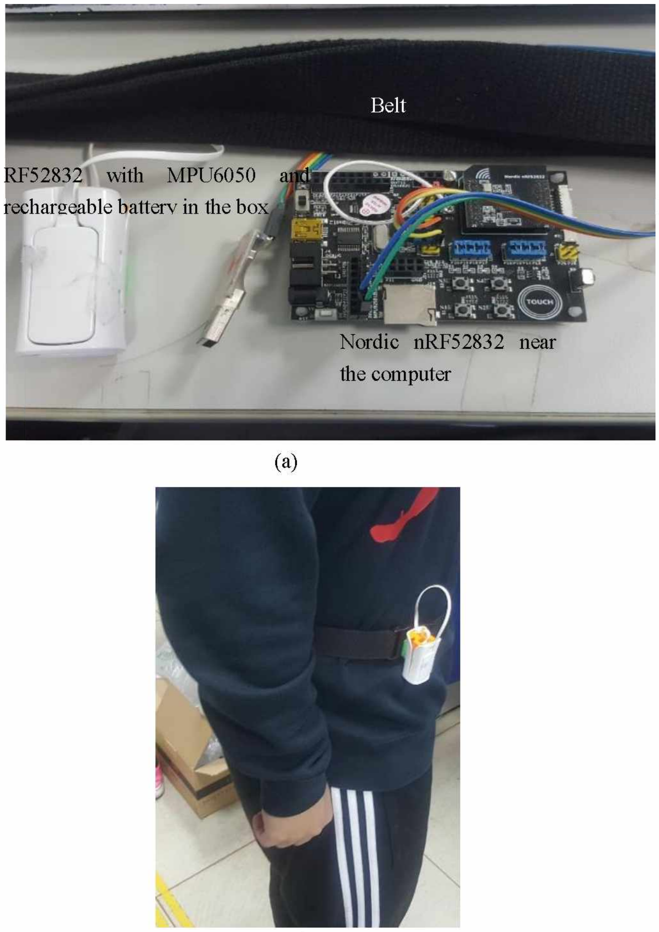


(a)

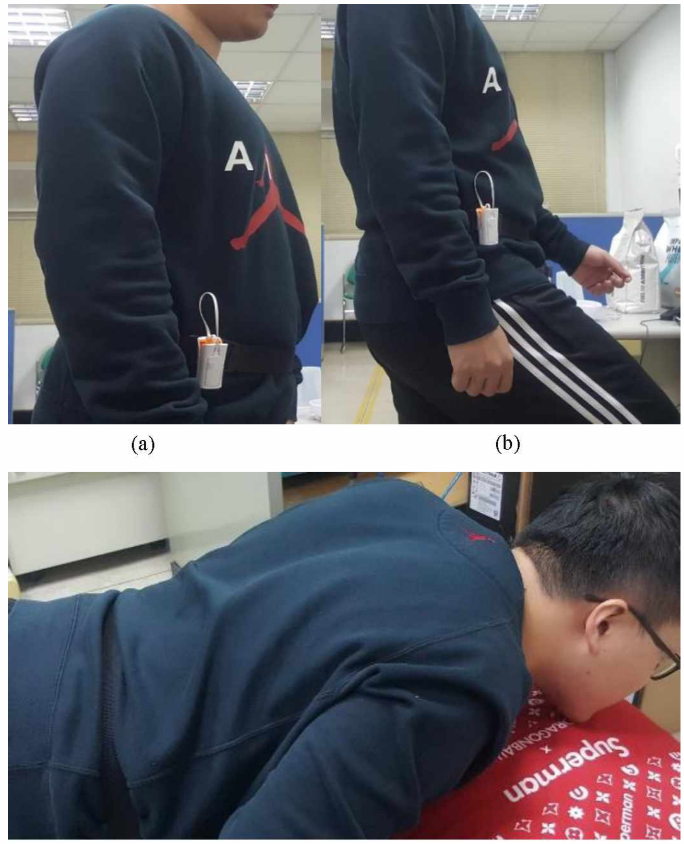
(b)

Fig. 1. (a) Fall detection device consist of MPU6050 and Nordic nRF52832. (b) The device can be place the user's waist using belt.

B. Behavior data

The data records by the MPU6050 and transmit to computer by Nordic nRF52832. In order to correct the G offset of the MPU6050, we put the MPU6050 on the horizontal plane and set G to zero through the Calibration program while the X and Y-axes acceleration will be 0 and the Z-axis acceleration is 1. Three-axis angular accelerations are all zero.

The behavior data can be produce many kinds of features, including three-axis acceleration, three-axis angular acceleration and Euler angle (Roll, Pitch and Yaw)[8]. Eight subjects (male, mean age =22) with different height and weight execute three kinds of behaviors: stand, walk, and fall, as show in Fig. 2. The period of each behavior is 30 second. Particularly, the meaning of fall is that can't climb for about 30 seconds after falling. The flowchart of experiment shows in Fig. 3



(a) (b)

(c)

Fig. 2 Three kinds of behaviors: (a) stand, (b) walk, and (c) fall

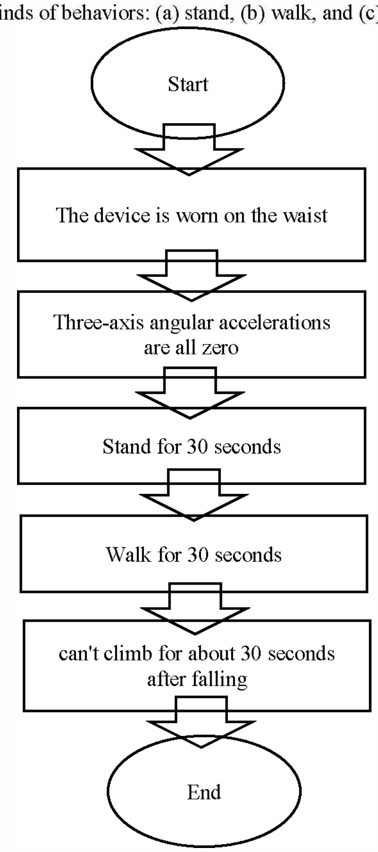


Fig. 3 The flowchart of experiment

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C. Sequence-to-sequence classification using Long-Term Short-Term Memory (LSTM) network

Structure of sequence-to-sequence classification is developed by LSTM network [9]. LSTM is manual recurrent neural network architecture for deep learning that can process a single data point and process the entire data sequence. In this study, the MPU6050 produced 9 features (three-axis acceleration, three-axis angular acceleration and Euler angle) at each times step for different motions, which are standing for 30 seconds, walking for 30 seconds, falling and sitting on the ground for 30 the seconds, are used to as inputs in the LSTM network. In order to classify the three different motions by LSTM network, this study defines the sequence of categorical labels corresponding to the activity at each time step.

There are two parts to define the LSTM network architecture (Matlab, deep learning toolbox): First part contains five parameters: sequenceInputLayer, lstmLayer, fullyConnectedLayer, softmaxLayer, classificationLayer. Second part is the specified training option, which contains three parameters, solverName, GradientThreshold and MaxEpochs. These parameters are described below:

- SequenceInputLayer: Input sequence data into the network. There are nine sequences in this paper, namely the three-axis acceleration, three-axis angular acceleration and the Euler angle (pitch, yaw and raw). Thus, the value of SequenceInputLayer is 9.
- LstmLayer: The long-term dependency between the time step and the sequence data in the learning time series. The LstmLayer has a set value of 200.
- FullyConnectedLayer: The fully connected layer multiplies the input by the weight matrix and then adds the offset vector. The parameter is set to 3 because there are three different actions, standing, walking and falling.
- SoftmaxLayer and classificationLayer: Divide the above fullyConnectedLayer parameters into 3 categories.
- solverName: This study adopts 'Adam'. Adam has a straightforward implementation high computational efficiency and the advantages of data and/or large parameters.
- GradientThreshold: Gradient threshold set to 2 to prevent a gradual explosion.
- MaxEpochs: An iteration is one step taken in the gradient descent algorithm towards minimizing the loss function using a mini-batch. An epoch is the full pass of the training algorithm over the entire training set. The MaxEpochs has a set value of 60.

D. Leave-one-out cross-validation(LOOCV)

This study records eight subjects' behaviour data by MPU6050. This study adopts the LOOCV method to verify the accuracy of fall detection algorithm. So, each subjects is requested to take turns being a testing data and remaining subjects are the training data in the LSTM network. This study adopts the accuracy (1) to evaluates the performance the proposed method.

$$\text{accuracy}(\%) = \frac{\textit{predicted classificaition from LSTM}}{\textit{Real classification}} * 100 \tag{1}$$

III. RESULTS

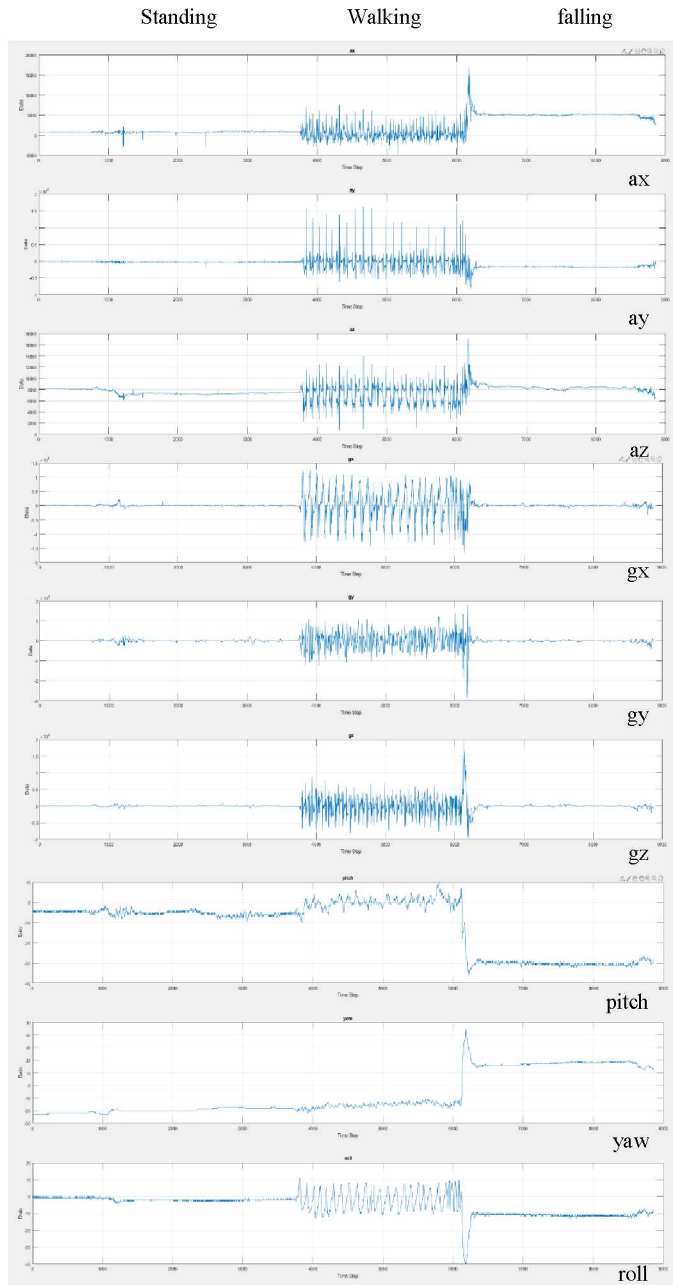
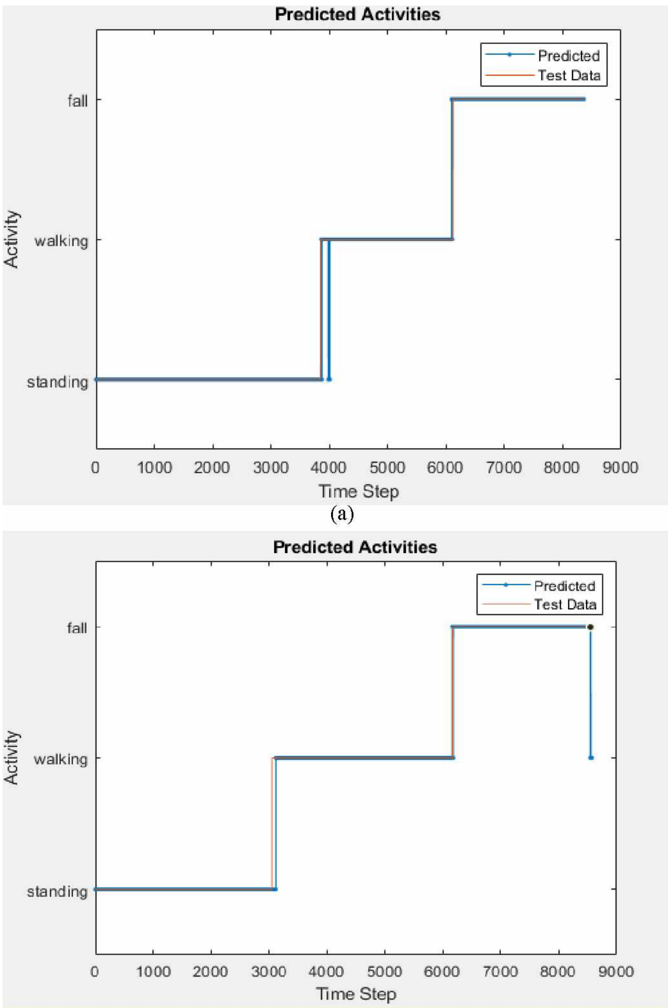


Fig. 4. 9 parameters of the testing data: three-axis acceleration, three-axis angular acceleration and Euler angle (Roll, Pitch and Yaw)

In the study, the fall detection device was placed at the wearer's waist. This device consists of the MPU6050, Bluetooth and rechargeable battery. The rechargeable battery can supply the MPU6050 and Bluetooth power. Then, the data of the MPU6050 is transmitted to the Nordic nRF52832 through the Bluetooth. The Nordic nRF52832 transfers the data to the computer by UART. The, this study uses Matlab2019b (Mathoworks) to classify the data as standing, walking, and falling by LSTM network. If the wearer falls on the ground and does not get up in 30 seconds, it can be known that the wearer is seriously injured due to the fall, and it is impossible to climb up. Fig. 4 shows the 9 parameters of one testing data: three-axis acceleration, three-axis angular acceleration and Euler angle (Roll, Pitch and Yaw). The motion includes standing, walking, falling. Particularly, the meaning of fall is that can't climb for about 30 seconds after falling.



(b)

Fig. 5. Result of classification by LSTM network for two testing data. Blue line is the predicted results and Red line is the real actions.

Fig. 5 and Table I show the results of classification by LSTM network for two testing data. In two testing data, the accuracy of standing are both 100%. The accuracy of walking are 98.15% and 97.72%. The accuracy of fall are 100% and 98.96% The predicted classifications by LSTM have high performance.

Table II compares the real actions in the testing data with the predicted results of the LSTM network across subject. The mean of accuracy of standing is 99.31%, the accuracy of walking is 98.91% and the accuracy of falling is 97.98%. The accuracy of the all datasets with selected set of features is higher than 97%.

TABLE I. Results of classification by LSTM network for two testing data

Predicted \ Test Data	**Standing**	**Walking**	**Falling**
Standing	3852	18	
Walking		2226	
Falling		24	2247
Accuracy (%)	100	98.15	100

Predicted \ Test Data	**Standing**	**Walking**	**Falling**
Standing	3052	68	
Walking		3049	25
Falling		3	2374
Accuracy (%)	100	97.72	98.96

TABLE II. Real actions in the testing data with the predicted results of the LSTM network across subject.

Subject	**Standing**	**Walking**	**Falling**
1	99.92	99.23	98.07
2	1	98.15	1
3	98	99.34	99.94
4	1	99.15	99.69
5	1	97.72	98.96
6	98.46	99.76	97.15
7	98.46	98.26	91.96
8	99.67	99.73	98.1
Mean (%)	99.31	98.91	97.98
STD (%)	0.8	0.72	2

IV. CONCLUSIONS

In this study, the LTSM network can distinguish between three different actions of standing, walking, falling. As results, if it can be integrated with equipment or systems, such as smart home, it will have better care for the elderly person and reduce the chance of serious injuries and deaths caused by falls. In the future, this proposed method would improve by collecting more data from different people.

REFERENCE

1. DESA U. United Nations, Department of Economic and Social Affairs, Population Division. World Population Prospects 2019: Highlights. 2019.
2. Bourke AK, Lyons GM. A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor. Medical engineering & physics. 2008;30(1):84-90.
3. Liu C-L, Lee C-H, Lin P-M. A fall detection system using k-nearest neighbor classifier. Expert systems with applications. 2010;37(10):7174-81.
4. Gunale KG, Mukherji P. Fall detection using k-nearest neighbor classification for patient monitoring. 2015 International Conference on Information Processing (ICIP): IEEE; 2015. p. 520-4.
5. Aziz O, Klenk J, Schwickert L, Chiari L, Becker C, Park EJ, et al. Validation of accuracy of SVM-based fall detection system using real-world fall and non-fall datasets. PLoS one. 2017;12(7).
6. Aziz NSNA, Daud SM, Sa'at NIM. Wearable Device-based Fall Detection System for Elderly Care Using Support Vector Machine (SVM) classifier. International Journal of Engineering & Technology. 2018;7(4.36):488-91.
7. Tang Y, Xu J, Matsumoto K, Ono C. Sequence-to-sequence model with attention for time series classification. 2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW): IEEE; 2016. p. 503-10.
8. Ludwig SA, Burnham KD. Comparison of Euler Estimate using Extended Kalman Filter, Madgwick and Mahony on Quadcopter Flight Data. 2018 International Conference on Unmanned Aircraft Systems (ICUAS): IEEE; 2018. p. 1236-41.
9. Graves A. Long short-term memory. Supervised sequence labelling with recurrent neural networks. Springer; 2012. p. 37-45.