Ans-Assist: Robust Human Fall Detection for Unconstraint Smartphone Positions using Modified Long Short-Term Memory Cell

Maria Seraphina Astriani, Yaya Heryadi, Gede Putra Kusuma, Edi Abdurachman

Abstract*: In many aging countries, where the population distribution has shifted to old ages, the need for automatic monitoring devices to help an elderly person when they fall is very crucial. Smartphone is one of the best candidate devices for detecting fall because accelerometer and gyroscope sensors embedded in it respond based on human movements. People usually carry their smartphone in any position and can make fall detection method difficult to detect when fall occurs. This research explored the model for unconstraint human fall detection by using the sensors embedded in smartphone for carried/wearable- sensor-based method. We proposed robust model called Ans-Assist using modified cell of Long Short-Term Memory based model as fall recognition model which can detect human fall from any smartphone position (unconstraint). Some experimental results showed that Ans-Assist achieved 0.95 (± 0.028) average accuracy value using unconstraint smartphone positions. This model can adapt the input from accelerometer and gyroscope sensors which are responsive when human fall.

***Keywords* : fall detection, unconstraint positions, accelerometer, gyroscope, smartphone.**

I. INTRODUCTION

Exponentially increasing aging population presents new critical challenges in multidisciplinary research area for health care and monitoring systems, such as fall [1]. Fall can occur to everyone. In 2017, World Health Organization provide the estimation of the elderly population that has the potential to fall and the results are quite shocking: it is start from 28% until 35% (age > 65 years old) and up to 42% (age >70 years old) [2]. Fall is considered as one of the major health problems in the world and it is on the top two main causes of death [3, 4]. If falls occur in this category of people (elderly or people with special health care - for example heart failure), it can cause a major health problem [5, 6].

The number of people living independently in their preferred environment is increasing, including people with special treatment and the elderly [6, 7]. Carriable or wearable sensor-based model of fall detection (sensor attached on the body) has the advantage of being able to move anywhere, so that some activities can still be monitored [6]. Inertial sensors, for example: accelerometer and gyroscope are usually embedded in smartphone and can detect Activities of Daily Living (ADL) [8, 9].

Many researchers feel inspired and challenged to conduct research by using sensors from the latest smartphones technology to detect human fall. Many models have been proposed by researchers to detect human fall, but the researchers always determine/ limit the position of smartphone that has been carried by people who use fall detection. This situation is not in accordance with real life condition because people will usually put their smartphone freely in any position they want [10].

The study by Yildirim stated that the model error rate for predicting ADL which is similar to fall is quite high, above 80% for False Negative [11]. Threshold-based model is not robust enough to accommodate this characteristic of this data and model-based (machine learning or deep learning) can be a good solution for detecting pattern for data that are hard to be separated. Most of the previous models proposed by researchers to recognize body fall are based on dataset collected from constraint smartphone whose pre-determined fixed position. This constraint makes the trained model less general because its application is limited. However, using smartphone sensors (accelerometer and gyroscope) for unconstraint smartphone positions make the model becomes more challenging to recognize human activity pattern. The main challenges for recognizing body fall based on unconstraint smartphone are: noisy dataset, lots of data variations because each smartphone sensor axis produces data based on many smartphone positions (for example: one ADL can produced different data on each sensor axis if the positions are different), and non-separable data because there are ADL data which pattern is similar to fall. Hence, the objective of this study is to create a robust model to detect human fall for unconstraint smartphone positions and can handle non-separable data. It is important to have this model because body fall can happen at any time in any smartphone position.

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The implementation of Long Short-Term Memory (LSTM) can be the answer to define the pattern of unconstraint smartphone positions and non-separable data because it can handle time-series preservation data and can remember past data that has dependency in its data for longer time [12, 13]. We propose Ans-Assist, model to detect human fall, using modified LSTM cell which using the inputs from each axis of accelerometer and gyroscope sensor in smartphone. The enhancement on the activation function in LSTM cell model can make it more robust to classify the non-separable ADL data for unconstraint smartphone position. Ans-Assist has an accuracy of 0.95 ± 0.028 and outperform unmodified LSTM model. In addition, Ans-Assist can also detect human fall for unconstraint smartphone positions with tremendously 8% more accurate.

II. RELATED WORKS

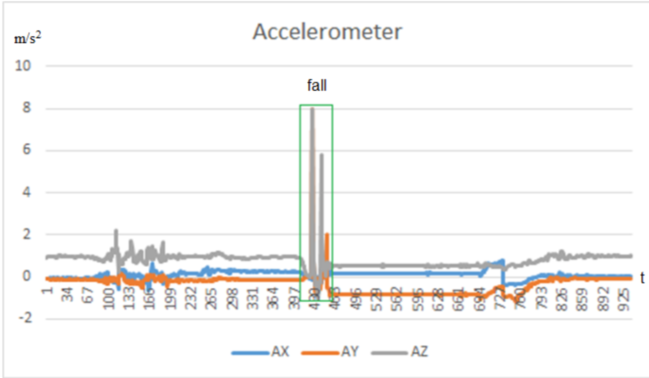
There are three categories of fall detection methods according to Yildirim: carried/wearable-based, image-based, and acoustic/vibration-based [11]. Accelerometer and gyroscope sensors on smartphone can be categorized as carried/wearable-sensor and are suitable for fall detection because they can detect the forces when human fall [14]. The disadvantage of this method are people need to carry/wear the sensor and the current method can only works properly when the sensor position been defined on the specific position. On the other hand, the model-based approach using machine learning or deep learning to detect more sophisticated pattern than threshold-based detection and it has better accuracy result [3].

One of the model-based approach, Long Short-Term Memory (LSTM) is very useful can be implemented to detect human fall because ADL and fall patterns usually need to be analyzed not only from one or two data before activity occurs. LSTM is the enhancement of Recurrent Neural Networks (RNN) which equipped with a special gating mechanism [12, 15]. LSTM can analyze the pattern and preserve it for much longer than ordinary RNN [12]. LSTM architecture consists of an input, output, and forget gate that allows it to reset its own state, making it possible to learn continual tasks. Forget gate and output activation functions are the most critical parts of the LSTM block.

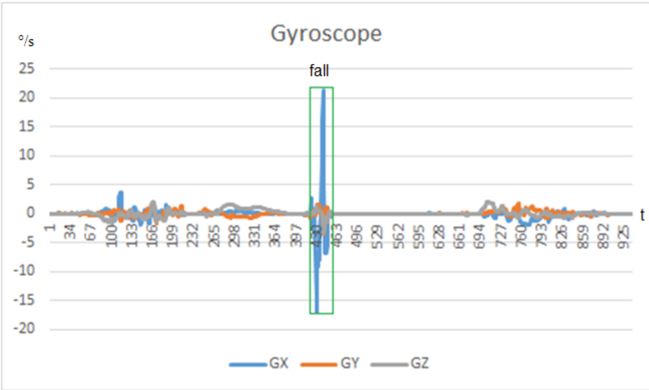
Smartphone is one of the common device that has been used everyday and it is convenience for people to carry because it can be put in a pocket, a smartphone armband, or even in a bag [11]. Smartphone is the best candidate device to detect human fall because it is equipped with accelerometer or gyroscope sensors, portable, and have been accepted by the elderly [11, 16].

III. PROPOSED METHOD

Sensors on smartphone (accelerometer and gyroscope) will respond if there is movement from human activity. Based on Fig. 1, both of sensors respond when human fallen. Accelerometer and gyroscope have x, y, and z axis for each sensor. These axes need to be measured together (based on the preliminary research we have conducted before) to increase the accuracy rate to detect human fall.



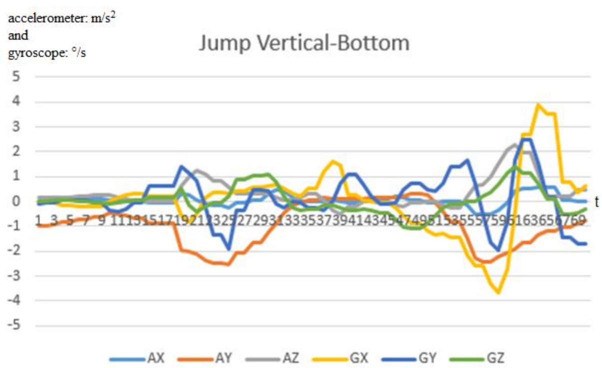
(a)



(b)

Fig. 1.Fall-face-up: (a) accelerometer sensor and (b) gyroscope sensor

Although the human performs the same activity, if the orientation of the smartphone is different, it will have the different result on each sensor and it is very challenging since the sensors data will not have the same data pattern every time the activity been perform (Fig. 2). Negative value on unconstraint data is very important and it has a meaning (smartphone position). If this value been process by sigmoid activation value in LSTM cell, the negative value will be normalized to zero and it will have no meanings. We modify this activation function in LSTM cell and replace 3 sigmoid activation functions (forget, input, and output gates) to tanh because negative value can be confined between zero and minus one value (Fig. 3).



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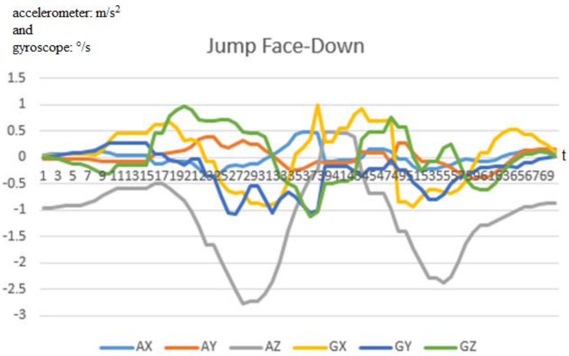

(b)

Fig. 2.Jump: (a) vertical-bottom and (b) face-down smartphone positions

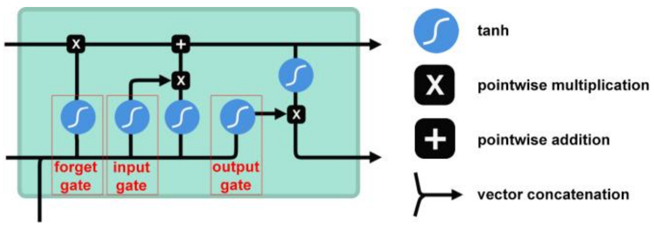

Fig. 3.Modified LSTM cell using tanh activation function

In this study, several models have been trained and tested. Based on the result, Ans-Assist model using the modification of activation function of LSTM cell is robust to handle not only for constraint data but it also can handle unconstraint smartphone positions data (Fig. 4). Researchers maintain the minimum number of layer to make the model can runs and process the data on the low power device; and can be embedded in smartphone by doing the transfer learning. Raw data from accelerometer and gyroscope sensors are taken from the smartphone as input for the model. These data are processed by LSTM whose cells have been modified using tanh activation function. At the next layer, the sigmoid activation function acts as a decoder to process the previous output and produce the result of classification (fall or non-fall).

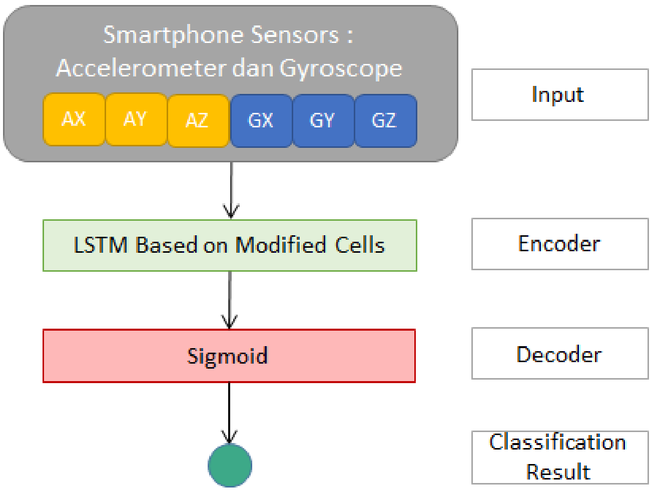

Fig. 4.Ans-Assist: human fall detection model for unconstraint smartphone positions using LSTM based on modified cells

The data of accelerometer and gyroscope sensors are presented in time-series data. Each time-window data on Fig. 5 will be processed by the model. One second of data captured can produced 60 time-window data and it needs 70 time-window data to be analyze by model before it can give the classification result (1.183 second). If the result is promising, this data will be processed with the following data to make the model has the ability to learn from past experience.

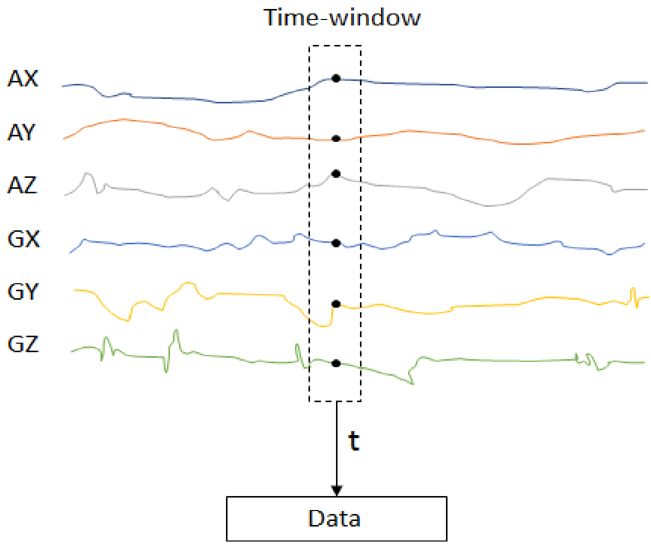

Fig. 5.Time-window data representation

IV. RESULT AND DISCUSSION

K-Fold Cross Validation been used to make all data equally been trained and tested. In general, each step will begin by reading accelerometer and gyroscope raw data which will then be processed by the model.

A. Data

A mobile application is made and installed in Android smartphone to collect raw data from smartphone sensors. The raw data (time-series) sensors are captured from a smartphone (Table I). Each sensor has X, Y, Z axes and there are six axis in total (AX, AY, AZ, GX, GY, and GZ) which A indicates accelerometer and G for gyroscope.

Table- I: Face-down raw data – sample for stand-fall activity

AX	AY	AZ	GX	GY	GZ
0.518	-0.141	-0.258	16.704	-1.837	1.283
-0.539	0.159	-3.068	0.67	-2.021	-0.744
-0.361	0.034	-0.969	0.02	-0.055	0.043
-0.445	0.06	-0.897	-0.004	0.018	0.006

Data is labeled and classified using two classes: fall and non-fall data. There are 1080 data in total: 720 data for non-fall and 360 data for fall.

Six different smartphone positions (face-up, face-down, vertical-top, vertical-right, vertical-left, and vertical-bottom) are used to represent the unconstraint smartphone positions.

Fixed orientation smartphone position (constraint) is used by the other researchers and it makes the experimental environment not quite close with the real situation because people usually placed the smartphone freely as they want. This challenge makes the method need to be built and tested is it robust enough or not to handle unconstraint smartphone positions from its sensors data.

B. Experimental Design

The primary dataset is used when conducting the experiment. Data is captured using Android smartphone by using various smartphone positions (six positions) and labeled into two classes: non-fall (ADL: jump, sit, walk, and stand) and fall (fall when stand and walk). Face-up position means smartphone faced upwards, face-down means it positioned downwards, vertical-bottom means smartphone on standing position, vertical-left means it is on the left landscape orientation (home button is on the left side), vertical-right means it positioned on right landscape orientation, and vertical-top means the home button is on the top side of smartphone.

There are 45 respondents in total from both gender (male 22 respondents and female 23 respondents), age 19 - 75 years old (adult 28 respondents and elderly 17 respondents), and using mattress for safety reasons. Height and weight of respondents are not measured in this experiment.

K-fold validation 5-fold is used on the experiment. Data will be randomized and divided into five sections. Four sections of the data will be a training data and the other section will be a testing data. This process will continue until all data has become training and testing data.

C. Model Implementation

The model is implemented in the device has the following specifications: i5 processor (1.60GHz), 4GB memory, and 2GB on board graphic card. The data captured by accelerometer (AX, AY, and AZ axis) and gyroscope (GX, GY, and GZ axis) are processed by modified cell of LSTM model. 1080 data (360 fall and 720 non-fall data) been used as an input and the model will give the output is the activity classified as fall or non-fall as a result. The implementation of modified cell of LSTM model for human fall detection on unconstraint smartphone positions has the 95% confidence interval of accuracy: 0.95 ± 0.028. Fig. 6 presents a plot of train and validation loss of Ans-Assist model.

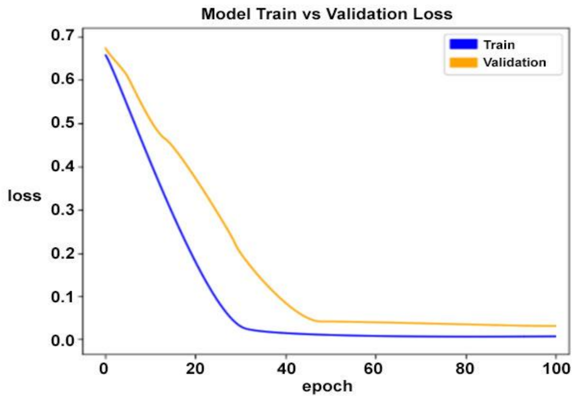

Fig. 6.Plot of model train and validation loss

We have compared Ans-Assist: modified LSTM cell model with other LSTM model without modification on the LSTM cell and our model outperform the result especially for unconstraint smartphone positions (Table II). This unmodified LSTM model [17] is used as a benchmark because the accuracy results of the model is the highest compared to other recent models that apply machine learning to detect human fall [18, 19].

Table- II: Experimental results - accuracy

	Constraint	Unconstraint
Ans-Assist: Modified LSTM Cell	0.96	0.95
Other LSTM Model [17]	0.94	0.87

V. CONCLUSION

Automatic human fall detection needed by elderly and even for people with special conditions to minimize the problems in post-fall incident. Smartphone can be used for detecting human fall because it has accelerometer and gyroscope sensors and been accepted for most of the people, including elderly.

Modified LSTM cell can answer the challenge to detect human fall because it is robust the handle the data not only for constraint smartphone position but also can handle unconstraint smartphone positions. Ans-Assist (the modified cell of LSTM model) has 0.95 ± 0.028 for the accuracy and outperform LSTM model without modification.

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