Low power consumption fall detection using three features

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Abstract. The increasing of longevity rates contributed to elderly and in line with the increased of medical needs especially on health care and monitoring systems area. To facilitate continuous monitoring and to address the need of healthcare which are non-invasive, affordable, easy-to-use, and non-invasive healthcare solutions are becoming increasingly important. Smartphone is a perfect device to detect human fall because it has various sensors (accelerometer, gyroscope, GPS, and many more), already been accepted by most of the people, and can reduce the electronic waste by giving a smartphone a second chance to become a health care and monitoring system. The research proposed a low power consumption human fall detection by using three features: Signal Vector Magnitude (with modification), Alim, and Tilt Angle Change as a solution to overcome two problems (health care and environment) by using the device that already been existed to reduce the electronic waste. Our proposed solution was able to reach 0.97 of accuracy result and work on the smartphone (low power device) for green computing.

Keywords: low-power device, human fall detection, signal vector magnitude, Alim, Tilt Angle Change

1. Introduction

Elderly population increase significantly and there are many critical challenges especially in developed countries for health care and monitoring systems area [1, 2, 3]. The increased of longevity rates have play a part to the elderly and thus medical needs. [1, 4]. Diseases related to respiratory system, mental health, eye, cardiovascular system, and skin are widespread worldwide. Nonetheless, these diseases can be prevented and/or handled properly by continuous supervision [5]. Time limitations are often seen as the main cause of the absence of people accompanying elderly (family, friends, caregiver, etc.) [6]. To facilitate continuous monitoring and to address the need of healthcare; non-invasive, affordable, easy-to-use, and non-invasive healthcare solutions are becoming increasingly important [5].

Healthcare solutions using special device or special sensor that can detect human activities that can be carried along with them is critically needed [7, 8, 9]. By growing demand to produce the electronic device with special sensor and method to detect fall, it can pose a risk to the environment for using a lot of materials, electricity to run the factory, pollution, and it can contribute to global warming [10, 11].

The tremendous advancement in communication technologies, high-speed computing, and energy efficient have revolutionized the global telecommunications industry [5]. Smart spaces have gained popularity in recent years due to advancements in sensor technology, ease of deployment, and the
reduction of hardware costs [12]. Many countries and organizations have drafted national legislation to reduce the amount and types of materials disposed in landfills [10]. Green computing encompasses the practice of environmentally manufacturing, operating, recycling and disposing of computers and electronic devices sustainably in the ICT sector [13, 14]. The recycling of electronic waste and equipment is important not only for reducing the amount of waste required for treatment, but also for promoting the recovery of valuable materials [10]. Burning E-waste can produce polyhalogenated aromatic hydrocarbons (PHAHs), dioxins, hydrogen chloride, polycyclic aromatic hydrocarbons (PAHs), and furans [11].

The research proposes a low power consumption human fall detection as a solution to overcome two problems (health care and environment) by using the existed device to reduce the electronic waste. Smartphone is one of the best candidates for this solution because it easy can be found in our daily life, portable, has sensors to detect the motions, and it has been accepted by elderly [15, 16, 17]. Accelerometer, GPS, and gyroscope sensors available on smartphone can maximally empowered as a communication tool and to detect human activities [17]. By maximizing its potential, the research can give an "extra life" to smartphones to be reuse and reduce electronic waste. The low power consumption human fall detection that we propose can work on smartphones that have low Central Processing Unit (CPU) power specifications and can achieve fast processing times.

2. Related works
According to eMarketer, smartphone is a technology that is currently widely used in daily life by almost one third of the world's population. Even though the size of smartphone is small, it has been equipped with various features such as communication components and sensors [15, 16, 17]. Two sensors that typically used for carried or wearable method are accelerometer and gyroscope [18, 19]. When a human fall, there are a sudden change in posture and body speed movements [6]. Falling movements are usually characterized by high acceleration compared to Activities of Daily Living (ADL) [20]. The changes in movement speed can be detected by using an accelerometer sensor while attached on the human body [6]. The use of an accelerometer sensor to detect human fall is not enough because falling movements have many variations. Accelerometer sensor can only detect the acceleration of movement and body orientation. When someone falls, it is often assumed that the final position movement is prone/laid horizontally on the floor. Gyroscope sensors can help the limitation of the accelerometer sensor to be able to identify falling movements more varied and can measure angular momentum [21].

Threshold-based fall detection method focuses on mathematical calculations accompanied by threshold implementation [22]. Method based on threshold can be developed relatively quick and have minimal computation process, but their abilities are quite limited when they have to face situations with challenging datasets such as human activities data that are similar with fall [6, 22]. Some threshold-based mathematical formulas to detect human fall are Accelerometer Amplitude, Signal Vector Magnitude, and Resultant Acceleration [18, 22, 23]. Signal Vector Magnitude, Resultant Acceleration, and Accelerometer Amplitude basically have formulas that are very similar to each other [18, 22, 23]:

\[
\text{Signal Vector Magnitude} = \sqrt{(AX^2 + AY^2 + AZ^2)}
\]  

Equation (1) is the Signal Vector Magnitude formula, where AX, AY, and AZ are representing the acceleration on accelerometer sensor of X, Y, Z axes. Signal Vector Magnitude (based on the input from accelerometer signal) can detect the significant changes when fall. If the peak value of (1) exceed the threshold, it can be categorized as fall.

Signal Vector Magnitude formula that do not include any gravity vector elements can be calculated to produce linear acceleration (Ali), and if the Ali value is calculated the vector will produce Alim [19]. Six axes in total (accelerometer (AX, AY, and AZ axes) and gyroscope (GX, GY, and GZ axes)) are needed to be able to calculate Ali (2) and Alim (3).
Another way to identify fall in human is to look at changes in human posture [6]. Changes in the degree of posture caused by falling forward, backward, right, or left can be measured using Tilt Angle Change formula (4). If human posture changes is greater than 60 degree, it means the human fall. AX, AY, and AZ are the axes (X, Y, and Z) of accelerometer sensor.

\[
\text{Tilt Angle Change} = \tan^{-1} \left( \frac{AY}{\sqrt{AX^2 + AZ^2}} \right)
\]  

Previous paper result usually used Signal Vector Magnitude based on accelerometer sensor data. Our proposed method combine both of accelerometer and gyroscope data in Signal Vector Magnitude (5) because gyroscope reacts if there is a movement. The proposed method also use the composite formulas based on the previous paper results (Ali, Alim, and Tilt Angle Change) and is expected to improve yield of accuracy while maintaining low processing time so that it can run on smartphone devices that have not so high specifications/low power consumption.

\[
\text{Signal Vector Magnitude (with adjustment)} = \sqrt{(AX^2 + GX^2) + (AY^2 + GY^2) + (AZ^2 + GZ^2)}
\]  

3. Proposed method

Various kinds of mathematical formulas which aim to detect fall human movements can be combined to produce methods with better accuracy. The focus on this experiment is to determine the feature by using AX, AY, AZ, GX, GY, and GZ as the inputs and determining the threshold value to be able to produce good accuracy. An illustration of the feature extraction process can be seen in Figure 1.
The research proposes a low power consumption fall detection method that consist the combination of three features used: Signal Vector Magnitude (with modification), Alim, and Tilt Angle Change - all these features are based on mathematical formula (Figure 2). The three features are then trained using a dataset for six smartphone orientation (face-up, face-down, vertical-bottom, vertical-left, vertical-right, and vertical-top) to get the threshold with the highest True Positive (TP) value and the lowest False Positive (FP).

Signal Vector Magnitude is one of the most popular formula used to detect human fall movements. The magnitude generated by the sensor will be calculated and generally human fall can be detected by this formula because fall have higher magnitude values compared to other non-fall movements. Signal Vector Magnitude which can only process accelerometer sensor data. We do some adjustments on this formula so it can accept the input from accelerometer and gyroscope sensors data.

Alim is used to calculate linear acceleration of human motion by inserting a gravity vector element (with the usage of gyroscope sensor). In order for Alim to be able to detect how much linear acceleration is occurred, Ali results need to be calculated into Alim to get the value of sum vector.

Tilt Angle Change is needed in order to accommodate the orientation of the smartphone that occurs when humans move. This formula is calculated the changes of human posture that occur before fall and after fall.

**Figure 1.** Feature Extraction Process.
Figure 2. Block Diagram of the Proposed Low Power Consumption Fall Detection Method Using Three Features Based on Mathematical Formula.

It is challenging to improve the accuracy result (based on the previous paper) while maintaining low processing time so the proposed solution can process the data and can provide the result with a waiting time that can still be tolerated by the user. Because the risk if someone fall is critical, the proposed solution need to have an ability to give the result in (approximately) one second after the data are read to be processed by the method. The research does the experimental test of proposed solution using 1.60 GHz processor and 4.00 GB of Random Access Memory (RAM) and it is able to provide the result (approximately) in 0.0008 seconds. Based on the test result, this method can be implemented in smartphone (smartphone is categorized as a low power CPU device compared to computer hardware specification) or other device that has lower hardware specification because it can still provide the result in (approximately) one second.

4. Experiment
4.1. Dataset
Raw time-series data are captured using smartphone from accelerometer and gyroscope. Each sensor has X, Y, and Z axes, containing a total of six axes (AX, AY, AZ, GX, GY, and GZ), where A means accelerometer and G means gyroscope. The data are classified and labelled into two classes: fall and non-fall. 252 data used in training - to determine the threshold, which consists of 84 fall and 168 non-fall data.

4.2. Experimental design
The research is carried out in indoor area. Data are captured by smartphone using constrained or fix smartphone orientations. The experiment uses the data from four non-fall activities: stand, stand-jump, stand-sit-stand, and walk, and two fall activities: walk-fall and stand-fall.
Model Implementation and Result
The proposed low power consumption fall detection method is trained by using computer to calculate the threshold of three features based on mathematical formula.

![ROC Curve - Accelerometer & Gyroscope](image)

**Figure 3.** ROC Curve of Accelerometer and Gyroscope Sensors – Training.

**Table 1.** Confusion Matrix of Training Data of Low Power Consumption Fall Detection Method Using Three Features Based on Mathematical Formula.

|                | Predicted: Fall | Predicted: Non-fall | Total  |
|----------------|-----------------|---------------------|--------|
| Actual: Fall   | TP=84           | FN=7                | 91     |
| Actual: Non-fall| FP=0            | TN=161              | 161    |
| Total          | 84              | 168                 | 252    |

**Training Accuracy - Threshold**

\[
\text{accuracy} = \frac{84+161}{84+7+0+161} \quad (6)
\]

\[
\text{accuracy} = \frac{245}{252} \approx 0.97 \quad (7)
\]

ROC curve is needed to determine the best threshold to get the highest accuracy (Figure 3). After the threshold determined, the proposed method consisting of three features based on mathematical formula: Signal Vector Magnitude (with modification), Alim, and Tilt Angle Change are trained and voting is used to determine the results and summed by using confusion matrix Y (Table 1). Accuracy of the proposed method is calculated by using accuracy formula (6) has can reach 0.97 for the accuracy result (7).

To compare the result gained from the proposed method, other experiment has been conducted (Table 2). The dataset is trained by using Signal Vector Magnitude (commonly used and only use an
accelerometer to determine the value of Signal Vector Magnitude) and the accuracy result is 0.76. The proposed method can boost the accuracy result up to 0.21 which is very important because if someone fallen and not been detected as fall, people will be at very high risk. The approximately time to process 1 data is good, fast to give fall or non-fall result – under 1 second even though Signal Vector Magnitude is the fastest one but people will not realize the difference between 0.0006 and 0.0008 second.

Table 2. Results of Fall Detection Methods.

|                      | Signal Vector Magnitude | Proposed method |
|----------------------|-------------------------|-----------------|
| Accuracy             | 0.76                    | 0.97            |
| Approx. time to process one set of data (in seconds) | 0.0006 | 0.0008 |

Low power consumption means the model can provide the result by using the device that have low CPU power specification and smartphone is one of them. Based on PC Magazine article (April 17, 2019), the baseline of RAM is 4 GB. By using 4.00 GB of RAM and 1.60 GHz of processor, the method can process one set of data from accelerometer and gyroscope sensors in (approximately) 0.0008 seconds. The approach on the proposed method must be able to provide the result within (approximately) one second after the set of data is read to be analyzed by the method. Based on the approximately time to process one set of data (in seconds) on Table 2, the proposed result promisingly has time to process less than one second to provide the result which can work on low power device (smartphone).

Figure 4. Flow of the Health Care and Monitoring System Based on the Proposed Solution.

The proposed solution can be implemented on smartphone as a system (Figure 4). If the method analyzes the data from accelerometer and gyroscope sensors and classify it as fall, smartphone activate GPS to get the location and send the information to the person been registered before. The information
can be sent by SMS and Voice Call. If the method classifies the data as non-fall, smartphone will continue to read the data from the sensors and analyze it using the method.

5. Conclusion
Health care and monitoring system to detect fall detection is needed for people who need special treatments and elderly because it will mitigate post-fall incident problems. Smartphone is a suitable device to detect human fall because it has various sensors (in example: accelerometer, gyroscope, and GPS), already been accepted by most of the people, and can reduce the electronic waste by giving a smartphone a second chance to become a health care and monitoring system. The combination of three features based on mathematical formula on the proposed low power consumption fall detection method has a better accuracy result (0.21) than Signal Vector Magnitude and can work on the smartphone (low power device) – green computing.

Acknowledgments
This work is supported by Research and Technology Transfer Office, Bina Nusantara University as a part of Bina Nusantara University’s International Research Grant entitled Robust Human Fall Detection Method For Health Monitoring with contract number: No.026/VR.RTT/IV/2020 and contract date: 6 April 2020.

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