Design and Implementation of Fall Detection System Using MPU6050 Arduino

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Design and Implementation of Fall Detection System Using MPU6050 Arduino

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Abstract. Fall is the most significant causes of injury for Elderly or Epilepsy. This has led to develop a many types of automatic fall-detection systems. However, prevalent methods only use accelerometers to isolate falls from activities of daily living (ADL). This paper proposes combination of a simple threshold method and acceleration measurement to detect falls and fall-detection. To demonstrate the activity of proposed scheme a device has been designed. We used an Arduino-UNO, also we used MPU6050 as a sensor and we can measure the velocity and acceleration by calculate the derivative for the phase this program was C-language. Several fall-feature parameters and possible falls are calibrated through an algorithm. The implementation of program built to read an analogue variable from its port as an additional adjustment to fixed the upper and the lower. The total sum acceleration vector ACC to distinguish between falling and ADL. The results using the simple threshold, PMU, and combination of the simple method and MPU were compared and analyzed. The proposed MPU reduced the complexity of the hardware also the algorithm exhibited high accuracy.

Keywords: Fall Detection Systems (FDS) · Activities of Daily Living (ADL) · MPU6050-Arduino

1 Introduction

Fall is the most significant causes of injury for elderly. These falls are because many disabling fractures that could eventually go in front to death due to complications. Most elderly (over 75 years old) have fallen at least once a year, and 24 % of them have severe injuries [1]. Among people affected by Alzheimer's disease, the probability of a fall increases by three times. Elderly care can be improved by using sensors that monitor the vital signs and activities of patients, and remotely communicate this information to their doctors and caregivers. For example, sensors installed in homes can alert caregivers when a patient falls. Some fall detection algorithms also assume falls happen when the body lies prone on the floor. But they are less effective when a person's fall posture is not horizontal as shown in Fig. 1.

The consequences of a fall can vary from scrapes to fractures and in some cases lead to death. Even if there are no immediate consequences, the long-wait on the floor for help increases the probability of death from the accident. For this reason, fall detection is an active area of research. Most of the research on falls in which accelerometers is

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Fig. 1. Falls of patient's body on the floor

used focus on determining the change in magnitude of acceleration. When the acceleration value exceeds a critical threshold, the fall is detected [2, 3]. A contribution is made towards such standardization by collecting the most relevant parameters, data filtering techniques and testing approaches from the studies done so far. State-of-the-art fall detection techniques were surveyed, highlighting the differences in their effectiveness at fall detection. A standard database structure was created for fall study that emphasizes the most important elements of a fall detection system that must be considered for designing a robust system [4], as well as addressing the constraints and challenges. In addition, fall activity patterns are particularly difficult to obtain for training systems. These systems successfully detect falls with sensitivities. However, focusing only on large acceleration can result in many false positives from fall-like activities such as sitting down quickly and running. Furthermore, previous studies used complex algorithms like support vector machine (SVM) [5] and Markov model [6] to detect the fall. However, accuracy of these systems has not been proven to be highly effective. They also use excessive amounts of computational resources and cannot respond in real time. In this paper we propose a new device based on microcontroller (Arduino-UNO) and the sensor is MPU6050 Accelerometer and Gyro Chip.

2 Fall Risk Factors

A person can be more or less prone to fall, depending on a number of risk factors and hence a classification based on only age as a parameter is not enough. In fact, medical studies have determined a set of so called risk factors:

- Intrinsic:
  1. Age (over 75)
  2. Chronic disease
  3. Previous falls
  4. Poor balance
  5. Low mobility and bone fragility

6. Sight problems
7. Cognitive and dementia problems
8. Parkinson disease
9. Use of drugs that affect the mind
10. Incorrect lifestyle (inactivity, use of alcohol, obesity)

- Internal Environment:
  1. Need to reach high objects
  2. Slipping floors
  3. Stairs
  4. Incorrect use of shoes and clothes
- External Environment:
  1. Damaged roads
  2. Dangerous steps
  3. Poor lighting
  4. Crowded places.

3 Mpu-6050

ITG MPU-6050 is a sensor that contains MEMS accelerometer and a MEMS gyroscope in one chip. Both accelerometer and gyroscope contains 3 axis that can captures x, y and z with 16-bits analog to digital conversion hardware for each channel. Mpu-6050 uses I2C for communication which is a multi-master, multislave, single-ended, serial computer bus with low speed but very useful because uses only two wires: SCL (clock) and SDA (data) lines. Although the breadboard and the wires are optional items, the two pull-up resistor are essential. The diagram in Fig. 2 shows how to connect the sensor to a Arduino Uno. It is also important connect all the sensor pins with the correct arduino pins. The pull-up resistor will always keep a small amount of current flowing between VCC and the pin, in other words, it will keep a valid logic level if it is not flowing current in the pin 5. Sensor VDD - Arduino 3.3 v or 5 v. Sensor GND - Arduino GND. Sensor INT - Arduino digital pin 2.

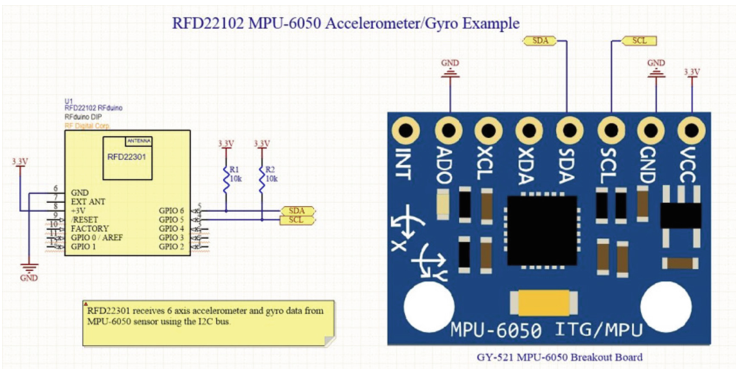


Fig. 2. Source: RFduino, image by unknown

Sensor SCL - Arduino SCL dedicated pin = A5. Sensor SDA - Arduino SDA dedicated pin = A4.

4 Fall Detection Algorithm

The total sum acceleration vector Acc, contain both dynamic and static acceleration components [3, 7], is calculated from sampled data as indicated in Eq. (1)

$$Acc = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2} \tag{1}$$

Where A_x, A_y, A_z are the acceleration in the x, y, z axes, respectively.

Similarly to the acceleration, the angular velocity is calculated from sampled data as indicated in Eq. (2)

$$w = \sqrt{(w_x)^2 + (w_y)^2 + (w_z)^2} \tag{2}$$

Where w_x, w_y, w_z the acceleration in the x, y, z axes, respectively.

When stationary, the acceleration magnitude, Acc, from tri-axial accelerometer is a constant, and angular velocity is 0^o/s. When the subject falls, the acceleration is rapidly changing and the angular velocity produces a variety of signals along fall direction.

Since the Fall Index (Acc) requires high sampling frequency and fast acceleration changes, it will miss falls that happen slowly. Hence, Acc is not used unless we want to compare the performances of our systems with previous studies that have used the same positions but with deferent speed and accelerations.

The lower and upper fall thresholds for the acceleration and angular velocity used to identify the fall are derived as follows [8]:

1- Lower fall threshold (LFT): the negative peaks for the resultant of each recorded activity are referred to as the signal lower peak values (LPVs). The LFT for the acceleration signals are set at the level of the smallest magnitude lower fall peak (LFP) recorded.
2- Upper fall threshold (UFT): the positive peaks for the recorded signals for each recorded activity are referred to as the signal upper peak values (UPVs). The UFT for each of the acceleration and the angular velocity signals were set at the level of the smallest magnitude UPV recorded. The UFT is related to the peak impact force experienced by the body segment during the impact phase of the fall.

Fall detection algorithms using thresholds are normally divided into two groups, one is based on the LFT comparison and the other is based on UFT comparison of acceleration data. Although past research has achieved some significant results, the accuracy is still below desired levels. In this study adjust the UFT and LFT and found the performance to be 83.33 % and 67.08 %, respectively [9]. Figure 3 shows the flowchart of our algorithm which implemented in the program of Arduino_UNO in C-language this program built to read an analogue variable from its port as an additional adjustment to fixed the upper and the lower ACC.

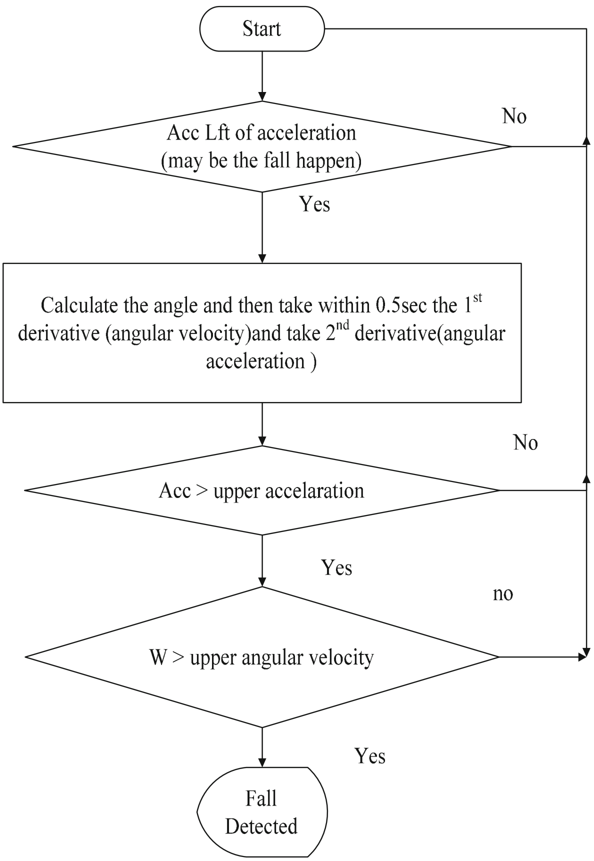
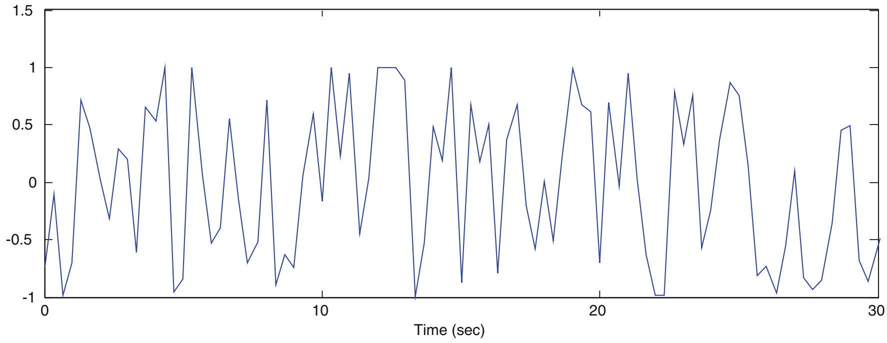


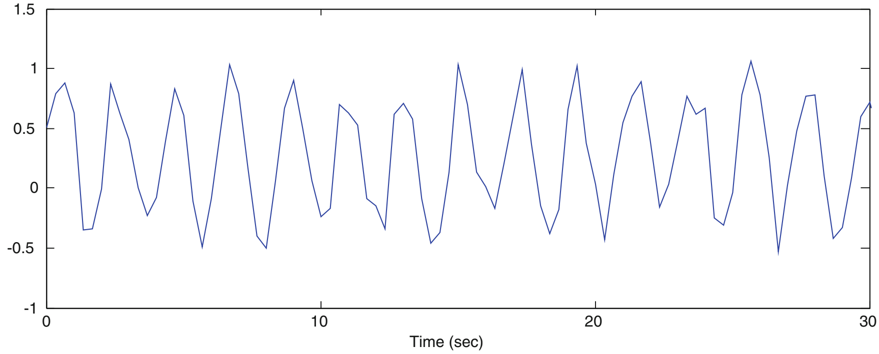
Fig. 3. Flowchart of fall detection schema.

5 Results and Discussion

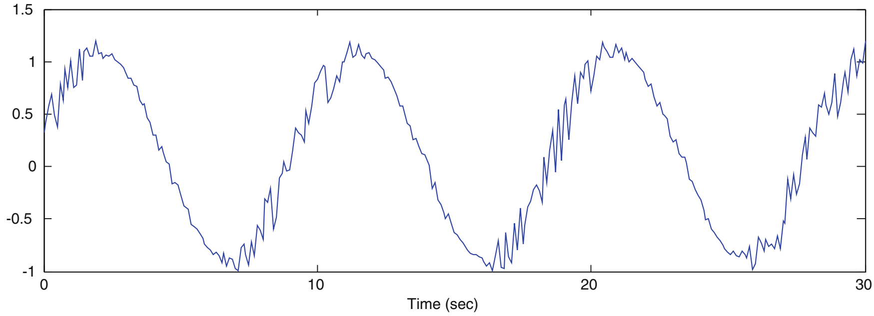
Some existing acceleration-based fall detection systems are only used to distinguish falls from ADL. However, some activities like sitting down fast also feature large vertical acceleration. Figure 4 shows the acceleration and rotational rate of the trunk where the cases as follows: (a) run on a damaged road, (b) walking fast (c) step up a Stair. In Fig. 4 along three cases there is no fall then there is no alarm. Figure 5 shows the acceleration and rotational rate of the trunk and thigh for sitting fast. Where the cases as follows: (a) is a dangers fall detected, (b) is a fall posture. In Fig. 5.a the fall detected very fast and give alarm in the first moment and continued along 30 s while in Fig. 5.b give alarm after 10 s because there is no fall.



(a) Run on a damaged road

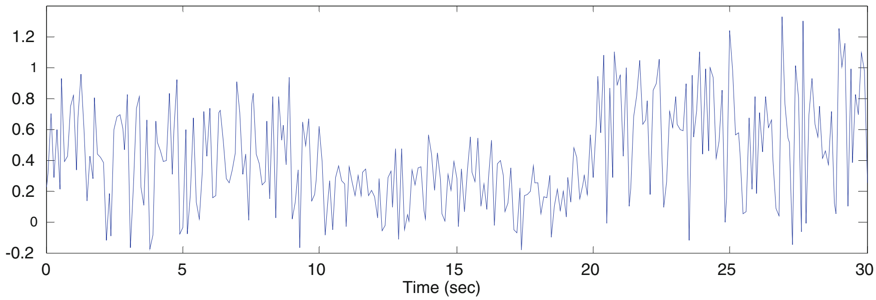


(b) Walking fast

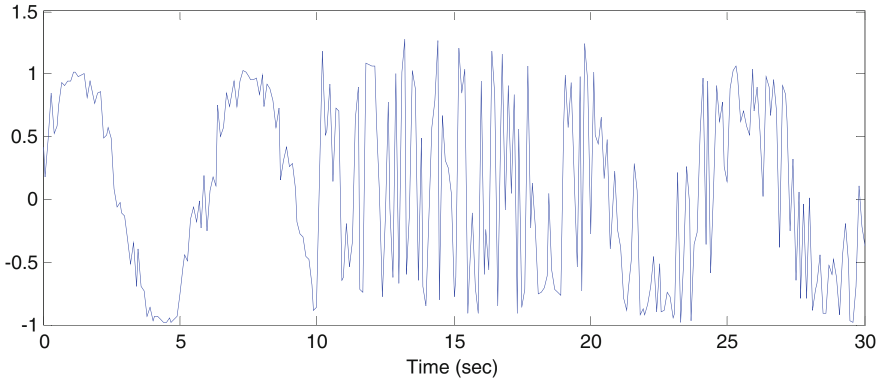


(c) Step up a Stair.

Fig. 4. Shows the acceleration and rotational rate of the trunk where the cases as follows: (a) run on a damaged road, (b) walking fast (c) step up a Stair.



(a) Dangers fall detected



(b) Fall posture

Fig. 5. Shows the acceleration and rotational rate of the trunk and thigh for sitting fast. Where the cases as follows: (a) is a dangers fall detected, (b) is a fall posture.

6 Conclusions

The several fall-feature parameters of the 6-axes acceleration were introduced and applied according the algorithm. Possible falls were chosen through the simple threshold and then applied to the MPU to solve the problems such as deviation of interpersonal falling behavioral patterns and similar fall actions. The test of the proposed device studied along a different 350 case studies. The parameters of upper and lower of acceleration and velocity have adjusted to give best fall detection with sensitivity, specificity, and accuracy which were over than 95 %. These results demonstrate the reduction of the computing effort and resources, compared to those of using all the events applied. Then the proposed algorithms were very simple because it depend on a simple sensors (measure the angle) and the program calculate the angular velocity and acceleration. They can be implemented into an embedded system such as an 8051-based microcontroller with 128 Kbyte ROM. In the future, if the proposed algorithms are implemented to the embedded system, its performance will be tested in a real time.

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