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DESIGN AND IMPLENTATION OF A WIRELESS FALL DETECTION NETWORK PROTOTYPE USING MEMS SENSORS

by

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Disclamer

I hereby declare that this thesis is a product of my own work, unless otherwise referenced. I also declare that all opinions, results, conclusions and recommendations are my own and may not represent the policies or opinions of Vietnamese - German University and Frankfurt University of Applied Science.

Ho Ngoc Khang Minh

Abstract

Falling is becoming a serious problem to elderly people with the age of over 65, often causing unpredictable injuries such as hip fractures, head traumas, etc. More seriously, falls may lead to disability or even death on the victim if assistances from caregivers are not received in time. From this situation, there is a need for a wireless communication network which can automatically detect the fall and send an alarm to the caregivers if there is no safe signal from the victim within 10 minutes. There have been several algorithms such as detection of body orientation after a fall, image processing to detect the fall or applying machine learning techniques (Support Vector Machine (SVM), Markov model) in classifying between falling and other activities of daily living (ADL). However, these complex techniques require a huge amount of computations which can result in the system being overloaded or heavily delayed.

Addressing this problem calls for less computation-intensive techniques while retaining the accuracy and robustness of the system. One such approach is the combination of data from both accelerometer and gyroscope. The focus of this thesis is developing a wireless fall detection network which can combines the data from above sensors to detect falls and distinguish them from fall-like activities. A comparison on the performance of this network with other existing works is also included to evaluate the robustness of the system.

Keywords: *elderly people, fall detection, accelerometer, gyroscope, wireless communication network*

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Acronyms

ADC analog-to-digital. 15

IMU Inertia Measurement Unit. 15

IoT Internet-of-Things. 17, 18

MCU Micro-Controller Unit. 17, 18

NCOA the National Council of Aging. 4

SSF Sensitivity Scale Factor. 15, 16

U.S. United State of America. 5, 8

WHO World Health Organization. 2, 5

1. Introduction

1.1 Introduction to Fall

Nowadays, fall is becoming a dangerous issue which mostly causes the injuries and even leads to disability or fatal death on human, especially the elderly. According to Hwang *et.at.* [2], in the United State, one-third to one-half of elderly people over 65 years old fall at least one time each year and two-third of them will do so again within the next 6 months. Every 11 seconds, there is an elderly person is treated in the hospital's emergency area due to fall-related injuries and every 19 minutes, one faller die [3]. It is also reported that one out every 200 falls results in a hip fracture on people with age among 65 and 69 and increase to one out of 10 for those aged 85 and more [4]. The most profound effect of falling is the loss of functioning associated with the dependency of the elderly for the rest of their life. Besides, a great amount time and money have been spent on the medical treatments for the falls. Approximately $179 million were used as direct medical costs for treating fatal falls and $19 billion for non-fatal fall injuries within 2000 [5].

1.2 Definition of a Fall

Before starting a research about falls, it is necessary to understand about the meaning of the term *falls*. According to World Health Organization (WHO), a fall is defined as an event which results in a person coming to rest inadvertently on the ground or floor or other lower level with or without loss of consciousness or injury [6].

1.3 Cause of a Fall

In recent years, a lot of researches have been done by different groups to find out the causes of falls. There have been different ways to classify the causes of a fall such as age and sex, drugs, cognitive functions, postural control, etc. However, because falling is an unintentional action, many causes usually combine to produce a fall. Therefore, these causes can be divided into two main categories, intrinsic and extrinsic, to ease the complication of research activities.

1.3.1 Intrinsic risk factors

Intrinsic factors are the factors which are within the body. It is also the physical aspect of the body that can cause injuries. Intrinsic factors include physical diseases such as cognitive impairment, postural hypotension, cardiovascular problems, etc.

Cognitive Impairment

It is well recognized that cognitive impairment is the common cause of fall on human, especially the elderly. Due to the research of Prudheim *et al.* in 1981, fallers have in general been found to have a higher prevalence of cognitive impairment than non-fallers [7]. It is also reported that human with dementia are approximately 3 times more likely to fall than non-demented [8]. The reason why patients with cognitive impairment are likely to fall is that they have increased reaction time, increased postural sway and increased leaning balance which result in the decrease on muscle strength, worse balance and poorer mobility.

Postural Control

Postural control is a complex motor skill that requires interaction of multiple body systems which results in the ability to maintain postural orientation or postural stability [9][10]. The impairment of postural control is indicated as one of significant causes of the fall during any activities at any age. Impaired control of gait and balance are two main aspects of the postural control that have been considered in many studies about falls. Subjectively assessed gait has been reported to be abnormal in many fall activities and other studies using more objective measurements have found some relations between the impaired gait and balance and risk of falling [11].

Cardiovascular problem

Cardiovascular disorders are responsible for approximately 77% of patients with unexplained or recurrent falls and falls associated with unexplained loss of consciousness [12]. There is a fact that fallers with cardiovascular disorders have a greater mortality than those with non-cardiovascular or unknown causes [13].

1.3.2 Extrinsic risk factors

Extrinsic factors are those related to the environment such as lighting, walking surface, loose carpets, and high or narrow steps.

Dim lighting or glare

Dim lighting is one significant cause of fall on human, especially on the elderly. While walking on the low light condition, the patient's visibility is reduced which prevents them from detecting the obstacles on the walking path and causing stumble and fall. Too bright lighting can also cause fall on human because of creating glares and distorting the way object look.

Bad staircase design

Bad staircase design is also another extrinsic risk that cause the fall on human. Too high or too low rise of staircases have caused a number of falls because people fail to perceive the abnormal elevation change or incur a misstep on descent. Besides, slippery surface of the treads can cause strip on patients while walking up or down the stairs. One more mistake of staircase design that can lead to the fall is lighting on the stair. Poor visibility and inadequate lighting can cause a user to misread the stair edge, resulting in faulty foot placement and falls.

1.4 Consequence of Falls

The consequences of falls are serious to human at any age in any circumstance, but to the elderly, they have significance beyond that in younger people. There are different consequences related to the falls on human including physical effects, psychological effects and other consequences such as dependency, hospital admission or economic consequences.

Physical consequences

Physical consequences of falls are always a significant aspect that many scientists have focused on in recent years. According to the the National Council of Aging (NCOA) of the U.S., falls are the leading cause of fatal injuries and the most common cause of non-fatal traumas [3]. There are several physical injuries such as bruise, fracture or head injury reported to happen with patients who suffer from falls. In such injuries, hip fractures and head traumas are two common problems which usually analyzed by researchers.

Hip fractures cause the greatest health problems and greatest number of death. It is reported that a quarter million hip fractures occur each year among people older than 50 years in the U.S. but more common in woman than men and increase in frequency with increasing age [11] [14]. Most patients with the hip fractures after falls are hospitalized, but about half of them cannot return home or live independently after that. In 1986, it costs for more than $3 billions for direct medical treatment of hip fractures [14].

Head injuries also usually happen to patients after suffering a fall. It is reported that people with the age of over 65 years old make up for 10-15% of admission to the hospital because of head injuries while three-quarters of them are caused by fall [11]. In California from 1996 to 1999, 71% of fall-related head injuries occurred in adults aged 65 and more [15]. The head trauma from previous fall can increase the risk of repeated fall and head injuries in the near future.

Finally, the most serious impacts of fall is fatal injuries causing death to patient. According to data from the WHO, the fall morality rate of people with the age of over 65 in the United State of America (U.S.) (in 2003) was 36.8 per 100 000 citizens [16]. The main reason of these accidental death is that many patients have lie on the ground for several hours before receiving the help from caregivers.

Psychological consequences

Fall can result in long lasting psychological impact, called fear of falling again, more than just short term injuries. For those people who have fallen one time before seem to have a feeling of vulnerability which limits them from their normal activities. They may be worried about falling and hurting themselves again, thus stop going out on their own or reduce their level of physical activities. Unfortunately, in attempting to reduce their risk of falling, they may increase risk of falling because of the attenuation of physical functions and mobility.

Other consequences

Some research indicated that there are other consequences such as dependency, hospital admission or economic consequence. As already mentioned, the fear of falling again prevent patients from living alone and start depending on the long-term nursing care. This consequence directly leads to increased dependency, which require more time and financial resources from both government and family.

Falls are also the main reason for fallers to be admitted to hospital as an emergency case. Due to the information provided by Accident Department at a sample of hospitals in England and Wales, in 1998, approximately 200 000 people over 60 are treated at this hospital per year because of a fall at home [17].

Finally, falls are also a economic burden of every countries around the world, especially for low and lower middle countries. According to the U.S. Center for Disease Control and Prevention, in 2015, there was $50 billion being used for fall injuries and expected to increase as the population ages and may reach $67.7 billion by 2020 [3]. These costs are spent for hospitalization, medical, pharmaceutical, nursing home and other costs which related to the medical treatments for fall patients.

1.5 Challenges in Detecting Falls

As mentioned in previous section, most of patient's death is caused by the late assistance from caregivers after fall accidents. Timely detection can minimize the negative impacts of falls on patients. However, depend on age and physical condition, different people have different gaits, different balance ability that result in several types of falls. These falls can happen in any direction at any speed. Therefore, it is still a challenge to design a system which can detect successfully all the falls of patients.

Another challenge in detecting the fall is that it is difficult for a system to distinguish a real fall from other fall-likes activities such as sitting, jumping or running, which also result in high acceleration. Therefore, it is required to collect a great amount of data from different subjects; and, then, there should be some analysis to find out the most common pattern of every fall. From that, researchers can design an algorithm to detect falls based on this pattern. However, it is not easy to collect real data for the system in the daily life on real human body, since it is an accidental, dangerous action which can happen randomly at any time. Therefore, it is a overwhelming task for researcher to built a dataset for their system.

1.6 Objectives

From above challenges, it is necessary to study and design a wireless sensor network which can automatically detect the fall of patient and send alarm to the caregiver instantly to reduce their time of arrival, and hence reduce mortality rate. The sensor node is portable and attached on the chest of user. This sensor node contains one accelerometer and one gyroscope to provide information about the body's acceleration and angular velocity during the fall event. This sensor node can connect to the host computer via Wi-Fi with the help of Wi-Fi module called ESP8266 from ESPRESSIF®company and send data directly to a monitoring software on the computer. Upon detecting a fall, sensor node will wait for the safe signal from patient within next 10 minutes. If there is no response, an emergency email will be sent immediately to the caregiver. There is also a super bright red led on the sensor node to indicate the fall and help caregiver to easily find out the patient.

1.7 Thesis Organization

In chapter 1, basic knowledge about falls as well as the causes and consequences of them are introduced. It is also provides the information about current challenges in detecting fall and motivation for this thesis. In chapter 2, a review of existing commercial fall detection devices in the market and researches related to this topic from other research group is included. Chapter 3 describes the problem of fall detection and method to solve this problem. Also in this chapter is the description of algorithm used in this thesis. Chapter 4 describes the system with both hardware and software aspects. Chapter 5 and 6 describe the data collection and analysis procedure as well as result assessment of the experiments on real human body. Finally, chapter 7 gives the conclusion for this thesis, limitation of current solution and recommendation for future works.

2. Literature Review

Nowadays, there are a lot of companies focusing on developing portable fall detection devices to suffice the need of current society where there are more and more elderly people fall every day. These products are used widely by many people around the world and have positive effects on health-care systems of these countries. Beside that, numerous universities and research groups carried out studies on the topic of fall detection from various perspectives and have great contributions to the evolution of health monitoring services.

2.1 Existing Commercial Devices

One popular fall detection device, which is highly evaluated by customers, is the Medical Fall Alert in the *Home Guardian* option from Medical Guardian®. It is designed in form of a lightweight wearable neck pendant. This pendant is waterproof and small enough that have no disturbance on user's daily activity. Medical Guadian®provides a home system including one base unit connecting to the monitoring station through landline and one auto-alert pendant on user body. Whenever detecting a fall, the wearable pendant will send a signal to the base unit and the base station will announce *"Fall Detected, Press or Hold Button to Cancel"*. If the patient actual need help, do not press the button. Then, the system will connect to operators at the monitoring center, they will ask if patient need help or not. If the patient cannot speak because of unconsciousness, the operators will automatically send emergency services to patient's home. The monthly fee for this service is around $44.95 per month and it is used inside the U.S..

Figure 2.1: Medical Guardian Fall Alert System

Another device on the market is myHalo™from MobileHelp™. This device has more advantages compared to Medical Guadian one because of full body monitoring functions. It can detect a fall, mornitoring heart rate, skin temperature, sleep/wake pattern, etc. and send alert signal to the authorized contacts. This product supports the medical alert outside the home powered by nationwide cellular network and do not require landline phones. It also provides precise location of patients when they go outside. This enable emergency call center to pinpoint patients' location and direct medical support to them. This service costs from $41.95 per month and support 24/7. However, because this system offers so many features, it seems to less focus on the fall detection.

Figure 2.2: myHalo Medical Alert System from MobileHelp™

2.2 Existing Products from Other Research Groups

Beside many commercial fall detection devices being available on the market, there are still many products from different research groups surrounding the fall detection topic. A group of Qiang Li and colleagues have used TEMPO (Technology-Enabled Medical Precision Observation) 3.0 sensor node for their project [18]. This sensor node contains one tri-axial accelerometer and one tri-axial gyroscope and controlled by an TI MSP430F1611 microcontroller. This group proposed an algorithm which combines the data from both accelerometer and gyroscope to reduce both false positive and false negative detection and improving the fall detection accuracy. This system is low computational requirements and real-time response. The authors stated that their method has difficulties in differentiating jumping into bed and falling against wall with a seated posture.

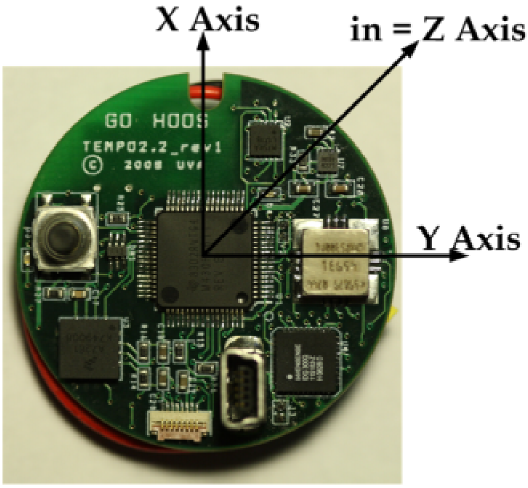

Figure 2.3: TEMPO 3.0 sensor node

Binh Nguyen and Jonathan Tomkun designed and created a fall detection system for the elderly as a wearable monitoring device which can distinguish between fall and non-fall events [19]. This device can link wirelessly with a pre-programmed laptop computer or Bluetooth-compitable mobile phone. Upon detecting a fall, the device communicates wirelessly with the laptop or cellphone to call 911 or issued emergency contacts. This device can also detect abnormal tilt and warns the user to correct their posture to minimize the risk of falling. In addition to visual LED to alert the fall, there are also audio and tacticle alert options for people with hearing or seeing disabilities. Regarding the performance of system, some actions have not been distinguished by one of four proposed algorithm to be falls or non-falls.

Figure 2.4: The final design of device from group research of Binh Nguyen and Jonathan Tomkun

3. Statement of Problem and Methodology

3.1 Problem

Nowadays, there have been various research groups studying on the academic area about fall detection on human. The majority of them focus on designing a new algorithm to successfully distinguish between fall and fall-like activities. From the first time, most of research groups used the algorithm mainly based on the data from only one accelerometer such as [20][21][22]. However, focusing only on the data from the accelerometer can result in many false positives as other activities such as sitting, running and jumping which may also cause large peak accelerations. After that, there are other algorithms rely on the detection of body orientation after the fall such as [23][24]. The main drawback of these strategies is that the fall can be confused by activities with similar postures such as sleeping, reclining, etc. It is also less effective when a person's fall posture is not horizontal. Then, there are some groups have nominated such complex algorithms that used Support Vector Machine (SVM)[25] and Markov model [26] to detect the fall. These techniques requires huge amount of computational resources which cause the delay on system which effect the robustness and accuracy of the system.

3.2 Methodology and Algorithm

From the disadvantages of prior works as mentioned above, this project proposes using an algorithm which combines data from one accelerometer and one gyroscope to detect the fall. The data from accelerometer provides valuable information regarding body inertial change due to impact, while the gyroscope's data provides information about the body's rotational velocity during a fall event. This method helps improving the accuracy of falling detection system without the need of complex computations.

This algorithm is nominated by Quoc T. Huynh *et al.* [27], which used data from both accelerometer and gyroscope sensors with predefined critical thresholds, to detect a fall with maximum sensitivity and specificity. Two parameters used to analyze in this algorithm are normalized acceleration and normalized angular velocity.

Normalized acceleration is the total sum acceleration vector, named $\boldsymbol{Acc_{norm}}$ containing both static and dynamic acceleration components in different directions. This parameter is calculated with the formula below

$$\boldsymbol{Acc_{norm}} = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2} \tag{3.1}$$

where A_x, A_y and A_z represent the acceleration of three directions *x, y, z.*

Normalized angular velocity is the total sum angular velocity vector, named $\boldsymbol{\omega_{norm}}$, containing the rotational velocity components in different direction. This parameter is calculated with the formula below

$$\boldsymbol{\omega_{norm}} = \sqrt{(\omega_x)^2 + (\omega_y)^2 + (\omega_z)^2} \tag{3.2}$$

where ω_x, ω_y and ω_z represent the angular velocity of three directions *x, y, z.*

When stay in stationary condition, the body of user gives the acceleration magnitude of a constant at +1g and angular velocity at $0^o/s$. When user falls, there is a rapid change in body's acceleration while angular velocity produces a variety of signals in the fall direction. To detect the fall, the acceleration and angular velocity are compared with critical thresholds. These thresholds are defined as follows by Quoc T. Huynh *et al.*

(a) *Lower fall threshold(LFT)*: local minima for the Acc resultant of each recorded activity are referred to as the signal lower peak values (LPVs). The LFT_{acc} for the acceleration signals is set at the level of the smallest magnitude lower fall peak (LFP) recorded.

(b) *Upper Fall Threshold(UFT)*: local maxima for the Acc and ω resultant of each recorded activity are referred to as the signal upper peak values (UPV_s). The UFT for each of the acceleration (UFT_{acc}) and the angular velocity (UFT_{gyro}) signals are set at the level of the lowest upper fall peak (UFP) recorded for the $\boldsymbol{Acc}$ and $\boldsymbol{\omega}$, respectively. The UFT_{acc} is related to the peak impact force experienced by the body segment during the impact phase of the fall.

When a fall happens, the normalized acceleration first falls below the LFT_{Acc} threshold which indicates the start of a fall event. In the next 0.5 seconds, usually called fall windows, data from both accelerometer and gyroscope are compared to UFT_{Acc} and UFT_{Gyro}. The fall windows was obtained from the literature [28][29]. If the magnitude of both parameters exceed the two upper thresholds, a fall is detected. However, if only one of these conditions is not satisfied, there is no fall detection. Quoc T. Huynh et al. [27] have proven, with practical experiments on real subjects, that the three conditions above just happen simultaneously only with a fall but not other activities like standing, running, jumping of sitting up. Figure 3.1 summarizes the main steps of this algorithm.

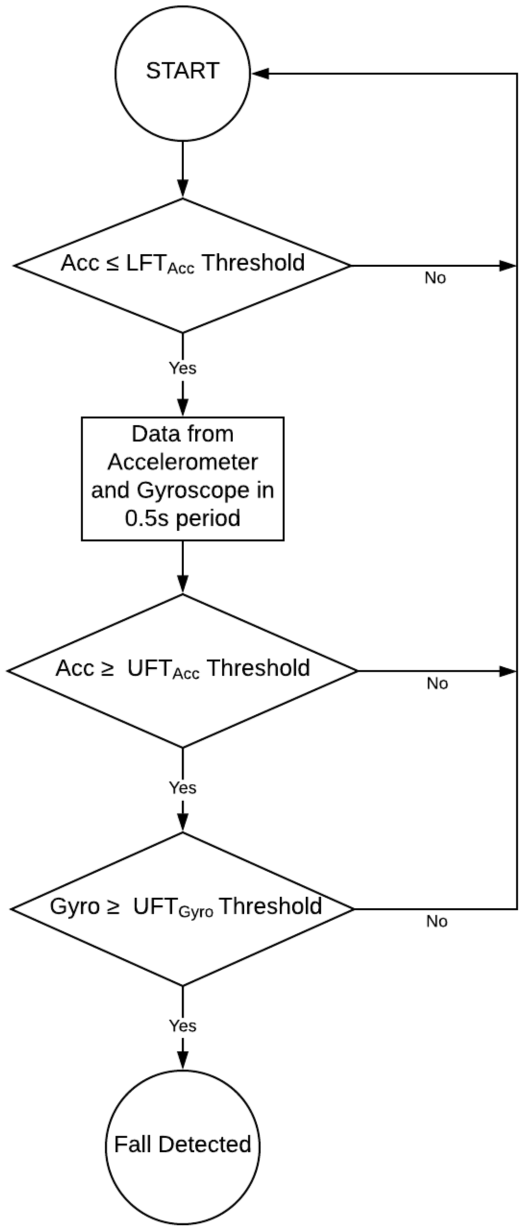

Figure 3.1: Fall detection algorithm

4. System overview

4.1 Hardware Components

4.1.1 Sensor

Since the algorithm requires both information about acceleration and angular velocity, an Inertia Measurement Unit (IMU) named MPU6050 from Invensense®, which contains one accelerometer and one gyroscope, has been chosen for its convenience. This sensor can also accepts inputs from an external 3-axis compass via I^{2}C sensor bus to provide a complete 9-axis MotionFusion^{TM} output.

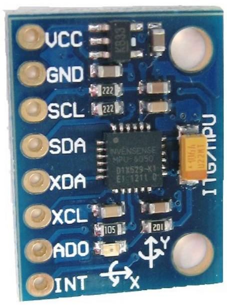

Figure 4.1: MPU-6050 by Invensense [1]

The accelerometer inside MPU6050 board can measure the acceleration in four different programmable full-scale ranges ($\pm 2g$, $\pm 4g$, $\pm 8g$ and $\pm 16g$). An integrated 16-bit analog-to-digital (ADC) supports simultaneous sampling of the accelerometer while requiring no external multiplexer. This accelerometer normally operates at a very small current of 500 µA with low power consumption. According to the data-sheet given by Invensense®, the raw output of the accelerometer is displayed in form of LSB/g. Divided with an appropriate Sensitivity Scale Factor (SSF), we can obtain the acceleration in g - standard gravity unit, which is used in this project. Each full scale has its own SFF. Table 2.1 shows the different full-scales of the accelerometer and table 2.2 shows the SSF for each scale.

Scale	TYP	UNIT
AFS_SEL=0	±2	g
AFS_SEL=1	±4	g
AFS_SEL=2	±8	g
AFS_SEL=3	±16	g

Table 4.1: Full-scale Range Table of Accelerometer

Scale	Sensitivity Scale Factor	UNIT
AFS_SEL=0	16,384	LSB/g
AFS_SEL=1	8,192	LSB/g
AFS_SEL=2	4,096	LSB/g
AFS_SEL=3	2,048	LSB/g

Table 4.2: Sensitivity Scale Factor Table of Accelerometer

With `AFS_SEL` being bits of the accelerometer configuration register of the sensor. These bits are used to select the full scale range of the accelerometer.

The gyroscope integrated on the same board can measure the angular velocity at 4 programmable full-scale ranges ($\pm 250^o/s$, $\pm 500^o/s$, $\pm 1000^o/s$ and $\pm 2000^o/s$). This sensor has an external sync signal which supports image, video capturing and GPS synchronization. Its normal operating current is 500 µA which enables the reduction on power consumption. The raw output of the gyroscope is displayed in form of LSB/($^o/s$). Divided with an appropriate Sensitivity Scale Factor (SSF), we can obtain the angular velocity with unit of ($^o/s$). Each full scale has its own SFF. Table 2.3 shows different full-scale of the gyroscope and table 2.4 shows the SSF for each scale.

Scale	TYP	UNIT
FS_SEL=0	±250	$^o/s$
FS_SEL=1	±500	$^o/s$
FS_SEL=2	±1000	$^o/s$
FS_SEL=3	±2000	$^o/s$

Table 4.3: Full-scale Range Table of Gyroscope

Scale	Sensitivity Scale Factor	UNIT
`FS_SEL=0`	131	LSB/$(^o/s)$
`FS_SEL=1`	65.5	LSB/$(^o/s)$
`FS_SEL=2`	32.8	LSB/$(^o/s)$
`FS_SEL=3`	16.4	LSB/$(^o/s)$

Table 4.4: Sensitivity Scale Factor Table of Gyroscope

With `FS_SEL` being bits of the gyroscope configuration register on the sensor. These bits are used to select the full scale range of gyroscope.

After getting acceleration and angular velocity in three different directions from two sensors, normalized acceleration and normalized angular velocity are calculated with formulas (3.1) and (3.2) and compared with thresholds to detect the fall.

4.1.2 Microcontroller

To perform all data processing and communications, the ESP8266EX Micro-Controller Unit (MCU) integrated with L106 32-bit RISC processor from Tensilica is chosen. This MCU archives extra low power consumption and reaches a maximum clock speed up to 160 Mhz, which is specially designed for mobile and Internet-of-Things (IoT) applications. The ESP8266EX MCU supports most of popular interfaces such as GPIO, UART, I^2C, ADC, PWM etc. to connect with external peripheral devices. The figure 4.3 shows the functional block diagram of ESP8266EX.

Figure 4.2: ESP8266 D1 Mini Board with an ESP8266EX MCU inside

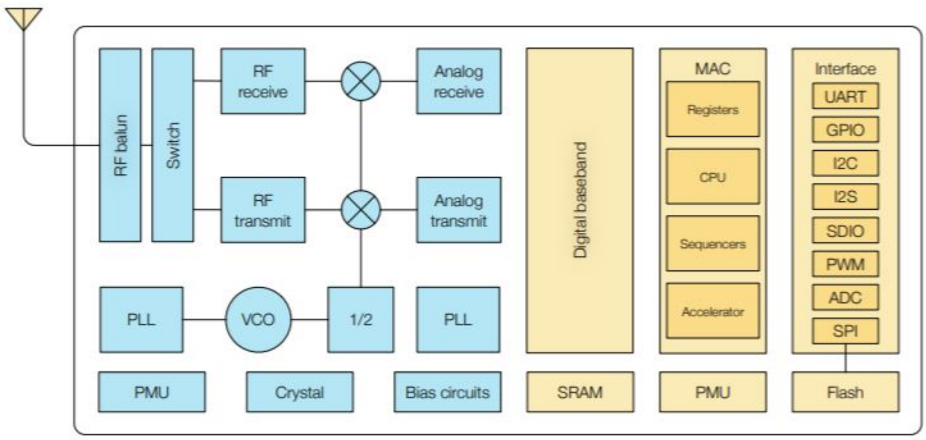

Figure 4.3: Functional Block Diagram of ESP8266EX MCU

The ESP8266EX MCU integrates memory units including one 50kB SRAM and one 16MB external SPI flash that are sufficient for most IoT applications. The SRAM size is less than 50kB when the MCU is working under Station Mode or connecting to a router. All user programs are stored in the external SPI flash and non-volatile after switching off the power.

4.1.3 Wireless Module

ESP8266EX MCU integrates a Wi-Fi module which is implemented TCP/IP protocol with the full 802.11 b/g/n WLAN MAC standard and Wi-Fi Direct specification. The ESP8266EX is designed with advance power management technologies. The low-power architecture operates in three modes: active mode, sleep mode and deep-sleep mode. ESP8266 consumes only20 µA in deep-sleep mode and the standby power consumption below 1.0mW. These two features which make the ESP8266 Wi-Fi module fully compatible with mobile wireless applications that require low power dissipation.

In this project, a standard TCP/IP protocol has been chosen because of its highly reliable connection and its ability to control data congestion. Additionally, this system also requires that the received data on the monitoring computer must be in the same order as the original one on sensor module. Therefore, TCP/IP is chosen because of its capability of ordering the received data and error recovery. Whenever there is an error on the connection, all the erroneous packets are retransmitted to the destination and rearranged in the correct order.

A brief description of the wireless communication system: there is a TCP server running on the monitoring computer and listening the requests from clients. The ESP8266 module (programmed in *client mode*) continuously sends sensors' data to the server via a Wi-Fi connection. All data is captured by a Python program and plotted on a visual graph. The received data is also stored in a database to serve later data analysis and algorithm optimization.

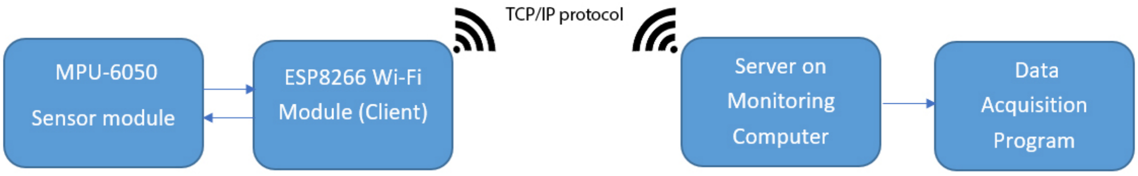

Figure 4.4: Schematic of wireless communication system

4.2 Software

4.2.1 Embeddded Software on Sensor Node

On the sensor node, the micro-controller board is programmed to read the data from sensors, calculate normalized parameters and send data to host computer. First, the microcontroller communicates with sensors, using I^2C protocol with the help of MPU6050 library provided by Invensense®, to set the clock source and full scale range for two sensors. It is also important to set the sensor board to wake-up mode in this step to make sure it working. After successfully connecting, the frequency of these two sensors are set to 1kHz with *setDLPFMode* function from the library. Normally, these sensors operate at the frequency of 8kHz, which means there are 8000 samples within one second, that is too much for the requirement of a fall detection system and usually causes congestion and lost data during the transmission from sensor node to the host computer. To avoid this problem, it is necessary to low down the internal sampling rate of two sensors. Next, like other sensors, both gyroscope and accelerometer always have non-zero errors even when leveling and need to be calibrated with a set of offset values before being used. These offset are calculated by another program included in the MPU6050 library and set into appropriate sensor's registers with provided function from the library. See the appendix C for the register map of the MPU6050 sensor.

After initializing the sensors, the sensor node establishes a wireless connection with the local network and host computer. While the host is not connected, the sensor node continuously calls for a connection and the led indicator on the micro-controller board keep brighting until receiving a success connection. After the connection is established, the sensor node

4.2.2 Data Acquisition Software

4.2.3 Data Analysis Software

4.3 System Intergration

5. Experimental and Procedure

5.1 Data Collection

5.2 Data Analysis

5.3 Experiment on Real Subjects to Evaluate the Performance of The Network

6. Results and Discussion

6.1 Results Assessment

6.2 Comparing the performance with existing works

7. Conclusion and Future Works

7.1 Summary

7.2 Limitations

7.3 Future works

A. C/C++ Code for Reading Data from Sensor

```
#include "Arduino.h"
#include "MPU6050.h"
#include "Wire.h"
#include "WiFiClient.h"
#include "ESP8266WiFiMulti.h"

ESP8266WiFiMulti WiFiMulti ;
#if I2CDEV_IMPLEMENTATION == I2CDEV_ARDUINO_WIRE
#include "Wire.h"
#endif

MPU6050 accelgyro;
//MPU6050 accelgyro(0x69); // <-- use for AD0 high

int16_t ax, ay, az;
int16_t gx, gy, gz;
float rotX, rotY, rotZ,normAcc;
float gyroX, gyroY, gyroZ, normGyro;
#define OUTPUT_READABLE_ACCELGYRO

#define LED_PIN 2
bool blinkState = false;

void Print_IMU()
{
#ifdef SERIAL_DEBUG
Serial.println("Accelerometer:");
Serial.print(rotX);
```

```
Serial.print("\t");
Serial.print(rotY);
Serial.print("\t");
Serial.println(rotZ);
Serial.println("Gyroscope: ");
Serial.print(gyroX);
Serial.print("\t");
Serial.print(gyroY);
Serial.print("\t");
Serial.println(gyroZ);
#endif
Serial.print(normAcc);
Serial.print(" ");
Serial.println(normGyro);
}

void init_IMU() {
// join I2C bus (I2Cdev library doesn't do this automatically)
Wire.begin();
Serial.begin(115200);

// initialize device
Serial.println("Initializing I2C devices...");
accelgyro.initialize();

// verify connection
Serial.println("Testing device connections...");
Serial.println(accelgyro.testConnection() ? "MPU6050 connection successful"
: "MPU6050 connection failed");

// use the code below to change accel/gyro offset values
```

```
Serial.println("Updating internal sensor offsets...");
//reading current sensor's offset
Serial.print("\n");
accelgyro.setXGyroOffset(55);
accelgyro.setYGyroOffset(-28);
accelgyro.setZGyroOffset(-2);
accelgyro.setXAccelOffset(-2581);
accelgyro.setYAccelOffset(-3937);
accelgyro.setZAccelOffset(1199);
}


void Init_Wifi()
{
// Initialize Wifi_connection
WiFiMulti.addAP("Connectify-me", "hazeduh5");
Serial.println();
Serial.println();
Serial.print("Wait for WiFi... ");
while(WiFiMulti.run() != WL_CONNECTED) {
Serial.print(".");
delay(500);
}
Serial.println("");
Serial.println("WiFi connected");
Serial.println("IP address: ");
Serial.println(WiFi.localIP());
delay(500);
}

void sendData()
{
```

```
const uint16_t port = 8000;
const char * host = "192.168.85.1"; // ip or dns

// Use WiFiClient class to create TCP connections
WiFiClient client;

if (!client.connect(host, port)) {
Serial.println("connection failed");
client.stop();
return;
}
client.print(normAcc);
//     client.print(" , ");
//        client.println(normGyro);
//Serial.println("closing connection");
client.stop();
}

void setup(){
Serial.begin(115200);
Wire.begin();
init_IMU();
delay(10);
Init_Wifi();
}
void loop() {
accelgyro.getMotion6(&ax, &ay, &az, &gx, &gy, &gz);
rotX = ax / 16384.0;
rotY = ay / 16384.0;
rotZ = az /16384.0;
normAcc = sqrt(rotX*rotX + rotY*rotY + rotZ*rotZ);
gyroX = gx /131;
```

```
gyroY = gy /131;
gyroZ = gz /131;
normGyro = sqrt(gyroX*gyroX + gyroY*gyroY + gyroZ*gyroZ);
Print_IMU();
sendData();
}
```

B. Python Code for Data Acquisition Program

```
import matplotlib.pyplot as plt
import matplotlib.animation as animation
from drawnow import *
import socketserver

accel = []
gyro = []
plt.ion() #tell the matplotlib that we want to draw live data
def makeFig():
plt.subplot(2,1,1)
plt.plot(accel, 'r', label= 'Normalized Acceleration')
plt.legend(loc='upper left')
plt.ylim(0,5)
plt.subplot(2,1,2)
plt.plot(gyro, 'b', label = 'Normalized Angular Velocity')
plt.legend(loc='upper left')
plt.savefig('testplot.png')

class myTCPServer(socketserver.StreamRequestHandler):
def handle(self):
data = self.rfile.readline()
dataArray = data.decode().split(',')
normAcc = float(dataArray[0])
normGyro = float(dataArray[1])
accel.append(normAcc)
gyro.append(normGyro)
if len(accel) > 100:
accel.pop(0)
```

```
if len(gyro) > 100:
gyro.pop(0)
drawnow(makeFig)
#create TCP server
serv = socketserver.TCPServer(("",8000),myTCPServer)
serv.serve_forever()
```

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