HANOI UNIVERSITY OF SCIENCE AND TECHNOLOGY
SCHOOL OF ELECTRICAL – ELECTRONICS

LARGE ASSIGNMENT REPORT

MICROPROCESSOR ENGINEERING

Theme:

Human Activity Recognition with angular speed and angular acceleration sensors. Application in bluetooth headphones.

Student group performs:

Dao Van Son	20224457
Luong Gia Nghiem	20224425
Pham Hoang Son	20224459

Instructor: Dr. Han Huy Dung

TS. Nguyen Huy Hoang

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Progress, Division of Work

Task	Mission Details	Member	Start time	End time
Topic selection	Identify topics to be included in the list of reference topics, qualifications, and desires of the whole group	The whole group	9/2024	10/10/2024
Gain knowledge	Learn about microprocessors, AI	The whole group	9/2024	31/10/2024
Requirements Analysis	Analyze the functional and non-functional requirements of the system	Van Son, Nghiem	1/11/2024	8/11/2024
Selection of sutras	Comparison and selection of components	Hoang Son	1/11/2024	8/11/2024
Data collection	Collect data of activities	The whole group	16/11/2024	24/11/2024
Data Pre-Processing	Data processing and standardization	Van Son	24/11/2024	30/11/2024
AI model design	NN model design distinguishes activities	Van Son	30/11/2024	15/12/2024
Microprocessor System Design	Connecting the processor to the sensors	Nghiem, Hoang Son	15/12/2024	1/1/2025
Embedding AI into the microprocessor	Deploying AI into microprocessors	Hoang Son	1/1/2025	7/1/2025
Finishing, testing	Testing activities	The whole group	8/1/2025	20/1/2025

CHAPTER 1: INTRODUCTION, ASKING QUESTIONS

1.1. POSE PROBLEMS

In the digital era, headphones have become an indispensable item in people's daily lives. According to headphone statistics, the global revenue of headphones in the consumer electronics segment from 2023 to 2028 is expected to reach $2.2 billion. As of 2022, on average, every person in the United States buys a new headphone every two years, 90% of survey participants said they own at least 1 headphone. In addition, there are many technologies to enhance the user experience with headphones such as noise cancellation, surround sound, ...

However, the use of traditional headphones still has certain limitations, especially in interacting and adapting to the user's activities and state. This is reflected in the fact that the user's mood and music preferences often change with activity. When exercising, they like exciting music to increase motivation, while working or studying prefer light music to concentrate. However, changing music according to current activities is still manual, disrupting the experience, especially when users are busy. From there, we realized that there was a need for a smarter headphone solution that could recognize user activity and automatically adjust the content of the music theme and settings on the headphones, in real time.

The topic "Recognizing human activity using angular speed and angular acceleration sensors. The application in Bluetooth headphones" was born to solve the above problem. This solution not only saves time and effort for users, but also brings a more personalized and optimal experience, contributing to improving the quality of listening to music

1.2 TARGET AUDIENCE

- Headphone manufacturing company

This is the main target group that the system targets. The system helps to enhance the user audio experience in a breakthrough way.

- Research and Training Agencies

Research and training institutions may be interested in this topic to develop technology; training human resources with expertise in this field.

1.3 IMPLEMENTATION METHOD

1. Research and analysis

Conduct research on the current demand for headphones, identify the causal factors and their influence. Evaluation of AI technologies and sensor devices can be applied to solve this problem.

2. System design

Identify the functional and non-functional requirements of the system. The system architecture design includes sensor devices, AI models, databases. Identify algorithms and data analysis methods to recognize human actions.

3. Build hardware modules

Based on the requirements of the system, select the appropriate sensor devices. The device design can be attached to the headset with the ability to calculate, give results to predict user actions, save as much energy as possible.

4. Build a software module

Building an AI model can predict user actions based on the parameters measured from the sensor.

5. Testing and evaluation of effectiveness

Deploy the system into a real-world environment and conduct a test of the system's operation. Evaluate the effectiveness of the system in predicting user actions. Measure system detection, accuracy, and reaction time.

6. Offer the optimal direction and improvement

Based on the results of the evaluation, proceed to give the optimal direction and improve the system in the future to improve efficiency and reliability.

1.4. OBJECTIVES

The main goal of this research is to develop a smart headphone system capable of recognizing human activity (HAR) and automatically suggesting appropriate audio content. Specifically, we set the following goals: Develop and install a microprocessor-based machine learning model from which it can recognize basic activities such as walking, running, standing, sitting, lying, climbing stairs, and other complex activities with high accuracy

1.5 EVALUATION CRITERIA

- Accuracy

The system's accuracy in recognizing actions. The system needs to ensure that it needs to be predicted with high accuracy, avoiding false detection, causing trouble to users.

- Cost

Evaluate the cost of implementing and operating the system. Ensure that the system is cost-effective and feasible in real-world implementation.

- Energy consumption

The system needs to consume less energy to extend the battery life of the passenger's wireless headphones

- Flexibility

The system's adaptability and scalability to integrate with a wide range of headphones and usage environments.

CHAPTER 2. PRODUCT REQUIREMENTS & SPEC

2.1. MARKET RESEARCH

In this study, we investigated and evaluated three types of headphones that are popular on the market today: Apple AirPods Max, Sony WH-1000XM5 and

Sony WF-1000XM4. These products not only stand out in terms of sound quality and design, but also possess advanced technological features such as active noise cancellation, wireless connectivity, and built-in virtual assistants.

Table 1. Comparison table of popular headphones

Criteria	Apple AirPods Max	Sony WH-1000XM5	Sony WF-1000XM4
Battery Capacity	20 hours	30 hours	8 hours (24 hours with charging case)
Operational Recognition (HAR)	Not Supported	Not Supported	It can sense the position and operation (riding vehicle, walking, running, stay), automatically adjust the sound.
Sensors	- Optical Sensor - Accelerometer - Gyroscope - Position Sensor - Ear Shell Detection Sensor	- Proximity Sensor - Accelerometer - Pressure Sensor	- Proximity Sensor - Accelerometer Sensor - Dual Noise Sensor
Connect	Bluetooth 5.0	Bluetooth 5.2	Bluetooth 5.2
Pricing	About 10 million VND	About 10 million VND	About 6 million VND

Apple AirPods Max bring a great audio experience with H1 chip technology, which supports recognizing and processing sound signals from the surrounding environment. The Sony WH-1000XM5 is a high-end product with powerful active noise cancellation and the ability to adjust the sound according to the user's needs. The Sony WF-1000XM4 is a version of the earbuds with impressive sound quality and smooth connection to mobile devices.

Based on the characteristics and technology of these headphone models, we found that our small module, if integrated with Human Activity Recognition (HAR), can be easily integrated into products such as the Apple AirPods Max, Sony WH-1000XM5 and Sony WF-1000XM4. This module will help expand the capabilities of these headphones, providing an intelligent and automated experience in recommending audio content tailored to the user's activity.

Bottom Line: Our module can be integrated into headphones such as Apple AirPods Max, Sony WH-1000XM5, and Sony WF-1000XM4,... to improve and enhance the user experience through activity recognition and automatic audio content suggestions.

2.2. GENERAL SPECS FOR HAR MODULES

2.2.1. Sensors

- Accelerometer: 3-axis MEMS, ±2g, 16-bit, 50 Hz.
- Gyroscope: 3-axis MEMS, ±2000°/s, 16 bit, 50 Hz.

2.2.2 Processing Performance

- Processor: ARM Cortex-M4 (or equivalent), 180 MHz, 128 KB RAM, 512 KB Flash.

2.2.3. Battery and Power

- Power consumption: 50-100mW.

2.2.4. HAR Features

- Activities: Walking, running, standing, sitting, lying down, climbing stairs, cycling, gym,...
- Accuracy: ≥ 90% (basic operation), ≥ 80% (complex operation).
- Latency: < 3s.

2.3. SPEC FOR HAR RECOGNITION MODULE (INSIDE THE HEADSET)

2.3.1. Objectives

Built into a compact Active Identification Block (HAR) inside the headset, capable of recognizing 6 basic operations and emitting a corresponding 6 LED control signals.

2.3.2. Identification activities

- Walking
- Walking Upstairs
- Walking Downstairs
- Ngồi (Sitting)

- Standing
- Lying

2.3.3. Input Data

Data from the sensors is characteristically preprocessed and extracted.

- Acceleration: (acc_x, acc_y, acc_z).
- Angular Speed: (gyr_x, gyr_y, gyr_z)

2.3.4. Identification model

- Type: Neural network.
- Input: The data collected from the sensor.
- Output: 6 states corresponding to 6 operations (one-hot encoding).

  For example: [1, 0, 0, 0, 0, 0] (Walking); [0, 1, 0, 0, 0, 0] (Going up the stairs);...

2.3.5. Performance Requirements

Accuracy:

- Minimum 90% for "walking, lying" activities
- A minimum of 80% for "going down stairs", "going up stairs", "sitting", and "standing" activities (can be improved).

Processing time: time from data collection to results: ≤ 3s.

Delay: LED Response Time: ≤ 1s.

Memory:

- The RAM is enough to store the model and temporary data.
- Flash is enough to store the model.

2.3.6. Outputs

Signal: 6 LED control signals

Describe:

- LED1: Walk

- LED2: Going up the stairs
- LED3: Going down stairs
- LED4: Sitting
- LED5: Standing
- LED6: Located

2.3.7. Energy

Power Consumption: Low, minimizing the impact on battery life.

0.1W when entering sleep mode

CHAPTER 3: THEORETICAL BASIS

3.1 ACCELEROMETER AND GYROSCOPE SENSOR

In the Human Activity Recognition (HAR) problem, two common types of sensors are accelerometers and gyroscopes. Accelerometer and gyroscope sensors provide critical information for the analysis of human activities, thanks to the measurement of acceleration and angular velocity on spatial axes.

The accelerometer measures linear acceleration in three axes: X, Y, and Z. This acceleration reflects the change in the speed of objects and can be used to measure the body's movement when performing activities. An accelerometer can provide information about whether a person is moving, standing still, or changing posture.

A gyroscope measures the angular speed, or rotational speed, of objects on three axes of space. This sensor helps identify changes in the direction of the body during activities, which is especially useful in distinguishing rotations or posture changes. The gyroscope provides data related to the rotation of the body, such as when the user turns their head or rotates their torso.

3.2 HUMAN ACTIVITIES

The dataset in the HAR problem consists of 6 common types of activities collected from these sensors, including:

- Walking
- Walking Upstairs
- Walking Downstairs
- Ngồi (Sitting)
- Standing
- Lying

Each of these operations has characteristic characteristics of acceleration and angular velocity, and they can be distinguished by the variation in the value of the accelerometer and gyroscope in three-dimensional space.

3.3 OPERATIONAL THEORETICAL ANALYSIS FROM SENSOR DATA

To distinguish between these operations, we need to analyze the difference between the acceleration data and the angular velocity data from the sensors.

1. Walking: When walking, the human body has a continuous and rhythmic movement. The accelerometer will record acceleration that tends to fluctuate cyclically, with a slight increase or decrease in acceleration on the X, Y, and Z axes. The gyroscope will show slight rotational movements, especially in the lumbar and shoulder areas.
2. Walking Upstairs: When walking up stairs, the body needs to change its posture more to overcome each step of the stairs. The acceleration data will show a marked change in acceleration along the Z-axis, when the body has to raise its legs to step up the stairs. The gyroscope will record a change in the rotation speed of the body, especially in areas with a lot of rotational motion.
3. Walking Downstairs: The data from the accelerometer when going down the stairs will be different from going up the stairs, because when going down the stairs, the body tends to slow down suddenly due to gravity. The accelerometer will record a rapid change in acceleration, especially in the Z-axis. The gyroscope will record a change in the direction of motion when the body is moving downwards.
4. Sitting: When sitting, the accelerometer will record a small acceleration, with almost no change in speed during this process, because the body is in a static state. The data from the gyroscope will also not change significantly, because there is no noticeable rotational movement.
5. Standing: The acceleration data when standing is similar to that when sitting, but with slightly greater acceleration, especially in the Z-axis due to gravity. The gyroscope will not record a noticeable change because the body does not have rotational motion.
6. Lying: When lying down, the accelerometer will record a small acceleration value, similar to when sitting, but with a different direction of acceleration, because the body is horizontal. The gyroscope will not record significant rotation, unless there is a slight rotation of the body.

Table 2. Changes in Angular Acceleration and Angular Speed with Operations

Activity	Accelerator	Angular speed (gyroscope)
Walking	Slight acceleration oscillation in the X, Y, Z axes, rhythm	Slight rotation speed, mainly in the lumbar and shoulder area
Walking Upstairs	Acceleration changes markedly in the Z-axis, increasing with leg lift	The rotation speed changes markedly as the body lifts
Walking Downstairs	Acceleration decreases rapidly in the Z axis due to gravity, which changes greatly when landing	Rotation speed changes when moving down stairs
Ngồi (Sitting)	Small acceleration, no big change	No significant change in rotation speed
Standing	Slightly greater acceleration, especially in the Z-axis due to gravity	No noticeable change in rotation speed
Lying	Small acceleration, different acceleration direction than sitting, horizontal	No significant change in rotation speed

The data collected from accelerometers and gyroscopes provide important information to distinguish between human activities. By analyzing the differences in acceleration and angular velocity between operations, we can build an effective human activity recognition system. The use of these sensors, combined with data analysis algorithms, helps the system accurately identify activities such as walking, stair climbing, sitting, standing and lying down.

CHAPTER 4 DESIGN AND IMPLEMENTATION

4.1 SYSTEM OVERVIEW DESIGN

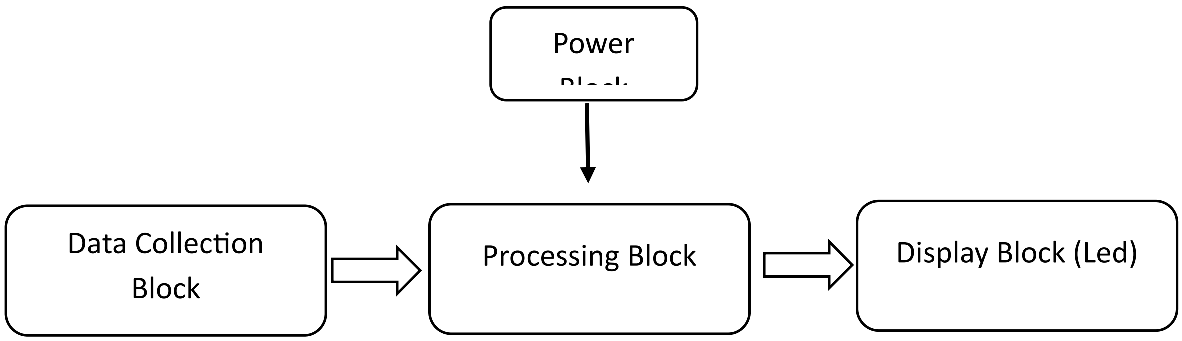

Figure 1. Block Diagram

Describe:

- **Data Acquisition Block:** Receives motion information from the ADXL345 accelerometer and L3G4200D-angle speed sensor.
- **Processing Block:** Processing input data, using a neural network (NN) model to classify and predict activity.
- **Display Block:** Displays the prediction results through the LED system.

4.2 DATA COLLECTION BLOCK

Objective: Collect and provide raw motion data to the processing block.

Table 3. Comparison Table of Data Collection Sensors

Feature	ADXL345	L3G4200D	MPU6050	ITG-3200
Sensor Type	Gia tốc kế (Accelerometer)	Gyroscope	Built-in Sensor (Accelerometer + Gyroscope)	Gyroscope
Number of measuring axes	3 Axis (X, Y, Z)	3 Axis (X, Y, Z)	3 Axis (X, Y, Z)	3 Axis (X, Y, Z)
Acceleration Measurement Range	±2g, ±4g, ±8g, ±16g	No acceleration, only angular speed measurement	±2g, ±4g, ±8g, ±16g	No acceleration, only angular speed measurement
Angular speed measurement range	No angular speed measurement	±250°/s, ±500°/s, ±2000°/s	±250°/s, ±500°/s, ±2000°/s	±250°/s, ±500°/s, ±2000°/s
Resolution	16-bit	16-bit	16-bit	16-bit
Sampling rate	Up to 3200 Hz	Up to 800 Hz	Up to 8000 Hz	Up to 1000 Hz
Communicate	I2C, SPI	I2C, SPI	I2C, SPI	I2C
Supply voltage	2.0V – 3.6V	2.4V – 3.6V	2.3V – 3.4V	2.3V – 3.6V
Operating Temperature	-40°C to +85°C	-40°C to +85°C	-40°C to +85°C	-40°C to +85°C
Dimension	3.9 mm x 3.8 mm x 1.0 mm	3.9 mm x 3.9 mm x 1.1 mm	4.9 mm x 3.9 mm x 1.3 mm	3.8 mm x 3.8 mm x 1.1 mm
Application	Motion detection, accelerometer	Measure the rotational movement of the body	Motion Detection and Angular Speed Measurement	Measure the rotational movement of the body
Advantage	High resolution, low cost	Accurate, easy-to-use angular speed measurement	Built-in both accelerometer and gyroscope	Low cost, easy to integrate

In Human Activity Recognition (HAR) systems, collecting data from sensors is critical to understanding and analyzing human movements. From the comparison with other sensors, we found that two of the most popular and widely used sensors in HAR applications are the ADXL345 angular speed sensor and the L3G4200D angular accelerometer. Both of these sensors play an important role in providing data on the user's body movements and posture.

4.2.1 Angular Speed Sensor (ADXL345)

ADXL345 is a three-axis accelerometer, capable of measuring acceleration on three axes of X, Y, and Z. With its high resolution and accurate measurements, ADXL345 is very popular in applications that require tracking the movement of objects. This sensor operates in the ±2g to ±16g range and delivers data at high frequencies, up to 3200 Hz.

ADXL345 have the following outstanding characteristics:

- Measurement of acceleration on three axes (X, Y, Z): The sensor provides acceleration data across three dimensions of space, which helps to accurately track the movement of objects in three dimensions.
- I2C/SPI Communication: The sensor can communicate with the microprocessor via I2C or SPI protocols, which is convenient for integration into embedded systems.
- High accuracy: ADXL345 is capable of accurate measurements with 10-bit or 13-bit resolution depending on the measurement range and sampling frequency.
- In human activity recognition systems, ADXL345 provide information about acceleration, which helps the model distinguish movements such as walking, running, standing, sitting, or changing body posture.

Function: Linear acceleration measurement, helping the system recognize activities such as walking, running, standing, sitting, and changing postures.

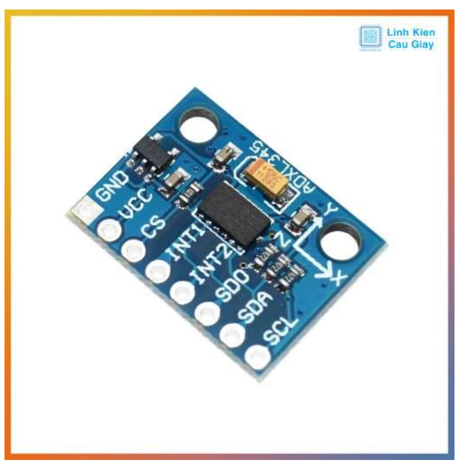

Figure 1. Angular Speed Sensor (ADXL345)

4.2.2. Angular Acceleration Sensor (L3G4200D)

L3G4200D is a three-axis angular accelerometer, which measures angular velocity around three axes of space. This sensor is useful in applications that require tracking rotational movements, such as turning heads, flipping, or rotating movements during physical activities. The L3G4200D sensor is capable of measuring angular speed in the range from ±250°/s to ±2000°/s, providing flexible measurement and high accuracy.

Outstanding features of L3G4200D:

- Measuring Angular Speed on Three Axes (X, Y, Z): This sensor measures the angular speed around three axes, helping to identify rotational or flipping movements.
- Wide measurement range: L3G4200D offers different measurement modes with 16-bit resolution, which increases the accuracy and sensitivity of data acquisition.
- I2C/SPI Communication: Similar to ADXL345, L3G4200D sensors also support communication via I2C or SPI protocols, which are easy to integrate into embedded microprocessors and systems.

Function: Measure angular speed, help identify rotational movements such as turning the head, flipping at an angle, or changing direction during physical activities.

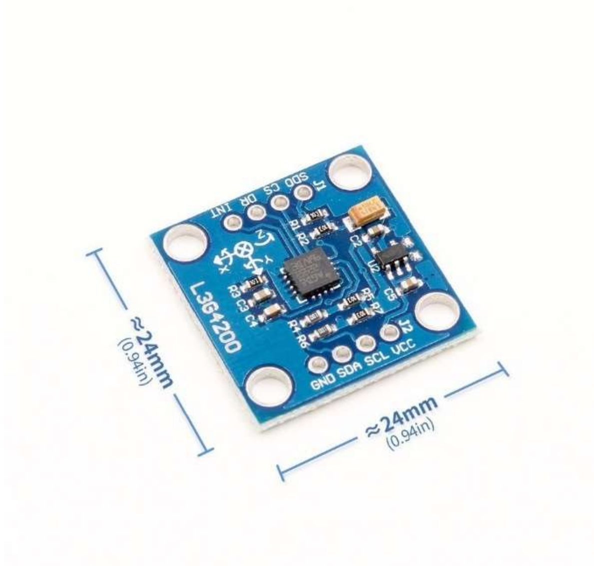

Figure 2. Angular Acceleration Sensor (L3G4200D)

When combined ADXL345 and L3G4200D, they provide a complete set of data on both acceleration and angular speed, which improves the accuracy and reliability of human activity recognition systems, thereby helping to distinguish complex activities such as walking, running, sitting, or other athletic and motor movements.

4.2.3 Implementation

Asynchronous reading of accelerated data may result in access to the accelerated data registers while they are being updated. To avoid this, we will use FIFO blocks.

In FIFO mode, data from measurements of the x, y, and z axes are stored in the FIFO. When the number of samples in the FIFO is equal to the level specified in the sample bits of the FIFO_CTL register, the watermark breaker is set. FIFO continues to accumulate samples until it is full (32 samples from measurements of the x, y, and z axes) and then stops collecting data. After the FIFO stops collecting data, the device resumes operation. Watermarking continues to occur until the number of samples in the FIFO is less than the value stored in the sample bits of the FIFO_CTL register. The watermark breaker will be used to give a signal to the working processor.

Each time data is read from the FIFO, the oldest x, y, and z axis data is fed into the DATAX, DATAY, and DATAZ registers. If a one-byte read is performed, the remaining data bytes for the current FIFO pattern are lost.

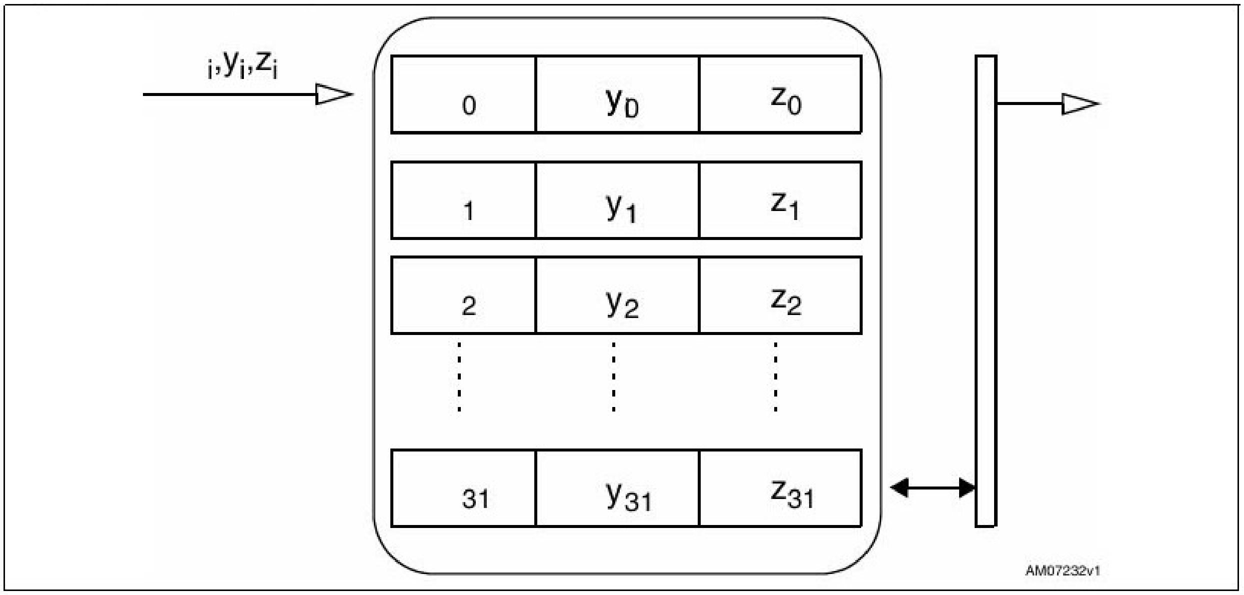

Figure 3. FIFO mode

```c
void adxl_init (void){
    adxl_write (0x31, 0b1);// chỉnh độ nhạy trên cảm biến là +-2g(19.6 m2/s)
    adxl_write (0x2c, 0b1001);// chỉnh tần số đo là 50 hz
    adxl_write (0x38, 0b10101000);// enable fifo, chọn ngưỡng data là 16
    adxl_write (0x2e, 0b10);//enable ngắt watermark(gửi tín hiệu khi đủ 16 dữ li)
    adxl_write (0x2f, 0b00000000);//chỉnh cho tín hiệu ngắt được thực hiện trên chân int1
    adxl_write (0x2d, 0x08);//bật chế độ do cho cảm biến
}
void l3g4_init (void){
    uint8_t chipID=1;
    l3g4_write(0x23, 0x20);// chỉnh độ nhạy là 500 dps, tần số đo là 50 (tần số nhỏ nhát)
    l3g4_write(0x24, 0b1000000);// bật chế độ sử dụng khối fifo
    l3g4_write(0x2E, 0b00101000);//bật chế độ fifo, cho ngưỡng là 16
    l3g4_write(0x2E, 0b00101000);//bật chế độ fifo, cho ngưỡng là 16
    l3g4_write(0x22, 0b100);//enable ngắt watermark(gửi tín hiệu khi data sẵn sàng) cho chân int2
    l3g4_write(0x20, 0b1111);// bật chế độ đo cho cảm biến
}
```

Figure 4. Programming code that communicates the register with the sensor

To operate with lower energy consumption, Standby mode can be used. In Standby mode, the current consumption is reduced to only 0.1 µA (typical). In this mode, the device will not take any measurements. Switch to Standby mode by clearing the measurement bit (Bit D3) in the POWER_CTL register. Putting the device into Standby mode retains the contents of the FIFO.

```
void standby_sensor(){
    l3g4_write(0x20, 0b0);
    adxl_write (0x2d, 0x0);
}
void wakeup_sensor(){
    l3g4_write(0x20, 0b1111);
    adxl_write (0x2d, 0x08);
}
```

Hình 5. Standby mode

4.3. PROCESSING BLOCK

In the development of the Human Activity Recognition (HAR) headset system, the choice of processor plays an important role, directly affecting the performance, scalability and cost of the product. We surveyed and selected between a number of popular processors, including STM32F429ZI, ESP32, and nRF5340, with the following key comparison criteria:

- Processing Performance: The ability to perform complex mathematical operations and algorithms, especially machine learning algorithms.
- Power Consumption: The level of energy consumption affects the battery life of the headphones.
- Connectivity: Wireless connection protocols (Bluetooth, Wi-Fi).
- Peripherals: Interfaces with sensors (I2C, SPI), GPIO pins that control LEDs, and other peripherals.
- Cost: The cost of the processor and related components.
- Ecosystem: User community, support documentation, software library.

4.3.1. Comparison of Parameters Between Processors

Below is a table comparing the main parameters between the three types of processors:

Table 4. Processor Comparison Table

Feature	STM32F429ZI	ESP32	nRF5340

CPU Architecture	ARM Cortex-M4F	Tensilica Xtensa LX6 Dual-core	ARM Cortex-M33 Dual-core
Clock Speed	180 MHz	240 MHz	128/64 MHz
RAM Memory	256 Kb	520 KB	1MB
Flash Memory	2 MB	4 MB / 16 MB	1MB/1MB
Connection Protocol	I2C, SPI, UART, USB	Wi-Fi, Bluetooth	Bluetooth 5.2, NFC
Peripheral	ADC, DAC, Timers, GPIO,...	ADC, DAC, GPIO, Touch,...	ADC, DAC, Timer, GPIO,...
Energy Saving Mode	Sleep, Stop, Standby	Deep Sleep	Low power, Sleep mode
Development Tools	STM32CubeIDE, Keil, IAR,...	Arduino IDE, ESP-IDF,...	nRF Connect SDK, Zephyr OS...
Cost	Average	Short	Medium - High
DSP/FPU Support	Have	Have	Have
AI Processing Capabilities	Relative	Relative	Relative

Analyze:

- ESP32: Despite its low cost and built-in Wi-Fi/Bluetooth, the ESP32 may not be suitable for applications that require high processing performance, stable performance, and real-time. The ESP32 ecosystem is more about IoT and simple applications.
- nRF5340: Has good energy efficiency and built-in Bluetooth 5.2, NFC but lower clock speed and higher cost, the ecosystem is sometimes more complex for beginners.
- STM32F429ZI: With good processing performance, integrated floating-point processor (FPU), rich peripherals, and a robust software development ecosystem, STM32F429ZI suitable for applications that require complex calculations, especially machine learning algorithms for operational recognition, at the same time, it has good energy saving ability when designed correctly.

Conclusion: With the above analysis, we decided to choose STM32F429ZI processor as the central brain of the HAR headphone system.

4.3.2 STM32F429ZI Processor Details

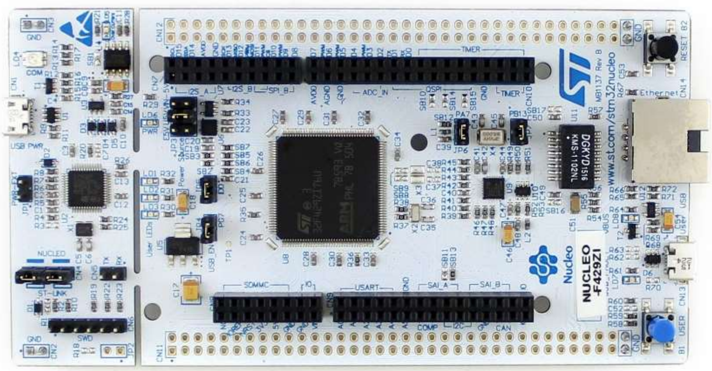

Figure 6. STM32F429ZI Processor

Hardware Architecture:

- Central Processing Unit (CPU): ARM Cortex-M4F (FPU support)
- Clock Speed: 180 MHz
- Memory:
  - Built-in Flash: 2 MB
  - SRAM: 256 KB
  - EEPROM emulation memory (optional)
- Clock:
  - HSI Internal Oscillation (16 MHz)
  - HSE Extraoscillator (4 – 26 MHz)
- Energy Saving Mode: Sleep, Stop, Standby, Shutdown

Peripherals features:

- GPIO (General Purpose I/O): 140 pins, configurable as input, output, interrupt, or analog mode.
- Timers: 17 16-bit/32-bit timers, support PWM, input capture, output compare, RTC.
- Communicate:
  - USART: Up to 8 communications

  - I2C: Up to 3 communications
  - SPI: Up to 3 communications
  - CAN: 2 giao tiếp
  - USB: Full-speed (OTG)
  - Ethernet: (MAC)
- ADC/DAC:
  - ADC: 12-bit, 3-set, 16-channel resolution
  - DAC: 12-bit, 2-channel resolution
- DMA (Direct Memory Access): Has 16 DMA channels

Main Specifications:

- Power Supply (Vdd): 1.7V – 3.6V
- Operating Temperature: -40°C to +85°C
- Flash Endurance: Up to 100,000 writes/deletes
- Confidentiality:
  - Flash Read/Write Protection
  - Supports encryption algorithms (AES)
  - Secure Boot (Secure Boot, TrustZone)

Suitable Applications:

- Digital Signal Processing (DSP)
- Motor Controls
- Signal recognition from the sensor
- Embedded applications that require complex computation
- Mobile HAR apps.

Conclude

The choice of processor STM32F429ZI ensure that the system has strong enough processing performance to meet complex operation recognition algorithms and at the same time maintain energy efficiency to extend battery life. The detailed specifications of the STM32F429ZI presented above help the reader better understand the capabilities of this processor, as well as its ability to meet the requirements of the system.

4.3.3. Implementation

In the STM32 microcontroller, RTC (Real-Time Clock) and Sleep Mode are two important features related to time management and energy saving. Here is a detailed description of each feature as well as their relationship

RTC (Real-Time Clock)

The RTC in STM32 is a real-time counter, capable of operating independently of the main microcontroller. It is often used to keep real-time (hours, minutes, seconds), manage schedules, or calculate elapsed time. The RTC can operate even when the system is in sleep mode or powered off, thanks to an auxiliary power supply (usually a CR2032 battery).

Some of the key features of RTC in STM32:

- Real-time measurement: RTC can maintain time and date.
- Alarm and Wakeup: RTC can set an alarm or wake up the system after a certain period of time.
- Low Power Mode: The RTC can remain active while the microcontroller is in sleep mode.

Sleep Mode

Sleep Mode in the STM32 is a power-saving mode that the system can enter when there is no need to perform complex computational tasks. In this mode, parts of the microcontroller such as the CPU can be turned off, while other components such as the RTC continue to function. The main purpose of this mode is to reduce energy consumption when there is no need to handle multiple tasks.

Features of Sleep Mode:

- CPU shutdown: The CPU stops working, but other components such as timers, peripherals, and RTCs may still work.

- Reduced Energy: Significantly reduces energy consumption when it is not necessary to maintain the operation of the entire system.
- Wake from RTC: The system can be woken up from Sleep mode by events from the RTC, such as alerts or interrupt signals.

Relationship between RTC and Sleep Mode

- RTC Maintains Time in Sleep Mode: When the system enters Sleep mode, the RTC can remain active and maintain real-time without interruption. This means that you can use the RTC to wake the microcontroller from Sleep mode after a specified period of time without losing time information.
- Wakeup from RTC: In Sleep mode, the STM32 can be woken up by an event from the RTC, such as when the clock reaches a certain value or when the RTC has a warning. This is useful in applications such as alarm clocks, periodic time measurement, or control systems that need to perform a task after a certain period of time.
- Power saving: When the microcontroller is in Sleep mode, but the RTC is still active, you can save power while still ensuring that the system can perform tasks over time (e.g., waking the microcontroller after a period of time). This is important in applications that require continuous operation with low power consumption, such as in wearables or automated sensing devices.

SPI

SPI (Serial Peripheral Interface) is a serial communication protocol widely used in embedded applications for communication between microcontrollers and peripheral devices (such as sensors, EEPROM, ADC, DAC, monitors, etc.). The STM32 supports SPI with high performance and flexible configuration options.

- Basic structure of SPI:

- Full-Duplex Communication: SPI allows data to be transmitted and received simultaneously on separate transmission lines.
- The main truths in SPI:
    - SCLK (Serial Clock): The clock signal provided by the Master.

    - MOSI (Master Out Slave In): Data from Master to Slave.
    - MISO (Master In Slave Out): Data from Slave to Master.
    - SS (Slave Select): Select the Slave device to communicate.
- Operating Mode:
    - Master or Slave.
    - The clock modes (Mode 0, 1, 2, 3) depend on the CPOL (Clock Polarity) and CPHA (Clock Phase) configurations.

-Advantages of SPI:

- High data transfer speeds (up to tens of Mbps).
- Giao tiếp Full-Duplex.
- There is no need for device addressing like I2C.

4.4 DISPLAY BLOCK

The display block uses LEDs to represent the various activities that the system recognizes. For simplicity and ease of deployment, the system will use 6 LEDs, including 3 LEDs controlled directly from the Nucleo F429ZI processor and 3 external LEDs.

On the Nucleo F429ZI board, there are GPIO pins that can be configured to control the LEDs. These LEDs will be used to display the status of the system, such as:

- LED1: Turned on when the user identification system is walking.
- LED2: Turned on when the user identification system is going up the stairs.
- LED3: Turned on when the user identification system is descending the stairs.

In addition to the LEDs on the Nucleo board, three external LEDs will be connected to the GPIO pins of the Nucleo F429ZI to display the remaining operations. Example:

- LED4: Turns on when the user identification system is seated.
- LED5: Turned on when the user identification system is standing.
- LED6: Turns on when the user identification system is lying down.

These LEDs will help users easily identify the activity being performed through visual signals, creating an easy-to-use and efficient interface.

4.5 OPERATION OVERVIEW

- **Data Collection:** ADXL345 and L3G4200D sensors continuously collect acceleration and angular speed data.
- **Communication:** Data from the sensor is transmitted to the Nucleo F429ZI processor via the SPI protocol.
- **Pre-processing:** Microprocessor performs data pre-processing: normalization
- **Inference:** The processed data is fed into the NN model to predict activity.
- **Display:** Prediction results are displayed through a system of 6 LEDs.

CHAPTER 5 DATA COLLECTION AND PREPROCESSING, TRAIN MODEL AI

5.1. OVERVIEW OF THE DATA COLLECTION PROCESS

In this study, the goal is to build a system capable of recognizing basic human activities through data collected from sensors. To ensure the accuracy and efficiency of the model, the data collection process is carried out carefully and systematically. Data is collected from two main types of sensors:

- ADXL345 Accelerometer: Linear acceleration measurement on three axes (X, Y, Z).
- L3G4200D Angular Speed Sensor: Measures angular speed on three axes (X, Y, Z).

The data collection process was carried out with the participation of 3 students. Instead of recording video and manually assigning labels to each frame, we opted for a method of assigning a specific activity and asking participants to perform it continuously for a certain period of time. This method significantly saves time on data labeling, while ensuring label accuracy.

Location: Volunteer's ear.

5.2. ACTIVITIES COLLECTED

We have collected data for the following activities:

- Walking: Moving on a flat surface with two feet.
- Walking Upstairs: Move up the stairs.
- Walking Downstairs: Move down the stairs.
- Sitting: Body posture when sitting on a chair or floor.
- Standing: Body posture when standing upright.
- Lying: Body position when lying on a flat surface.

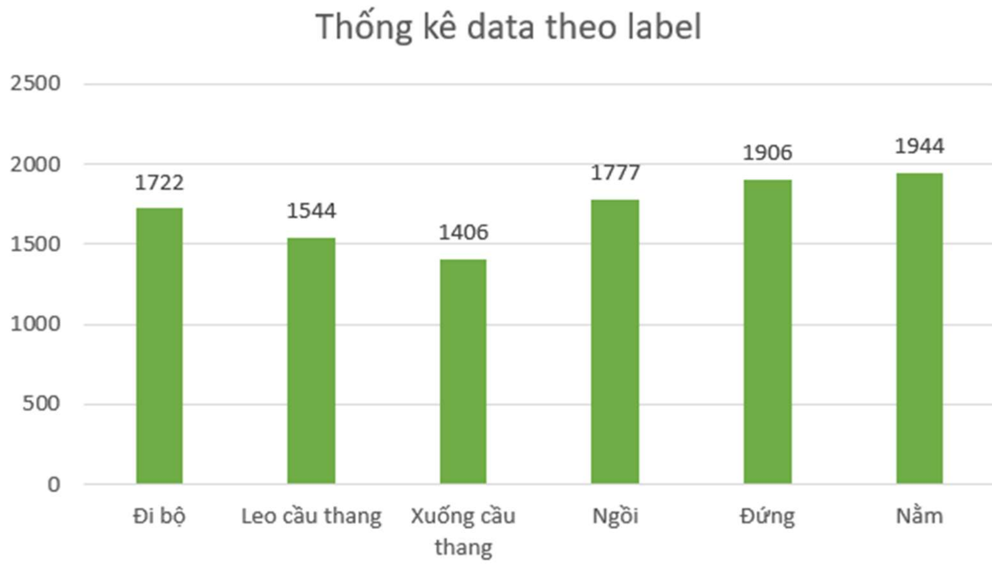

Figure 7. Statistics of data by label

5.3. DETAILS OF DATA COLLECTION FROM SENSORS

The sensors are configured to collect data according to the following parameters:

- Sampling frequency: 50 Hz. This means that every second, the sensor will record 50 data samples from each axis.
- Sampling time: 2.56 seconds. Each time the data is collected, the sensor will operate for 2.56 seconds, generating 128 data samples per axis (50 Hz * 2.56 s = 128 samples).
- Axes noted:
  - Acceleration: acc_x, acc_y, acc_z (unit: g).
  - Angular speed: gyr_x, gyr_y, gyr_z (unit: degrees/sec - °/s).

During the collection process, each data sample will be assigned a label corresponding to the activity that the participant performs during the measurement period. This label will serve as the target output when training the model.

5.4. DATA COLLECTION PROCESS

The data is collected through a microcontroller system, which connects directly to the sensors. The process includes the following steps:

Sensor Configuration:

- Sensor configuration to ensure a stable sampling frequency of 50 Hz.

- Ensure synchronization between the two sensors, so that the data corresponds to the same time.

Data Collection:

- The acceleration and angular speed values are recorded directly from the sensor over a period of 2.56 seconds.
- Data is stored in the form of columns corresponding to axes: acc_x, acc_y, acc_z, gyr_x, gyr_y, gyr_z.

Labeling: Each operation is assigned a label before collection, to ensure the accuracy of the data.

5.5. DATA PREPROCESSING

After collection, the raw data from the sensor needs to be processed and normalized to ensure the machine learning model can effectively learn from the input data.

5.5.1. Data Normalization with Z-Score

To ensure that all axes and sensor types are of equal importance, the data is normalized using the Z-score method. The Z-score formula is as follows:

$$Z = (x - \mu) / \sigma$$

In which:

- x: Original data value.
- μ: The average of the entire dataset for a particular axis.
- σ: The standard deviation of the entire dataset for a particular axis.

Results after normalization:

- The average value of each feature (sensor axis) will be 0.
- The standard deviation of each feature will be 1.
- Normalization helps reduce the influence of different scales between sensors and axes, and helps machine learning models converge faster.

5.5.2. Post-processing data structure

After normalization, each data sample is represented as a time series with the following characteristics:

- acc_x, acc_y, acc_z (128 values).
- gyr_x, gyr_y, gyr_z (128 values).

In total, each data sample will be represented as a 6x128 tensor (6 sensor axes and 128 values per axis).

```
[
  [
    [acc_x_values],
    [acc_y_values],
    [acc_z_values],
    [gyr_x_values],
    [gyr_y_values],
    [gyr_z_values],
    [label]
  ],
  [
    [acc_x_values],
    [acc_y_values],
    [acc_z_values],
    [gyr_x_values],
    [gyr_y_values],
    [gyr_z_values],
    [label]
  ],
  ...
]
```

Figure 8. Data storage structure

The normalized and labeled data is stored in NumPy.npy format for convenient use during model training.

The standardization and processing of data is an extremely important step in ensuring the quality of input for machine learning models. The data collected from the sensor often contains a lot of noise and scale differences between sensors. By standardizing, the model can better learn from the data, minimize errors, and improve accuracy when predicting activities from sensor data.

5.6. TRAINING MODEL AI

The data, after being divided into training and test sets, will be used to train the neural network (NN) model. This model consists of 2 hidden layers with a size of 16 and 8 neurons, respectively. The input layer is 768 in size, while the output layer has 6 neurons.

During training, the model will optimize weights and biases to minimize loss functions through optimization algorithms such as Gradient Descent. After completing the training process, we will obtain a file containing the optimized weights and biases.

The size of the file weight is calculated based on the number of weights and biases in the model. Specifically, the total number of weights between classes is 12,464, and the total bias is 30. With each weight and bias stored as a double-type number (8 bytes), the size of the weight and bias file would be about 99 KB.

CHAPTER 6: SYSTEM TESTING AND EVALUATION

6.1. SYSTEM TESTING

6.1.1. Testing objectives

The main objective of the system testing process is to evaluate the actual performance of the headset in human activity recognition (HAR). Specifically, we focus on the following aspects:

- Accuracy: Determines the ability of the system to correctly classify various activities (walking, running, standing, sitting, lying down, going up/down stairs).
- Stability: Evaluate the stability of the system under various environmental and time conditions.
- Latency: Check the system's response time from data collection to identification.
- Energy Efficiency: Evaluate the battery life and energy consumption of the system.

Data Analysis:

- Compare the predicted results of the system with the actual operation.
- Calculation of performance metrics (accuracy, latency, error rate,...)

6.1.2. Test results

Below is a table recording the test results, in which, each cell represents the predicted result of the system (Display Result) compared to the actual operation (Actual Operation), marked with an "X" if there is a deviation:

Walk:

Table 5. Walking test results

Attempts	1	2	3	4	5	6	7	8	9	10
Activity	Walk	Walk	Walk	Walk	Walk	Walk	Walk	Walk	Walk	Walk
Results displayed	Walk	Walk	Walk	Walk	Walk	Walk	Walk	Walk	Walk	Walk
Assess (False: x)										

Going up the stairs:

Table 6. Test results of climbing stairs

Attempts	1	2	3	4	5	6	7	8	9	10
Activity	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs
Results displayed	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Walk	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs
Assess (False: x)						X				

Going down the stairs:

Table 7 . . Test results of going down the stairs

Attempts	1	2	3	4	5	6	7	8	9	10
Activity	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs
Results displayed	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs	Walk	Going up the stairs	Going up the stairs	Going up the stairs	Going up the stairs
Assess (False: x)						X				

Sit:

Table 8 . . . Seated activity test results

Attempts	1	2	3	4	5	6	7	8	9	10
Activity	Sit	Sit	Sit	Sit	Sit	Sit	Sit	Sit	Sit	Sit
Results displayed	Sit	Sit	Sit	Stand	Sit	Stand	Sit	Sit	Sit	Sit
Assess (False: x)				X		X				

Stand:

Table 9 . . . Vertical operation test results

Attempts	1	2	3	4	5	6	7	8	9	10
Activity	Stand	Stand	Stand	Stand	Stand	Stand	Stand	Stand	Stand	Stand

Results displayed	Sit	Stand	Stand	Stand	Stand	Stand	Stand	Stand	Sit	Stand
Assess (False: x)	X								X	

Lie:

Table 10. The results of the operation test are located

Attempts	1	2	3	4	5	6	7	8	9	10
Activity	Lie	Lie	Lie	Lie	Lie	Lie	Lie	Lie	Lie	Lie
Results displayed	Lie	Lie	Lie	Lie	Lie	Lie	Lie	Lie	Lie	Lie
Assess (False: x)										

6.2. ANALYSIS OF TEST RESULTS

Based on the results obtained, we offer the following analyses:

Overall accuracy:

The system achieves 100% accuracy in identifying "Walking" and "Lying Down" activities. This shows that the machine learning model has learned the distinguishing characteristics of these activities effectively.

Detailed analysis of deviation cases:

- Error in identifying "Going up stairs" and "Going down stairs": In one test (times 6 and 8), the system misidentified "Going up stairs" and "Going down stairs" to "Walking". This shows the similarity in signals between these two activities, especially when the speed and footsteps of the participants are not too different. Training data may not cover enough variations of stair ascent activity.
- Confusion between "Standing" and "Sitting": In one test (6th, 4th, 1st, 9th), the system misidentified the "Standing" activity as "Sitting". This shows the difficulty of distinguishing between these two activities, especially when the user does not change much in posture or has minor changes in the process of standing.

Main causes:

- This confusion stems from the fact that the sensors (especially the accelerometer) on the Z axis do not have a major variation between the "Stand" and "Sit" operations. When the user is standing or sitting, the acceleration on the Z-axis is usually at a stable level, close to the gravitational field acceleration, making it difficult for the model to distinguish between these two activities.
- The lack of variation on the Z-axis makes the characteristics extracted from this axis ineffective in distinguishing these two activities. The model can rely on the X and Y axes, but when the differences are not obvious, it causes deviations.

Peripheral factors: Peripheral factors such as wind, weather conditions, and other interference during measurement.

6.3. ENERGY TESTING

- With V= 5 (V) continuous energy consumption module with an average current of 50.25 mA.

- Battery capacity: 1000 mAh

The module will last about ~20 hours

→ Evaluation: This energy consumption indicates that the system is relatively energy-efficient, but further optimization is needed to extend the service life.

6.4. SYSTEM EVALUATION

6.4.1. Technical Evaluation

- Accuracy: The system is highly accurate in identifying basic activities (walking, going down stairs, lying down) but there are still some errors when recognizing "Walking up stairs", "Standing" and "Sitting" activities. In particular, it is necessary to focus on improving the accuracy of distinguishing between "Standing" and "Sitting".
- Performance: The system has a fast response speed (latency of less than 1s) and high reliability, meeting the basic technical requirements of the problem. However, it is necessary to further optimize the program code and use a more powerful processor to be able to meet more demanding requirements.

- Energy: The system consumes energy at an acceptable level, but needs to be improved to increase uptime.

6.4.2. Product Design Evaluation

- Compactness and Portability: Currently, further research is needed to reduce size and weight, increase convenience and portability.
- Aesthetics: The design of the headphones needs to be improved to appeal to users.

6.4.3. Applicability

The system has high application potential in many fields:

- Health Monitoring: Monitor the activities of the elderly, patients, or people who need health monitoring.
- Sports: Support users to exercise, analyze performance, track physical indicators.
- Interactive Apps: Control the device, create interactive apps using gestures.
- Support for people with disabilities: Support for people with hearing and visual impairments.

CHAPTER 7: PROPOSAL FOR DEVELOPMENT DIRECTION

Based on the results of testing, analysis and evaluation above, we offer the following development directions:

7.1. IMPROVE ACCURACY AND PERFORMANCE

Collect more data:

- Specialized Data: Enhanced data collection for "Stair Climbing", "Standing", and "Sitting" activities with various variations in speed, posture, and conditions.
- Diverse data: Collect data in a variety of environmental conditions and from a variety of users to increase the generalization of the model.
- Real-time data: Use data augmentation techniques during training to generate more data samples, helping the model learn features more efficiently.

Model optimization:

- Network architectures: Experiment with different neural network architectures, especially those that are capable of handling temporal and spatial signals well (e.g., LSTM networks or attention-using models).
- Data augmentation: Use data augmentation methods to create new data patterns, helping the model learn features more effectively. Data augmentation methods can include adding noise, rotating, shifting, or distorting the data.

Calibration: Research and integrate automatic calibration algorithms to minimize the influence of peripheral factors, differences between sensors.

7.2. FEATURE EXTENSIONS

- Identify more activities: Expand the system's recognition capabilities to include a variety of activities (e.g., climbing, jumping, swimming, yoga, hand activities).

- Complex Activity Analysis: Develop algorithms to analyze complex sequences of activities, such as distinguishing combined activities such as walking and stopping, walking and turning,...
- IoT connectivity: Integrate wireless connectivity protocols (e.g., Bluetooth, Wi-Fi) for data transmission and remote system control, facilitating the development of mobile applications or web platforms.

7.3. HARDWARE DESIGN IMPROVEMENTS

- Size reduction: Research and use more compact, high-performance components to reduce the size of boards and headsets.
- Energy saving: Optimize circuit design, select components that consume less energy, use sleep modes.
- Enhanced durability: Choose materials that are more resistant to impact, water, and dust.

7.4. PRACTICAL APPLICATION

- Mobile app development: Create an included mobile app so users can track activity, customize settings, view information, and suggest content.
- Medical applications: Develop medical applications to track patient activity, support rehabilitation activities, or provide information to doctors.
- Apps in sports: Develop apps to analyze sports activity, provide information about workout performance, assist users in improving workout mode, or track progress.
- Support for people with disabilities: Design appropriate interfaces and features to support people with hearing and visual impairments in daily activities.

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