AN ABSTRACT OF THE REPORT OF

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Title: Movement Pattern Detection Through IMU and Barometer

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Movement pattern detection can be applied in a variety of applications such as assisting independent living of seniors at home, behaviour understanding in surveillance systems, sports analytics, and robotics. This project develops a scheme that fuses information from different sensors to detect movement patterns. This report contains three main parts: information collection and processing, pattern detection using the information collected, and algorithm implementation and results. The information needed for movement pattern detection comes from an inertial measurement unit (IMU) and a barometer. The information from the accelerometer and the gyroscope is first combined by using a complementary filter. The measurements in the body coordinates of the IMU are then transformed into data in the earth coordinates via quaternions. We then develop a scheme that exploits the advantages of the vupport vector machine and the k-nearest neighbor algorithm for motion detection. These schemes are finally implemented to detect four different movement patterns: walking, running, standing up and falling down, which are classified into static and dynamic motions. For dynamic motion, the difference of tilt angle and height could be used to distinguish the standing-up and falling-down patterns; for static motion, the difference of velocity in the horizontal plane could be used to distinguish the walking and running patterns.

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Movement Pattern Detection Through IMU and Barometer

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Yang Qian, Author

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Chapter 1: Introduction

With the twentieth centurys drastic increase in human population, population aging is becoming a major cause for concern. According to information from the United States Bureau of Statistics, the world entered a collective stage of aging in 2001 [37]. In the United States, the population aged 65 and over numbered 49.2 million in 2016, which represents 15.2 percent of the population, about one in every seven Americans [4]. With currently-existing organizations and service staff struggling to adequately care for an aging population, there is increasing need for the use of technologies that can assist with this care. Human motion detection technology, which detects and reports on movements of the human body, can offer solutions to these issues. Motion detection devices can provide movement information and real-time statements. In the medical fields, these devices can help personnel to accurately determine what is happening in a human body. In addition to helping with elderly protection, care, and independent living, human motion detection technology can also be beneficial in exercise. These devices can discourage unhealthy physical habits and increase motion persistence [35].

Most movement motion detection technologies can be divided into two categories: visual detection and sensor network [5, 6] detection. Visual detection makes decisions based on video information. It captures and analyzes data from movement behaviors in videos. Sensor network detection uses different sensors information to make decisions. These two types of technology have different advantages and disadvantages. Visual detection can be applied in a wide-range area and detect multiple targets at the same time. But it also has many limitations. For example, video-capture cameras are normally inconveniently fixed in a single location. Additionally, when the atmosphere captured by video is insufficiently bright or weather is foggy, video definition can decrease sharply, causing failures of motion detection [38]. Sensor network detection is the alternative to visual detection. It often comes in the form of a wearable device, such as a watch. Sensors in these devices can record different data without being hindered by weather, time, or location [38]. By analyzing these data, the device can sense specific movement patterns. There exist extensive precise radio frequency (RF) localization techniques [23–28] that use wearable location sensors to detect various motions. For example, the pulsed ultra-wideband signaling [7–17] based localization schemes could achieve centimeter-accurate positions [18] for accurate motion detection. However, but such systems are often very complex. This project uses the inertial measurement unit (IMU) and the barometer to conduct sensor network detection. The IMU device includes a three-axis accelerometer and a three-axis gyroscope which can measure the body coordinates' accelerations and angular velocities. The barometer can measure the pressure and temperature at measure points.

In this experiment, with the help of a complementary filter algorithm to fuse the data from different types of sensors, we use a scheme which combines the advantages of the k-nearest neighbor (KNN) and the support vector machine (SVM) to detect four different human body movement patterns: the standing-up pattern, the falling-down pattern, the running pattern, and the walking pattern.

Chapter 2: Background

This chapter introduces the two different types of hardware and the algorithms typically used in motion detection experiments. These sensors use USB cable connected to the computer port to transfer measured data. In this experiment, most calculations take place in the computer.

2.1 Hardware

Movement patterns can be detected more effectively through the use of multiple sensors. Acceleration can transform into velocity and displacement, while angular velocity can transform into rotation angle. This project uses an IMU to detect movement. The system consists of two different sensor devices: the IMU and the barometer.

2.1.1 Inertial Measurement Unit

The IMU combines a 3-axis accelerometer and a 3-axis gyroscope to measure acceleration and angular velocity in three different directions at the same time.

The IMU has multiple frequency choices. Frequency determines the sampling time and measure rate. Higher frequency increases accuracy, but it also increases the level of calculation required. The frequency we chose for this experiment was 104 hz, meaning the system released a signal 104 times in one second. This frequency was chosen to balance the need for accuracy and the required calculation speed.

Acceleration is measured using an accelerometer in the IMU. In this device, the unit of data measured is based on gravity acceleration. Due to the effect of gravity, there is always an acceleration which is valued at gravitational acceleration points at the ground. This means the measurement from the accelerometer does not exactly equal the acceleration in real time. The accelerometer's measurements can only be used in velocity or displacement calculations after removing the effect of gravitational acceleration. The method for doing this is covered in chapter 3. The accelerometer is a sensitive instrument and can be easily affected by noise, especially when used in a high-frequency atmosphere. Because of offset and noise effects, the accelerometer cannot export accurate data at the beginning of its use. It becomes more reliable over the course of operation.

The gyroscope in the IMU measures the instantaneous angular velocity. The unit of measured data in the gyroscope is degree per second. The gyroscope is accurate at the beginning of use because the operation time is short, which means angular errors cannot accumulate. After a long period of operation, the gyroscope will drift, causing angular errors to accumulate after each sampling time, which means results from the gyroscope cannot be used directly to calculate rotation angles. When using the gyroscope, it is necessary to implement a method to compensate for gyroscopic drift.

2.1.2 Barometer

The barometer is a sensitive instrument that measures the air pressure of different points [1]. Air pressure in different heights can determine height change of measure points. Because of the weight effect, the IMU cannot measure height change accurately. With the help of a barometer, the displacement in height can be measured in the system.

2.2 Algorithm for Motion Detection

This section briefly introduces two algorithms that are widely used in movement pattern classification. In this report, the advantages of two algorithms are combined to effectively measure and classify human motion.

2.2.1 k-Nearest Neighbor

KNN is a motion detection method that combines ease of use with efficiency. It is also used in data mining and machine learning. This algorithm selects specific data as a sample. By comparing all other data with the sample, the system can find the first k times different data that are most similar to the sample. The k different data belong to the same category as the sample. The KNN algorithm can be applied in many situations [21]. The KNN algorithm does not require a training period; it only needs to internally compare different samples. This level of efficiency makes it easy to add new data into the database. However, the KNN algorithm often takes an extended period of time to make calculations and may provide inaccurate decisions, particularly when applied in large database situations. Noisy data can also negatively affect the results of KNN, particularly when the k value is small. These limitations can make it more difficult to achieve accurate classification through the KNN algorithm.

Parameter K is the most critical value in this algorithm. If the K-value is small, noise can greatly affect the resulting samples. For example, if K equals 1, when an erroneous data point is closest to the sample by coincidence, the answer is not accurate. If K is a very large value, the model becomes oversimplified, meaning even data far away from the sample can be recognized as belonging to the same category. Additionally, the KNN algorithm cannot make decisions at real time when it is applied to human motion detection. This algorithms decisions can only be made over an extensive time period after all data has been measured. Therefore, the results of the KNN algorithm cannot be directly applied to this project.

2.2.2 Support Vector Machine

SVM is an algorithm that distinguishes two categories in feature space [2]. This method needs to find a plane to divide the samples into two different categories.

The most critical part of the SVM algorithm is finding where the dividing plane is located [19]. As the following figure shows, to divide the two categories, the SVM algorithm needs to find the greatest gap between two different categories and make sure the dividing plane has a similar distance to the nearest point. This determination can be made through comparison between the dividing plane and each new point.

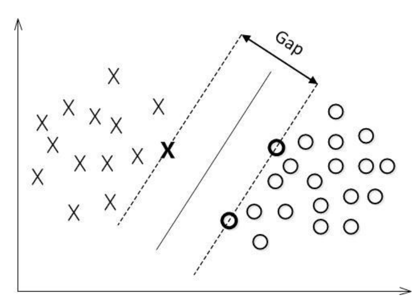

Figure 2.1: Support Vector Machine Sample

The SVM algorithm's judgment conditions change depending on the dimension. In two dimensions, a line can divide the plane into two categories, while in three dimensions, to separate the space, the SVM needs to use a plane. As the dimension increases, the SVM algorithm becomes more complicated. Pressuring determining data into lower dimensions can make motion detection easier. In order to use the SVM algorithm, sample data first needs to be separated. At least two sets of data are required to determine plane division. In human motion detection, different motion data need to be measured beforehand. By comparing these data, SVM can find the most suitable plane for different motions [22].

Chapter 3: Solutions to Data Analysis

3.1 Data Analysis System Description

This chapter introduces the methods this project uses to analyze data from different sensors. Due to offset effects and variations between coordinates, the data from sensors cannot be used directly. The IMU is the most important unit in this human motion detection system because it can provide the real-time acceleration and the angular velocity of the same point at high frequency. Acceleration can transform into movement velocity and angular velocity can transform into the rotation angle. The accelerometer and the gyroscope in the IMU are sensitive Micro-Electromechanical Systems (MEMS) devices [36]. While these devices have high accuracy and low consumption, they are easily affected by the environment, rendering calibration necessary before the experiment. Calibration can remove the initial sensor offset to reduce error rates in measured data during early measurements. While errors can never be entirely avoided, extensive operation of the IMU's gyroscope creates drifting, especially in the rotation angle, that can eventually affect the whole system. The complementary filter is an effective and efficient way to remove this gyroscopic drift. By combining rotation angle and acceleration, the complementary filter can transform original data into different coordinates, which makes the data easy to modify and calculate. With accurate acceleration in the suitable coordinate, the trapezoid integral method can calculate the velocity and displacement in the x and y directions accurately. For height change, because of weight effect, the displacement in the vertical plane is not accurate with the acceleration in the vertical direction.

3.2 Calibration

This section explains how we calibrated the errors of the accelerometer and the gyroscope in three different axes, as well as how we removed basic errors of the barometer. In the experiment, the system needed to use the barometer and IMU simultaneously, but the pressure of each measured point was determined by many different factors and standard pressures at different places are different.

Because the MEMS IMU device is a very sensitive device, calibration of the barometer is not suitable for all situations. During the operation period, minor environmental inflections can cause major device errors. Calibration is necessary to remove these sensing errors before operation. In experiments with hardware devices, calibration is also needed to avoid calculation and location errors. The IMU consist of two different sensors: the accelerometer and the gyroscope. A similar method is used to remove errors in both of these sensors. For the accelerometer, the earths gravity effect causes an acceleration value at $9.81m/s^2$, which is the value of gravity acceleration continuously points at the earths core. This report uses the least square method to calibrate the accelerometer [32]. The least square method is an optimal mathematical technology that finds the optimum matching data by minimizing the quadratic summation of the errors. This method can apply the estimated error data to real measured data to make the quadratic sum converge to 0. When the IMU device is statically placed at the horizontal plane, the acceleration at the x-axis and the y-axis should equal 0, while the acceleration at z-axis should equal the gravitational acceleration. In calibration, the device needs to be statically placed at the horizontal plane to measure the acceleration data in three different axes for a few seconds. In this period, the measured data should always fit the set values. Because of the noise effect, sensitive acceleration data shakes rapidly. The error and count times must be recorded.

$$Acc_{Real} = Acc_{Measured} - Sum_{Error}/Count \tag{3.1}$$

Where Acc_{Real} represents what the actual acceleration should be, $Acc_{Measured}$ represents the data read from the IMU accelerometer sensor. Sum_{Error} represents the quadratic summation of errors that do not match set value and $Count$ represents the number of measure times.

According to the equation 3.1, the accurate value of acceleration in three directions can be found easily, but gravitational acceleration can affect all directions in the real rotation period. To compensate for gravitational acceleration, the plane must be kept perfectly horizontal during the calibration period. The method for calibrating the gyroscope is similar. Unlike the accelerometer, the gyroscope is not affected by gravity. When in static motion, the angular velocities in all three different directions should equal

0.

For the barometer, there is no fixed pressure value for a specific point, and due to the effects of temperature and standard pressure, the barometers pressure readings at the same point may be inconsistent. In this experiment, to calculate the height change of different points, we only needed to know the pressure change of those points. Because the original offset cannot affect the change of pressure, it is unnecessary to calibrate the barometer before use. This report uses the average pressure at a specific point as the starting point pressure.

3.3 Quaternion Rotation

In the IMU data record, acceleration has three directions along the x-, y- and z-axes. These three axes are all based on the IMU body coordinates. The x-axis and y-axis are both at the IMU body plane, while the z-axis is perpendicular to the IMU body plane. In typical calculations, these accelerations should be based on the earth coordinates, also called the east-north-up (ENU) coordinates [3]; in the ENU coordinates, the x-axis points toward the east, the y-axis points toward the north, and the z-axis points toward the sky. By contrast, the movement in body coordinates changes with each new sample. If the IMU device rotates, the accelerations point in different directions, while in the ENU coordinates, accelerations and displacements point in fixed directions. It is therefore easy to determine the movement trajectory and compare different movement patterns in ENU coordinates.

3.3.1 Coordinate Matrix

To transform measurements in body coordinates into data in earth coordinates, we built a rotation matrix using rotation angles, also called Euler Angles, in three different directions. The counter-clock rotation around the z-axis is a positive yaw rotation, the counter-clock rotation around the x-axis is a positive roll rotation, and the counter-clock rotation around the axis of y direction is a positive pitch rotation. The rotation directions are shown in Figure 3.1.

Using the rotation angles in three different directions, the relationship between body coordinates and earth coordinates can be written into a transform coordinate matrix, as

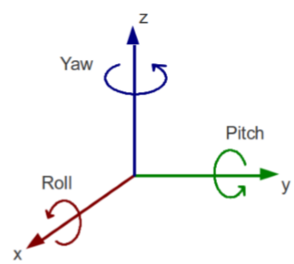

Figure 3.1: Rotation Direction

the following formula shows.

$$c_b^n = \begin{bmatrix} cos\theta cos\psi & -cos\phi sin\psi + sin\phi sin\theta sin\psi & sin\phi sin\psi + cos\phi sin\theta cos\psi \\ cos\theta sin\psi & cos\phi cos\psi + sin\phi sin\theta sin\psi & -sin\phi cos\psi + cos\phi sin\theta sin\psi \\ -sin\theta & sin\phi cos\theta & cos\phi cos\theta \end{bmatrix} \tag{3.2}$$

where θ angle represents the rotation angle in the pitch direction, ψ angle represents the rotation angle in the yaw direction, and ϕ angle represents the rotation angle in the roll direction. In the original calculation, the IMU device cannot directly export the rotation angle in different directions. The use of quaternions can compensate for the loss of rotation angle.

3.3.2 Quaternion

Quaternions are a number system that extends the complex numbers [34]. Normally, each rotation in three dimensions can be seen as rotation through a fixed vector. The quaternion number system can represent the fixed vector [20]. It has four different values and represents the vector information in three dimensions. Like complex numbers, quaternions have both real parts and complex parts. The general quaternion form is as follows:

$$Q = q_0 + q_1 i + q_2 j + q_3 k \tag{3.3}$$

where q_0 represents the real part of the quaternion, q_1, q_2, q_3 represent the values of the complex parts, and i, j and$k$ are quaternion units which are similar to the complex units.

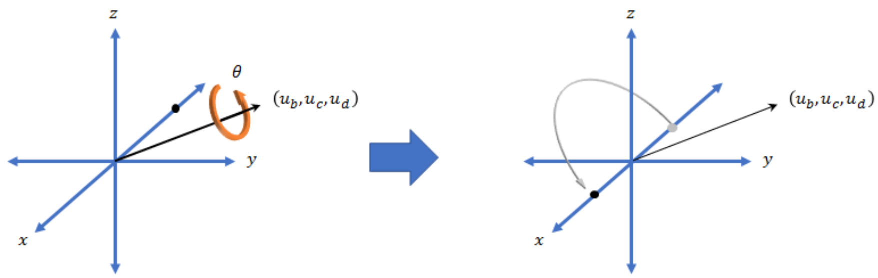

Figure 3.2: Quaternion Rotation

Their relationship is as follows,

$$ii = kk = jj = -1 \tag{3.4}$$

The conjugate version of quaternion is as follows,

$$Q^* = q_0 - q_1 i - q_2 j - q_3 k \tag{3.5}$$

The quaternion and its conjugate version can transform any acceleration vector in the IMU body coordinates into data in the NEU coordinates. The formula is shown below,

$$Acc_{NEU} = Q * Acc_{Body} * Q^* \tag{3.6}$$

whereAcc_{NEU} represents the acceleration in NEU coordinates and Acc_{Body} represents the acceleration in body coordinates from the IMU.Q^* is the conjugate version of the quaternion.

Since quaternions can successfully transform the coordinates of acceleration vectors, it is necessary to get accurate data through the sensor devices.The gyroscope can provide the quaternions with updated information each sampling time [31]. The relationship is shown below,

$$\dot{Q} = \frac{1}{2} * S(w) * Q \tag{3.7}$$

where $\dot{Q}$ is the differential version of the quaternion. Through sloving differential equation, an updated quaternion equation can be obtained each sampling time as follows,

$$\frac{Q_{k+1} - Q_k}{dt} = \frac{1}{2} * S(w) * Q_k \tag{3.8}$$

Simplifying the equation results in the final formula.

$$Q_(k+1) = \frac{dt}{2} S(w) Q_K + Q_k \tag{3.9}$$

where $S(w)$ is determined by angular velocity every sampling time. $S(w)$ and Q are shown as following,

$$S(w) = \begin{bmatrix} 0 & w_1 & -w_2 & -w_3 \\ w_1 & 0 & w_3 & -w_2 \\ w_2 & -w_3 & 0 & w_1 \\ w_3 & w_2 & -w_1 & 0 \end{bmatrix} \tag{3.10}$$

$$Q = \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix} \tag{3.11}$$

The initial quaternion matrix begins at $[1, 0, 0, 0]$. As shown in the progression from equation 3.6 to 3.11, the system can transform acceleration from body coordinates to ENU coordinates during each sampling. After obtaining the quaternion value, the coordinate matrix can be transformed into the quaternion version. The formula is shown as follows,

$$c_b^n = \begin{bmatrix} 1 - 2(q_2^2 + q_3^2) & 2(q_1 q_2 + q_0 q_3) & 2(q_1 q_3 - q_0 q_2) \\ 2(q_1 q_2 - q_0 q_3) & 1 - 2(q_1^2 + q_3^2) & 2(q_2 q_3 + q_0 q_1) \\ 2(q_1 q_3 + q_0 q_2) & 2(q_2 q_3 - q_0 q_1) & 1 - 2(q_1^2 + q_2^2) \end{bmatrix} \tag{3.12}$$

Every acceleration vector in the body coordinates can also be transformed into ENU coordinates through matrix 3.12. Through the coordinate transformation calculation process described in this section, the system can retrieve and isolate acceleration information. For rotation angle information, the complementary filter provides vital assistance in removing gyroscopic drift.

3.4 Complementary Filter

When using the gyroscope, it is difficult to remove all errors every sampling time. In the process of calculating rotation angle, angular velocity data errors tend to accumulate. The rotation angle equation is shown as follows.

$$Angle(t) = Angle(t-1) + w * dt \tag{3.13}$$

Over time, these errors have major effects on calculations. One solution is to combine predicted value with measured value to determine relative rotation angle. Predicted values and the data from the last sampling can be used to correct the current data. The measured value is the data obtained from sensor devices. The Kalman filter is a well-known algorithm that minimizes errors by combining these two values.The Kalman filter involves complicated calculations; the filter requires the use of five different functions. Some of the parameters of these functions need to be fixed ahead of time, a process that can also cause errors. This project chooses a complementary filter to update values and remove errors [36].

The complementary filter combines the data from the gyroscope and the accelerometer; both a low-pass filter and a high-pass filter are applied to remove the noise in the calculation. Because the IMUs accelerometer can be easily affected by high-frequency noise, it is often inaccurate in short-term operation; in long-term operation, the accelerometers relative error rate tends to be minimal if compared to all processes. A low-pass filter can remove the accelerometer noise and increase accuracy. In contrast, the gyroscope is very accurate in short term operation, while in long time operation, its accuracy decreases due to the effect of gyroscopic drift. A high-pass filter can remove gyroscopic drift and increase the gyroscopes long-term accuracy. While these two IMU sensors have different limitations that hinder accuracy, in both cases, the complementary filter is an effective way to increase accuracy and modify data with errors [30].

3.4.1 Implementation

Each rotation angle calculation contains three different directions. Rotation angles in the pitch and roll directions can be calculated using the accelerometer and the gyroscope. For the gyroscope, the rotation angle every sampling time equals angular velocity times sampling time [36]. The accelerometer can calculate the rotation angle in different directions. The equations for the accelerometer are shown as follows.

$$AccelerometerRoll = arctan(\frac{ay}{\sqrt{ax^2 + az^2}}) * \frac{180}{\pi} \tag{3.14}$$

$$AccelerometerPitch = arctan(\frac{-ax}{\sqrt{ay^2 + az^2}}) * \frac{180}{\pi} \tag{3.15}$$

Because the IMU used for this project only has an accelerometer and a gyroscope, the rotation angle in the yaw direction cannot be obtained directly from acceleration data. In this report, the rotation angle in the yaw direction is calculated using the angular velocity from the gyroscope. With the angles from the roll and pitch rotations, the complementary filter has the following equation:

$$Angle(t) = K * (Angle(t-1) + Gyroscope(t-1) * dt) + (1-K) * Accelerometer(t-1) \tag{3.16}$$

where $Angle$ represents the rotation angle in different directions (either roll or pitch). K represents the complementary filter factor, the value of which should be in a range between 0 and 1. $Gyroscope$ is the value taken from the gyroscope sensor; the unit of angle here must be taken in degrees rather than degrees per second. $Accelerometer$ represents the angle calculated from the three-direction acceleration [30]. Rotation angles can be calculated from the accelerometer and the gyroscope. The value of K determines which sensor the system can trust more and is determined by the following equation:

$$k = \frac{tau}{tau + dt} \tag{3.17}$$

where tau is the desired time that represents how fast the IMU reading to response, and dt is the sampling time of the system which is determined by the frequency.

3.5 Velocity and Displacement

Through the acceleration in three directions, velocity and displacement can both be calculated. While direct calculation can result in a high level of error, this project uses the trapezoidal integral method to accurately determine velocity and displacement. As

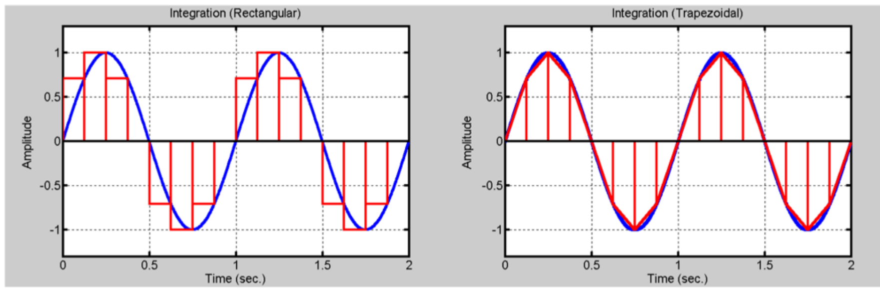

Figure 3.3: Trapezoidal Integral

shown in figure 3.3,the area of the integral place is either greater or less than than the real value. By contrast, the trapezoidal method produces data that can fit the curve. The trapezoidal integral method has two equations which contain the change of velocity and displacement [36]. The first formula calculates the velocity base on the acceleration, while the second formula is based on the velocity calculated by the first formula.

$$Velocity(t) = Velocity(t-1) + \frac{Acceleration(t) + Acceleration(t-1)}{2} * dt \tag{3.18}$$

$$Displacement(t) = Displacement(t-1) + \frac{Velocity(t) + Velocity(t-1)}{2} * dt \tag{3.19}$$

Where $Acceleration$ represents the acceleration value from coordinate-transformed data, $Velocity$ represents the velocity in different sampling times and $Displacement$ represents the displacement in different sampling times. Through the trapezoidal integral method, the velocity and displacement can be calculated accurately.

3.6 Height Change

The IMU can provide accurate movement displacement in the x- and y-planes, but the IMUs weight negatively affects the accuracy of acceleration in the z-direction, rendering vertical height change readings unreliable [34]. In this situation, the barometer, which measures test point pressure, can be an effective tool for calculating height change. Because it is in a fixed environment,the barometer is not easily affected by noise. Pressure change can forecast height change through the barometric formula, which is shown as follows,

$$h = 44300(1 - \frac{p}{p_0})^{0.19} \tag{3.20}$$

Where h is the height compared to sea level, p is the pressure of the test point, and p_0 is the standard air pressure at sea level,which is 1013.25 hpa.

Using the barometric formula, it is possible to calculate height difference through pressure changes. The major goal of this project was to determine different movement patterns; the barometer can be used to determine increase or decrease of height, which in turn can help to determine movement patterns of the human body.

Chapter 4: Solutions to Motion Detection

With the aid of the the calculations described in Chapter 3, the velocity and acceleration in the three directions x, y and z provide enough information for motion detection. This chapter combines SVM and KNN two well-known algorithms to detect four different human movement patterns.

4.1 Feature Extraction

The human body in life has many different movement patterns and complicated processes governing its movement. Human motion patterns can be detected and studied by analyzing the process of each movement and extracting the feature of each motion. Although human movements can be affected by environment and other external circumstances [22], they are all made up of a series of basic actions in sequence [38]. This section states some of these basic actions:

a. Rotation. The human body rotates in different directions along the human vertical axis.

b. Horizontal movement. This is one of the most common actions in everyday life; walking and running both constitute this action.

c. Center of gravity change. This includes actions in which the center of gravity moves up or down, such as standing up or falling.

d. Attitude Change. Attitude changes affect individual parts of the body, but do not change the human body pattern in the horizontal plane. An example of this action would be bending over.

The human body's movement patterns arise through a combination of these four different actions, meaning specific actions can be used to determine human movement patterns.

Feature Extraction is an important process in motion detection. These features can provide useful information compared to complex original data. In this report, the most useful features are three different values: tilt angle, acceleration and height change.

4.1.1 Tilt Angle Extraction

During movement, the human body must have some angle changes in the vertical plane. But in different patterns, the angle changes vary significantly. In this report, the tilt angle determines the directions in pitch and roll, while the rotation in yaw only affects the attitude of the human body [22].

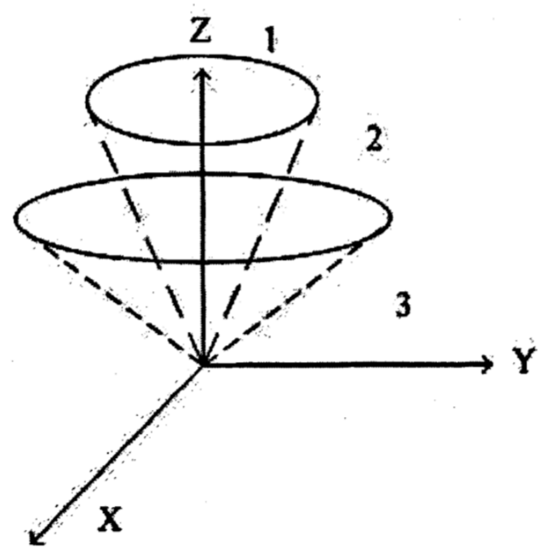

Figure 4.1: tilt Angle Classification

In figure 4.1, the x-, y- and z-directions represent the coordinates of ENU. This figure separates the tilt angle into three different aspects. Region 1 represents the upright stage, Region 3 represents the horizontal stage, and Region 2 represents the transition stage. Based on multiple tests, the distinguished angle of regions 1 and 2 is 16 degrees and the distinguished angle of regions 2 and 3 is 46 degrees. During walking movement patterns, tilt angle changes are very small, and the tilt angle of the human body should always fit into Region 1. When people stand up, the upper body should tilt forward and then recover, two movements that take place in Region 1 and 2. For Region 3, tilt angle is minimal; only during falling-down movement patterns does tilt angle appear in this region.

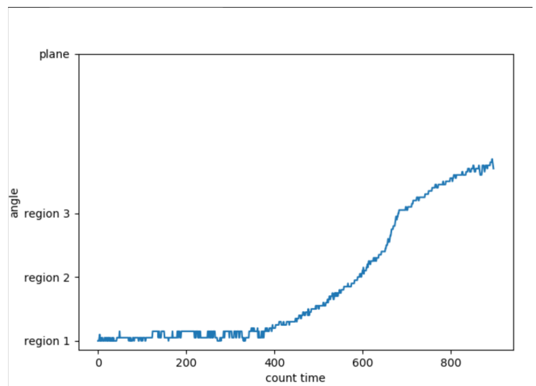

Figure 4.2: Tilt Angle of Falling Down Pattern

Figure 4.2 shows the tilt angle of the falling-down pattern. The tilt angle starts at about 7 degrees and rises to approximately 80 degrees. The tilt angle during the falling-down movement pattern covers Regions 1, 2, and 3.

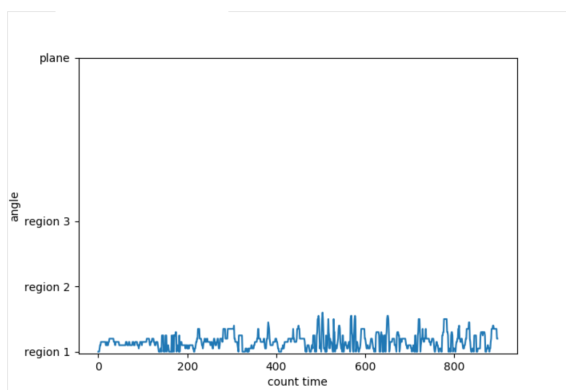

Figure 4.3: Tilt Angle of Walking Pattern

Figure 4.3 shows the tilt angle of the walking pattern. The tilt angle starts around 0 degrees and always stays in Region 1.

These comparisons indicate that tilt angle can distinguish between static motion and dynamic motion.

4.1.2 Acceleration Extraction

Acceleration is the most useful feature in human motion detection, because acceleration can offer direct information on the velocity of different patterns. Although the motions of walking and running have almost the same tilt angle, they produce different velocity measurements in the horizontal plane. Acceleration can help distinguish movement patterns when tilt angle alone is insufficient to make determinations.

Through simulation comparisons, this experiment sets the boundary between walking and running at a velocity of 4 m/s. Because of inevitable minor errors in the experiment, even if people are standing up, a speed may still be registered on the horizontal plane. This experiment sets the boundary between a walking pattern and a static state at a velocity of 1 m/s.

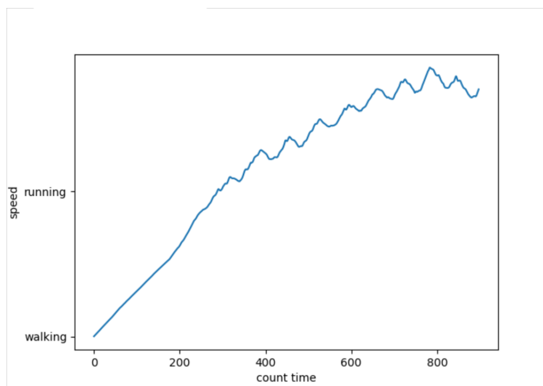

Figure 4.4: Running Speed

Figure 4.4 shows the a test sample starting from a static motion and accelerating to a running pattern. Once this process is complete, the speed indicated in the horizontal plane remains continuously in the running pattern range.

4.1.3 Height Change Extraction

Height change alone cannot directly indicate the movement pattern. When a person is running, their height change should always fluctuate in a fixed range. Because the range only represents the intensity of movement, height change has little effect on determining the distinctions between a running pattern and a walking pattern. When a person falls down or stands up, height change can be a significant indicator of the movement pattern. The heights in the beginning state and end state should vary significantly. If a person falls down, their height should decrease.The height change process is shown in figure 4.5,

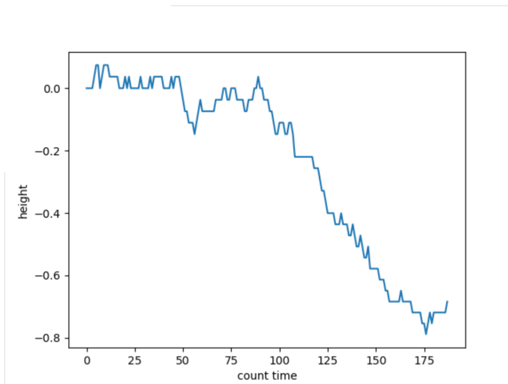

Figure 4.5: Height Change

This figure shows the height change comparison in the falling-down pattern. Height change can provide another way to distinguish the falling-down pattern from the standing-up pattern.

4.2 Movement Pattern Detection

4.2.1 Static Motion and Dynamic Motion

In this report, four different movement patterns can be recognized: standing up, falling down, running, and walking. Through feature extraction, this report separates the four different patterns into two categories: static motion and dynamic motion [22].

In Figure 4.6, the standing-up pattern and the falling-down pattern belong to the dynamic motion classification, while the walking pattern and the running pattern belong to the static motion classification.

The classification of dynamic motion and static motion transforms the four movement patterns into a dichotomy problem. In this process, using tilt angle as the decision condition, the SVM algorithm classifies movement patterns into categories. If a move-

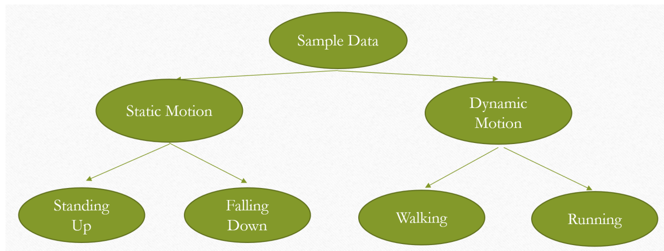

Figure 4.6: Static Motion and Dynamic Motion

ment's tilt angle is in Region 1, the movement pattern belongs to static motion, which means it must be either a walking pattern or a running pattern. On the contrary, if the tilt angle covers Regions 2 or 3, the movement pattern belongs to the dynamic motion. In this situation, the movement must be either a standing-up pattern or a falling-down pattern. Once a movement pattern is determined, this report recommends the use of a similar KNN algorithm method to determine whether the movement pattern happens in real time. Ideally, the KNN algorithm can find k different data close to the sample. The experiment was unable to include a specific sample that could represent specific movement patterns, as most movement patterns tilt angles and accelerations fell across a varied range. This report determines the acceleration or tilt angle range for different movement patterns. If the count time of the data in a given range reaches the set value k, we can surmise that a movement pattern occurs..

4.2.2 Standing Up Pattern and Falling Down Pattern

Once a movement pattern has been classified as belonging to the category of dynamic motion, the specific movement pattern can be determined. The standing-up pattern and falling-down pattern are quite different in tilt angle and height in vertical direction.

When a person stands up, the body tilts forward and then moves upward until finally the body attitude becomes stable. In this process, the tilt angle increases from almost 0 degrees to Region 2. Because a person's position improves during this process, displacement in the vertical direction is positive. The whole process should last approximately 1 second. Identification of the sample standing-up pattern is based on displacement and vertical tilt angle. Displacement needs to be be positive compared to the start motion, while the tilt angle during the process should cover Regions 1 and 2, but not reach Region 3.

When a person is falling down, by contrast, the body tilts forward or backward, then moves downward until finally, tilt angle reaches almost 80 degrees. During this process, vertical direction acceleration reaches a high value, almost matching gravity acceleration. Vertical displacement is negative and horizontal acceleration and displacement are also small, although the acceleration of the falling-down motion in a horizontal plane is greater than the acceleration of a standing-up motion. Identification of the sample falling-down pattern is based on tilt angle and displacement. Displacement needs to be negative comparing to the beginning state, while the tilt angle during the process must reach Region 3.

4.2.3 Running Pattern and Walking Pattern

Once a movement pattern has been determined to belong to the static motion classification, it can be either a running pattern or a walking pattern. The distinction between these two patterns is less extreme than the distinction between the patterns that belong to the dynamic motion classification. Regardless of whether a person is running or walking, the movement is in one specific direction and tilt angle is fixed in Region 1. Acceleration plays a vital role in distinguishing these two patterns.

The velocity in a horizontal plane should be different depending on whether a person is running or walking. The coordinate transformation method detailed in Chapter 3 allows us to calculate the velocity in the x- and y-directions; the quadratic sum of velocity in x and y directions represents the velocity square in a horizontal plane. When velocity is in the range of 0 m/s to 4 m/s, a person is considered to be in a walking pattern. When velocity is greater than 4 m/s, this person is considered to be in a running pattern.

Chapter 5: Result

5.1 Hardware Components in Experiment

In this experiment, the basic measurement devices are the IMU and the barometer. This section introduces the details of devices used in this experiment.

The LSM6DSO unit is a 6DoF IMU with a 3D digital accelerometer and a 3D digital gyroscope; the unit boosts performance at 0.55 mA in high-performance mode and enablins always-on low-power features for an optimal motion experience. The LSM6DSO has a full-scale acceleration range of 2/4/8/16 g and an angular rate range of 125/250/500/1000/2000 dps [29]. The following figure shows the architecture of the LSM6DSO.

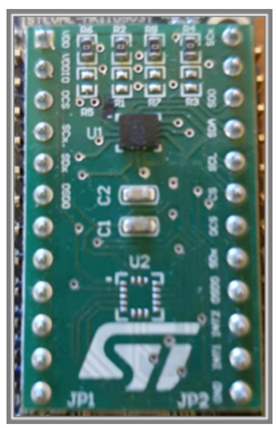

Figure 5.1: LSM6DSO

The SET001V1 unit is a high-performance barometer unit. It can provide real-time pressure and temperature in high frequency. The following figure shows the architecture of the SET001V1.

The two units are both fixed in the MCU unit and connected to the computer port to transmit data information signals.The entire data analysis process is conducted at a computer port. The hardware system is shown in figure 5.1.

Figure 5.2: SET001V1

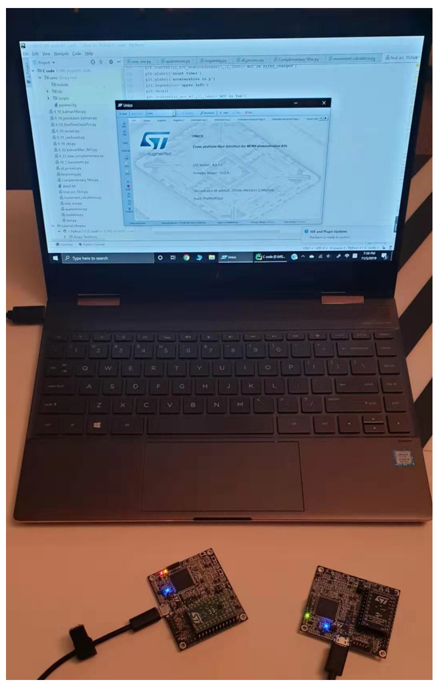

Figure 5.3: Hardware Device

5.2 Result of Experiment

This experiment is based on the simulation of human body motion.

The first experiment shows the process of a test person in static motion; the test person starts in a walking motion and then increases speed to a running motion. The feature of static motion is mainly based on velocity in a horizontal plane.

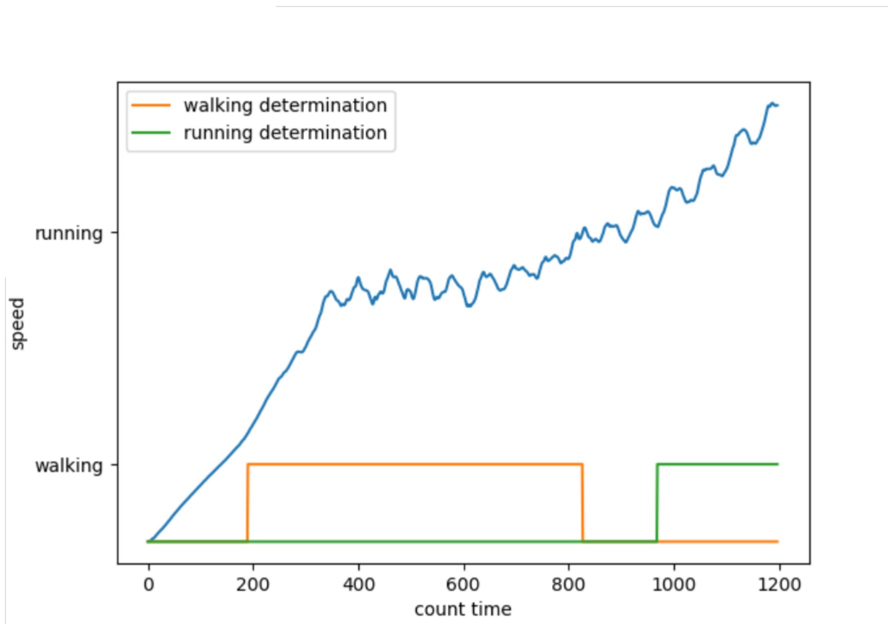

Figure 5.4: Result of Walking to Running Pattern

As shown in figure 5.2, the speed starts from 0 and continuously increases as the test subject moves to a walking pattern and then to a running pattern. There are two different color lines, each representing whether a current movement pattern is occurring or not. The K value is equal to 100. When the value fits the requirements of a particular motion, the system begins to count; when the count number reaches K, the movement pattern is distinguished. This process explains why between the walking pattern and the running pattern, there is a state that cannot be clearly distinguished. For static motion, the accuracy can reach over 95%.

The second experiment shows the process of a test person in dynamic motion; the test person stands up and then falls down. During the whole process, the tilt angle of the test person increases to Region 2 and then returns to almost 0 degrees. When the person falls down, the tilt angle continuously increases until it reaches Region 3. In this experiment, the system uses the absolute value which makes the determination of movement patterns much easier. As shown in figure 5.2, there are two different color

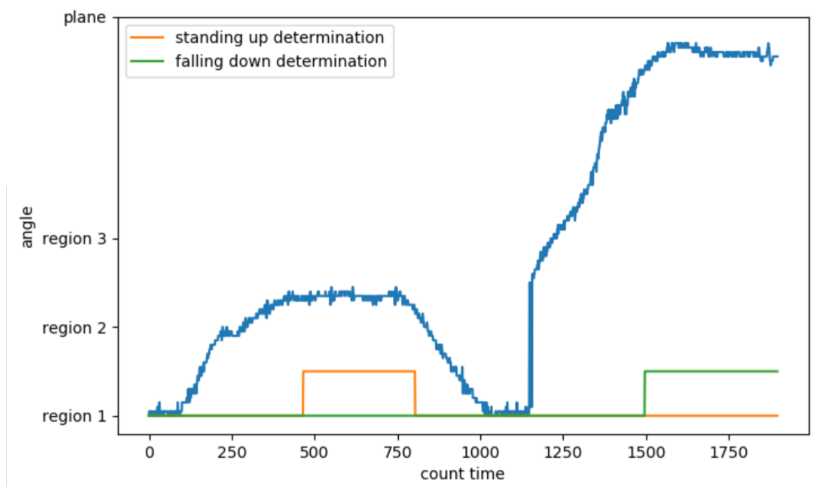

Figure 5.5: Result of Standing Up to Falling Down Pattern

lines, just as there were in the static motion experiment. When the determination line does not equal 0, this represents that the human body is currently in a specific movement pattern. The result of this experiment successfully demonstrates the process of standing up and then falling down. For dynamic motion, the accuracy of experimental results is around 90%.

Chapter 6: Discussion and Conclusion

6.1 Discussion

This report provides insight into human motion detection technology through use of the IMU and the barometer. Because there are still many points that can be improved, this section identifies problems existing in project.

The first potential issue is device inadequacy. This project simulated different human patterns through technological systems. In real application, devices should be worn on the human body, which means an additional wireless unit is needed to accomplish wireless transmission. But in this experiment, due to device limitations, the IMU and the barometer both needed to be connected to the computer port. During the simulation process, the length of cable limits many movements. This limitation was unavoidable in this situation, as the entire system depended on the IMU and the barometer to measure data. In real use, the use of two different sensors alone cannot guarantee the data measured is at exactly the same point, because it is impossible for two sensors to be placed at exactly the same point. If, in future sensor device development, all sensors can be combined in a single board, this inadequacy can be solved.

The second limitation of this project involves its ability to accurately real-life movements. Because the data used for different movement patterns is based on measurement through simulation, these samples cannot possibly represent all people. For example, when a person stands up extremely quickly and the count number cannot reach the set value k, the system is unable to recognize this motion. To achieve a more accurate result, more samples need to be taken to increase the data base.

The third limitation of this project is the transient process during different movement patterns. For example, when a person changes from a walking pattern to a running pattern, the system determines different patterns through the change in velocity. Humans, by contrast, are capable of performing a quick walking pattern or a slow running pattern that the system cannot fully classify. To solve this inadequacy, more sensors need to be added in the experiment; for example, the tilt angle of knee bend or the duration between running and walking could provide more specialized information.

6.2 Conclusion

This research has studied practical methods to detect movement patterns by using an IMU and a barometer, which can be easily integrated into wearable sensors because of their small form factors and low power consumption. The method developed in this project first uses quaternions to transform the coordinate of different sensors and remove the rotation error via a complementary filter. The tilt angle of different movement patterns and the velocity in horizontal plane provide the status information of the dynamic and static motions. The k-nearest neighbors algorithm and a support vector machine are incorporated into an algorithm for pattern classification. This algorithm is implemented in a hardware and software platform, to detect four type of motions: walking, running, standing up and falling down. Experimental results have shown classification accuracy of over 90% for these movement patterns.

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