Detection of Human Body Movement Patterns Using IMU and Barometer

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Abstract— **With the 20th century's drastic increase in the human population, population aging is becoming a major cause for concern. With current organizations and service staffs struggling to adequately care for an aging population, there is an 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. In general, motion detection technologies are divided into two categories: visual detection and sensor network detection. This paper proposes the combined use of an inertial measurement unit (IMU) and a barometer to conduct sensor network detection. The IMU device includes a three-axis accelerometer and a three-axis gyroscope used for body coordinates' accelerations and angular velocities. The barometer is used to measure pressure and temperature at various points. In this paper, the *k*-nearest neighbor (KNN) and the support vector machine (SVM) act as a complementary filter algorithm to detect four different human body movement patterns: the standing-up pattern, the falling-down pattern, the running pattern, and the walking pattern. The proposed algorithm was tested in a hardware and software platform, and the results have shown a classification accuracy of over 90% for these movement patterns.**

Keywords—Detection, human body motion, inertial measurement unit (IMU), *k*-nearest neighbor (KNN).

I. Introduction

The aged population is at its highest level in all of human history. During the 21st century, we're going to see faster aging than ever. This is not a temporary change, according to an extensive study done by the UN. The study examined how the world population has aged and will continue to age from 1950 to 2050. This is a global phenomenon and will affect people in every single country. Like most developed nations, the UK population is aging. The percentage of those aged over 65 increased from 14.1 percent in 1975 to 17.8 percent in 2015, and it is projected to jump to nearly a quarter of the population by 2045. The UK, through its Government's Industrial Strategy, is investing over £300 million in creating new care technologies and services that harness the power of technology to meet the needs of their aging society [1]. According to the States Bureau of Statistics, the world entered a collective stage of aging in 2001 [2]. In the United States, citizens aged 65 and over numbered 49.2 million in 2016, representing 15.2 percent of the population, about one in every seven Americans [3].

Digital technology offers a golden opportunity to reimagine how we can support and empower an aging population to lead us combat common problems that seniors encounter. If we can match technology with seniors' needs and wants, we can improve their lives and help society as a whole.

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 feedback. In the medical field, these devices can help personnel to accurately determine what is happening in the 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 [4].

Most movement motion detection technologies can be divided into two categories: visual detection and sensor network detection [5,6]. 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-open area and detect multiple targets at the same time. However, 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 the weather is foggy, video definition can decrease sharply, causing motion detection failures [7]. Sensor network detection is an 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 delayed by weather, time, or location [7]. By analyzing this data, the device can sense specific movement patterns. Extensively precise radio frequency (RF) localization techniques [8-9] are available that can use wearable location sensors to detect various motions. For example, pulsed ultra-wideband signaling [10-11] based localization schemes could achieve centimeter-accurate positions [12] for accurate motion detection.

Bouten et al. [13] were researchers of body activity remote monitoring. They developed a system consisting of a single triaxial accelerometer and a data processing unit that could be used to measure angular motion by the acceleration of the human body. Their research developed a positive relationship between accelerometers and energy spending, which became the catalyst for the ensuing wearable sensor movement. Later work by Najafi et al. [14] showed that gyroscopes could be used to monitor physiologic changes and that would encourage others to use inertial measurement units (IMUs: electronic devices featuring a triaxial accelerometer and triaxial gyroscope capable of measuring both acceleration and angular velocity around three orthogonal axes) to track falls using accelerometry signals [15]. Steps and falls can be detected with a triaxial accelerometer and barometric pressure sensor [16,17]; body movement can be tracked non-invasively with a magnetic and inertial measurement device (MIMU) [18], and an embed IMU in a piece of footwear—comprised of power, strain, electrical field, and twist sensors—for numerical posture analysis [19]. All the above methods achieve a certain degree of precision and efficiency in human motion recognition.

Although these types of motion detection systems are well established for identifying a person's motion, they are affected by low power consumption. Furthermore, easily integrated wireless sensors for use in motion detection have not been extensively studied.

This paper proposes the IMU and the barometer to jointly 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 and the barometer can measure the pressures and temperatures at various points. Furthermore, with the help of a complementary filter algorithm to fuse the data from different types of sensors, we used a scheme that 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.

II. Proposed system

This section presents 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 any measured data. In this experiment, most calculations take place within the computer.

A. *Hardware*

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

(i) 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. The frequency determines the sampling time and measure rate. A higher frequency increases the accuracy, but it also increases the level of required calculations. 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 that 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 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 one 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.

(ii) Barometer

The barometer is a sensitive instrument that measures the air pressures of different points. Air pressure in different heights can determine the 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.

B. *Algorithm for Motion Detection*

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

(i) *k-Nearest Neighbor*

The 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 nd the nearest *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 [20]. 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 KNN's results, particularly when the *k* value is small. These limitations can make it more difficult to achieve an 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 that even data far away from the sample can be recognized as belonging to the same category. Additionally, the KNN algorithm cannot make decisions in real-time when it is applied to human motion detection. This algorithm's decision can only be made over an extensive time period after all data has been measured.

(ii) *Support Vector Machine*

The SVM is an algorithm that distinguishes between two categories in a featured space [13]. This method needs a plane in order to divide the samples into two different categories. The most critical part of the SVM algorithm is finding where the dividing plane is located [21]. As the following figure shows, to divide the two categories, the SVM algorithm needs the greatest gap between two different categories and in order to make sure the dividing plane has a similar distance to the nearest point. This determination can be made through a comparison between the dividing plane and each new point. 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 _rst needs to be separated. At least two sets of data are required to determine the plane division. In human motion detection, different motion data needs to be measured beforehand. By comparing these data, SVM can find the most suitable plane for different motions [22].

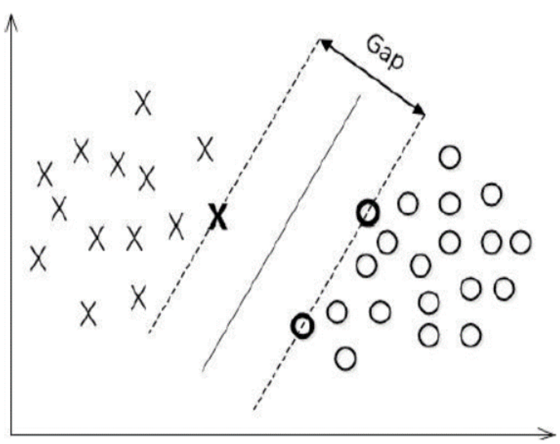

Figure 1: Support Vector Machine Sample

The SVM [23] is usually used as a binary classifier. The basic form of SVM, which classifies an input vector x ∈ R n, can be expressed as:

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i \varphi(x_i)\, \varphi(x) + b = \sum_{i=1}^{N} \alpha_i y_i\, K(x_i, x) + b \quad (1)$$

where φ is a non-linear mapping function $\varphi(x)$: $R^n \rightarrow R^m$, ($n \leq m$). "·" refers to the inner product operator, and xi, yi, and ai are the i^{th} training sample, its class label, and its Lagrange multiplier, respectively. $K(\cdot,\cdot)$ is a symmetric positive-definite kernel function, and b is a bias term. The sign of f(x) indicates class membership.

III. Movement Pattern Detection

In this paper, four different movement patterns can be recognized: standing up, falling down, running, and walking. Through feature extractions, this report separates the four different patterns into two categories: static motion and dynamic motion [22]. In figure 2, 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 a tilt angle as the decision condition, the SVM algorithm classifies movement patterns into categories. If a movement'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 paper 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 precise movement patterns, as most movement patterns tilt angles and accelerations fell across a varied range. This report determines the acceleration of tilts' angle ranges 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 has occurred.

During movement, the human body must have some angle changes in the vertical plane. Nevertheless, in different patterns, the angle changes vary significantly. In this paper, the tilt angle determines the directions in pitch and roll, while the rotation in yaw only affects the attitude of the human body [22]. In figure 3, 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.

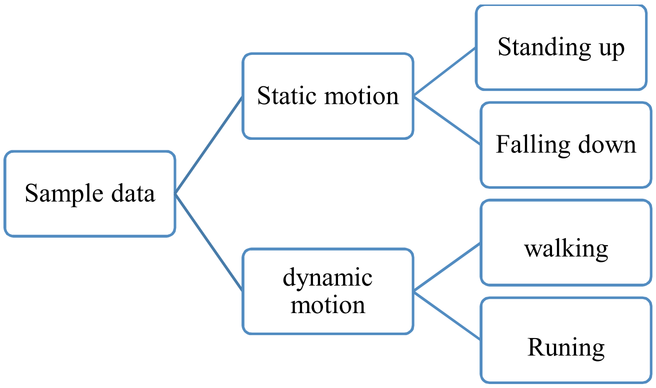

Figure 2: Classification of motion

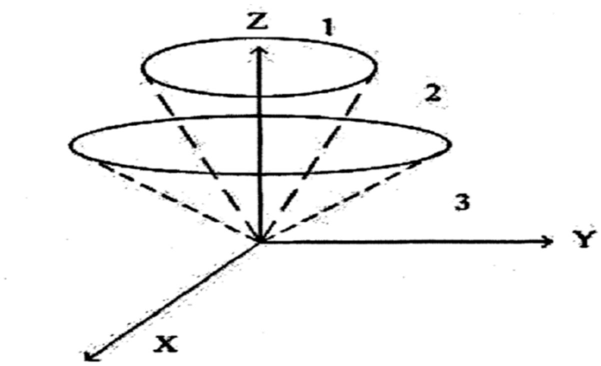

Figure 3. Tilt angle classification

A. Dynamic motion

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 *a* 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. The identification of the sample standing-up pattern is based on the displacement and vertical tilt angle. Displacement needs to 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. tilts forward or backward, then moves downward until finally, the tilt angle almost reaches 80 degrees. During this process, vertical direction acceleration reaches a high value, almost matching gravity's acceleration. Vertical displacement is negative and horizontal acceleration, and the displacements 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. The identification of the sample falling-down pattern is based on tilt angle and displacement. Displacement needs to be negatively compared to the beginning state, while the tilt angle during the process must reach Region 3.

B. Static motion

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 the 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.

IV. Experimental Setup

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. In this experiment, with the help of a complementary filter algorithm to fuse the data from different types of sensors, we used a scheme that combines the advantages of the KNN and the SVM to detect the four previously described human body movement patterns. In this experiment, the basic measurement devices are the IMU and the barometer. 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 enables 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. Figure 4 shows the architecture of the LSM6DSO.

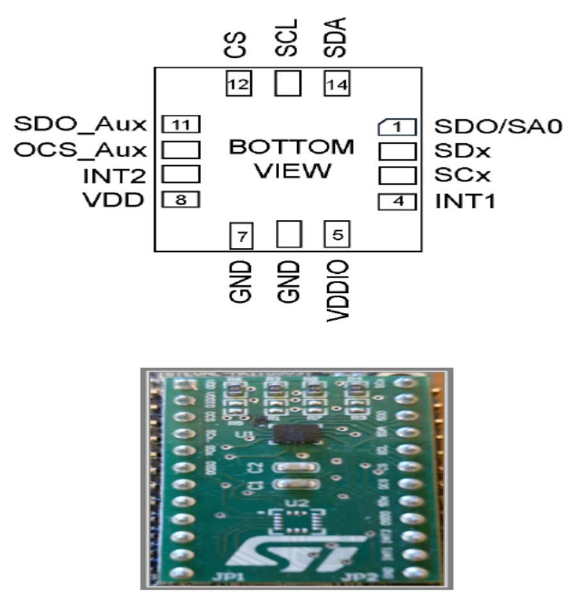

Figure 4. LSM6DSO pin configuration

The SET001V1 unit is a high-performance barometer unit. It can provide real-time pressure and temperature changes in high frequency. Figure 5 shows the architecture of the ET001V1.

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 6.

Figure 5. SET001V1

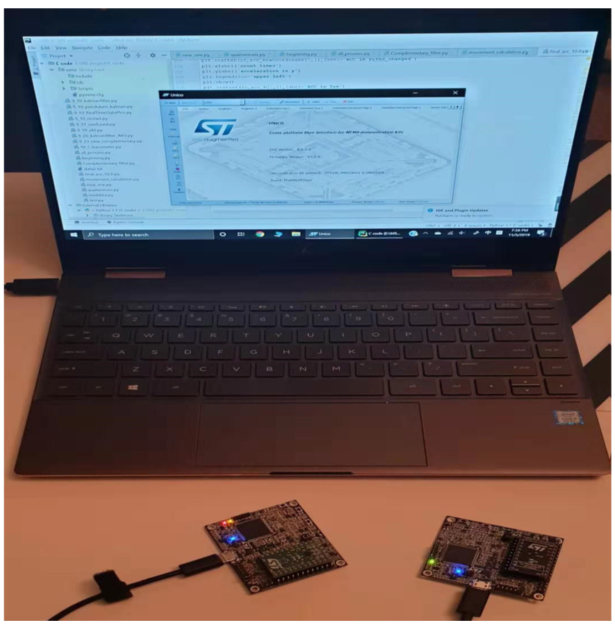

Figure.6 Experimental setup

V. Result and discussions

This experiment is based on the simulation of human body motion. The first experiment shows the process of a test person is 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.

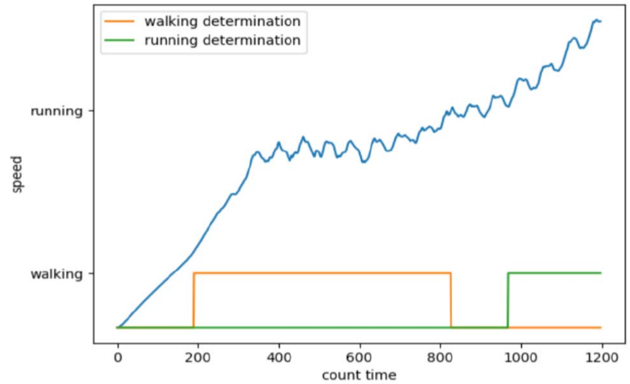

Figure 7. Result of walking to running pattern

As shown in figure 7, 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, 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 8, there are two different color lines, just as there were in the static motion experiment. When the determination line does not equal 0, this indicates 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%.

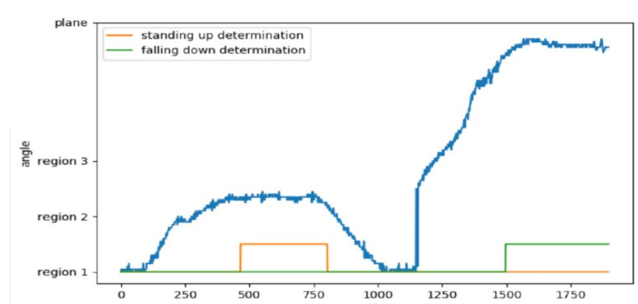

Figure 8. Result of standing Up to falling down pattern.

Finally, the reduction in hardware complexity leads to significant cost savings and the possibility of developing a portable and low-cost commercial device. The result is a highly accurate and robust sensor that provides a low-cost solution for the wireless detection and monitoring of human body movements.

VI. Conclusion

This paper has studied the practical methods for detecting 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 tilt angle of different movement patterns and the velocity in the horizontal plane provide the status information of the dynamic and static motions. The KNN's algorithm and a SVM are incorporated into an algorithm for pattern classification. This algorithm is implemented in a hardware and software platform to detect four types of motions: walking, running, standing up, and falling down. Experimental results have shown a classification accuracy of over 90% for these movement patterns.

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