Design of a Fall Detection Product Based on Arduino

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Abstract:
The article proposes a design scheme for a fall detection product. The design utilizes a MAX6050 three-axis gyroscope sensor and a two-axis angular velocity sensor for fall detection. At the same time, a vector machine model is established, combining the advantages of both the threshold method and machine learning to reduce the probability of misjudging falls. The hardware of this system consists of five components: a triaxial acceleration data acquisition module, a biaxial angular velocity data acquisition module, a data analysis and processing module, a GPS positioning module, and a wireless data transmission module. The triaxial acceleration data acquisition module and the biaxial angular velocity data acquisition module collect human acceleration and angular velocity data, which are further processed through a threshold algorithm and a support vector machine model to effectively distinguish between daily activities and falling behaviors, thereby reducing the probability of false fall detections. Simultaneously, the system sends the location information of the injured person via data transmission, achieving a closed loop of fall detection and rescue. Experimental results demonstrate that this design can accurately detect fall behaviors, deploy an airbag within 1 second, and promptly send location information, providing a new approach for the research on anti-fall products.

Keywords: arduino; fall detection; wearable; threshold algorithm.

INTRODUCTION

The research on fall detection can be traced back to the 1980s, when scholars mainly focused on statistical studies of falls [1]. With the continuous development of computer technology, technologies such as deep learning, artificial neural networks, video image analysis, and wearable sensors have been successively applied to fall detection [2-5].

Currently, there are mainly four methods for fall detection: (1) Fall detection based on environmental perception. Some scholars have deployed infrared sensors based on a mechanism that utilizes changes in infrared radiation in stereo views, and referred to structured tomography to detect human fall behavior [6-7]. Some scholars also use audio and vibration signals for fall detection [8-10].These methods offer good comfort, but their application scope is limited and they are easily affected by noise [11]. (2) video-based method for fall detection. Currently, there are two types of fall detection based on video: 3D video and 2D video. Vaideh et al. [12] implemented an automatic video-based system for detecting human fall behavior. Rougier et al. [13-15] through a series of research, developed a method using a monocular 3D camera to track changes in human head data, predict head shape and position, and calculate head velocity deviation in conjunction with a detection module, further judging fall behavior based on predefined thresholds. However, while video-based fall detection methods offer high accuracy, their application scope is limited, posing privacy and security concerns and incurring higher costs. (3) Fall detection based on wireless signals. This method analyzes the impact of human activities on wireless signals under different states, interprets the changes in wireless signals corresponding to various human activities, and further determines the state of wireless signals during a fall, thereby judging the occurrence of a human fall. For example, a human fall detection system based on a network of pyroelectric sensors [17] and a Radio Tomographic Imaging (RTI) system based on RSSI (Received Signal Strength Indicator). Fall detection based on wireless signals has minimal interference and can protect user privacy, but it has high requirements for the environment. (4) Fall detection based on wearable devices. This detection method obtains human motion information data through sensors, utilizing accelerometers, gyroscopes, etc., to detect human fall behavior [19-20]. For example, Alwan et al. [20] collected human motion data through vibration sensor devices installed on the floor, and combined data analysis to judge fall behavior; Sixsmith et al. [21] collects data on human position, speed, etc. through infrared detectors installed on the surrounding walls, and predicts fall behavior based on changes in the data. This method is not affected by the detection environment, has strong real-time performance, and high accuracy, and has always been a key focus of scholarly research.

In summary, wearable fall prevention technology is relatively mature and offers high reliability and stability. However, there are also some issues with its products during use, such as the device being heavy, low comfort, prone to misjudging fall behavior, and insufficient battery life. This article aims to develop an Arduino-based smart anti-fall belt. The design utilizes a MAX6050 three-axis gyroscope sensor and a two-axis angular velocity sensor for fall detection. At the same time, a vector machine model is established, combining the advantages of both the threshold method and machine learning to reduce the probability of misjudging falls. Additionally, the design incorporates sharklet antibacterial material to enhance the comfort of wearing the product.

DESIGN OF A FALL DETECTION SYSTEM

Structure of a Fall Detection System

The hardware of the fall detection system consists of five components: a three-axis acceleration data acquisition module, a two-axis angular velocity data acquisition module, a data analysis and processing module, a GPS positioning module, and a wireless data transmission module. The three-axis acceleration data acquisition module transmits data on changes in acceleration around the X, Y, and Z axes of the human torso to the acceleration sensor. The two-axis angular velocity data acquisition module acquires data on changes in angular velocity in the vertical direction of the human body, including front-to-back and left-to-right orientations. The data processing module analyzes the changes in acceleration and angular velocity data of the human body, and tests the probability of a fall based on a fall detection algorithm. If a fall is detected, it combines the positioning data and body detection data to send fall information to the family members' phones and nearby hospitals, facilitating timely rescue. A detailed system structure diagram is shown in Figure 1.

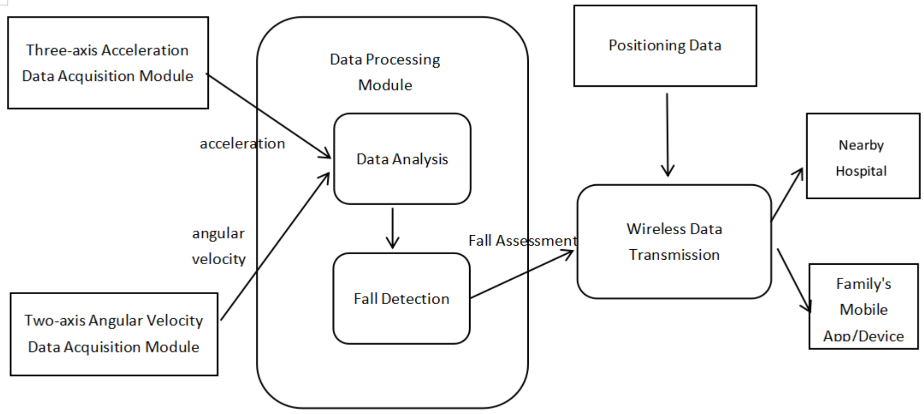

Figure 1. Structure diagram of the fall detection system

The hardware architecture of this project mainly includes the following modules:

Sensor module: used to monitor the wearer's posture changes and determine if a fall event has occurred.

Airbag protection system: when a fall is detected, it activates a servo to control the inflation of the airbag, providing protection for the wearer.

Bluetooth module: real-time data transmission to mobile devices, facilitating monitoring of the wearer's condition by family members and caregivers.

Main control board: using Arduino as the main control board, responsible for coordinating the work of various modules, as well as handling data analysis and alarm tasks.

Arduino serves as the main control board, responsible for coordinating the work of various hardware modules. The main control board processes sensor data, determines if the wearer's posture indicates a fall, and controls the servo to activate the airbag protection system. At the same time, it is also responsible for data exchange with the Bluetooth module, sending fall event information to the mobile App.

We used the Arduino UNO development board, which features rich I/O ports and high processing capabilities, making it suitable for real-time data processing in this project. The specific details are shown in Figure 2:

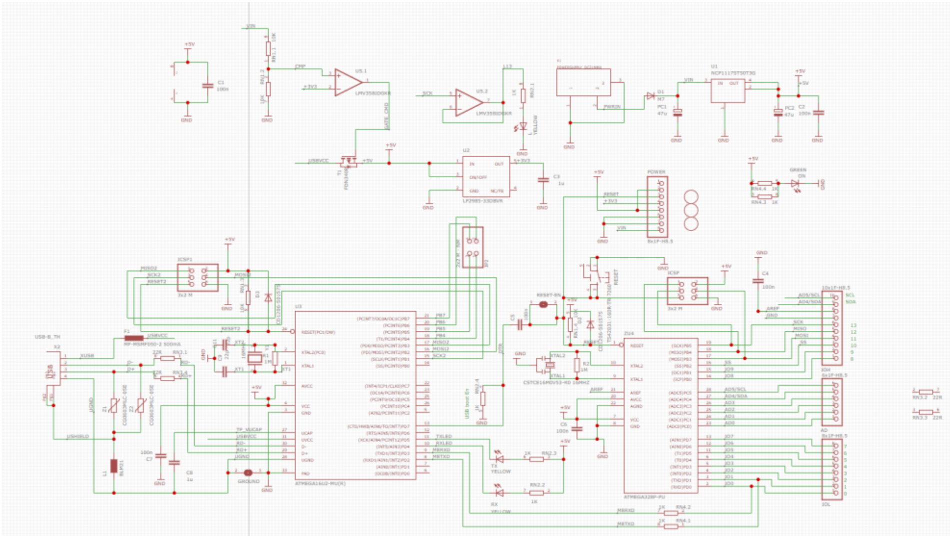

Figure 2. Schematic diagram of the main control arduino UNO2.2 sensor module

The sensor module is the core component of this system, responsible for capturing the wearer's acceleration and angular velocity data to determine their fall status. We have chosen two sensors, an accelerometer and a gyroscope, to obtain the wearer's motion information in three-dimensional space.

Three-axis acceleration data acquisition module

In this paper, the MPU6050 (as shown in Figure 3) three-axis gyroscope sensor is used to collect three-axis acceleration data of the human body in motion, detecting changes in data under scenarios such as tilting, movement, vibration, and impact force. It further outputs the X, Y, and Z three-axis acceleration information generated by the human body in different motion states. For the data detected by the three-axis gyroscope, the acceleration components GYR_X, GYR_Y, and GYR_Z rotating around the X, Y, and Z coordinate axes are all 16-bit signed integers. When viewed from the origin towards the direction of the rotation axis, a positive value indicates clockwise rotation, while a negative value indicates counterclockwise rotation.

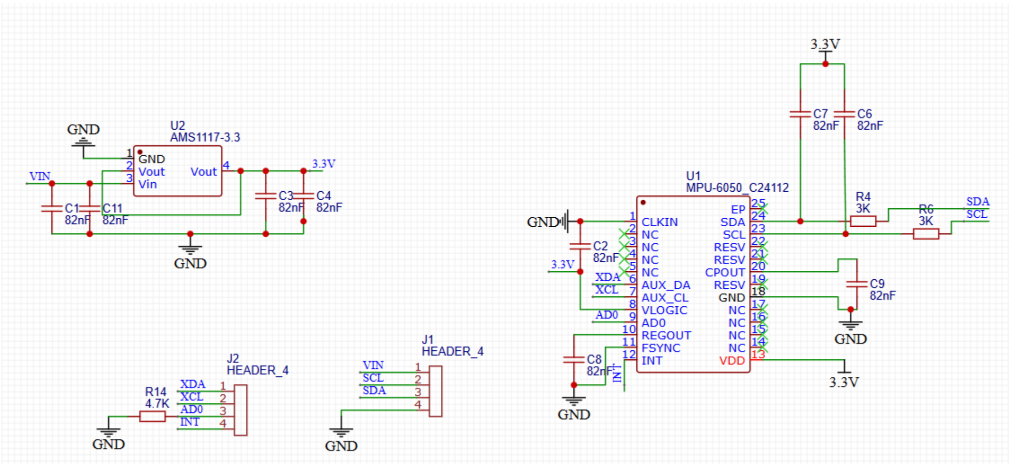

Figure 3. Schematic diagram of MPU6050

Two-axis angular velocity data acquisition module

Using the MPU6050 three-axis gyroscope sensor, roll, pitch, and yaw angles can be derived from the acceleration data while obtaining three-axis acceleration information. Furthermore, by integrating the angular velocity data from the gyroscope, fall detection can be performed based on these data. To improve the accuracy of detection, this paper employs a Kalman filter, which takes the angle value, angular velocity value, and time increment on one axis as inputs, and estimates a noise-reduced angle value, thereby enhancing the accuracy of fall detection.

Location Data Module

The fall detection product for the elderly primarily aims to accurately identify the fall status of elderly individuals (as shown in Figure 4) and promptly provide intervention and medical assistance. Therefore, incorporating a location data module can quickly and accurately pinpoint the location of an elderly person when they fall, allowing for immediate contact with family members or the nearest hospital, significantly reducing the delay in treatment, and achieving a closed-loop process of fall detection and response.

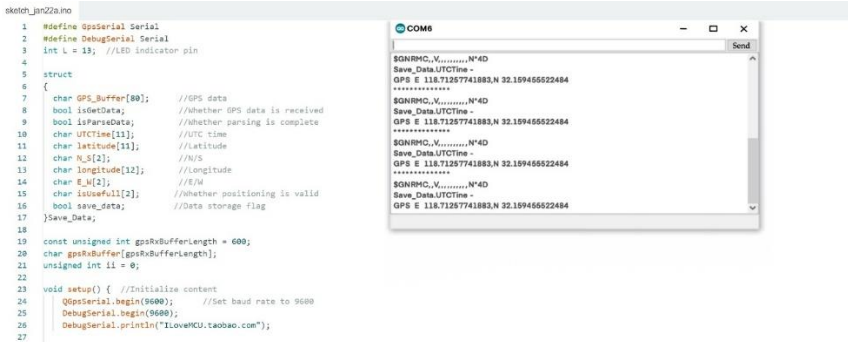

Figure 4. Hardware of the localization module and raw latitude/longitude data

Data Processing Module

During the data analysis and processing, a vector machine model is established to combine the advantages of both the threshold method and machine learning, thereby improving detection accuracy. The study extracts data from various positional states such as walking, squatting, sitting, and falling, and classifies them into a daily behavior data sample set and a fall behavior data sample set. Because the human body generates acceleration peaks when hitting a low-level surface or the ground during a fall, when analyzing fall behavior, three-axis acceleration data from forward, backward, left, right, and walking movements can be collected to calculate the resultant acceleration. Based on the calculated data, it determines whether a fall has occurred. If a fall is detected, the servo motor rotates 90 degrees, activating the trigger to puncture the gas cylinder and inflate the airbag. A three-axis gyroscope is used to detect the fall status (as shown in Figure 5), controlling the servo motor to rotate and trigger the airbag deployment (as shown in Figure 6).

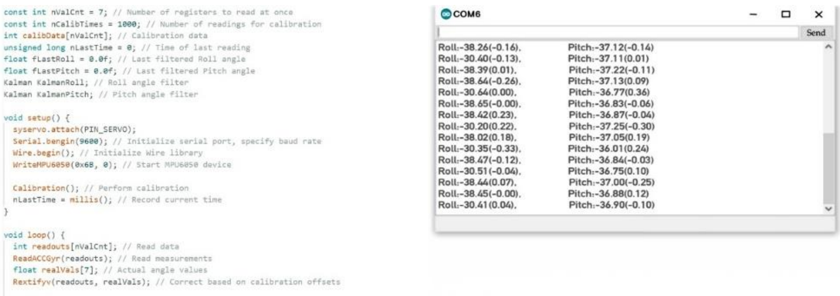

Figure 5. Data from the three-axis gyroscope processed by kalman filtering

Figure 6. Diagram of the airbag deployment mechanism

Airbag Protection System

Once the system detects a fall event, the airbag protection system is activated. The airbag inflates through a servo-driven mechanism to protect the wearer from injuries caused by the fall.

Servo Drive: The servo is a core component of the airbag protection system, controlling the inflation process of the airbag through rotation. We use the SG90 servo, which offers good precision and response speed. When the system determines a fall has occurred, the servo immediately rotates to trigger the airbag inflation.

Airbag: The airbag is made of traditional medical-grade airbag material, capable of inflating rapidly and providing sufficient cushioning force. The expansion effect of the airbag after inflation can effectively mitigate the impact force from the fall, thereby reducing the injuries caused by it.

Data Transmission Module

The Bluetooth module is primarily used to transmit real-time information related to fall events to a mobile app. Through the mobile phone, family members or caregivers can promptly learn about the wearer's status and provide remote assistance. The JDY-08 Bluetooth chip uses hardware serial ports (0, 1) for communication between the PC and Arduino, and employs software serial ports to convert pins (4,5) into serial ports for connecting the Bluetooth module. Commands are sent through the Arduino IDE's serial monitor to the Arduino core board, which then forwards them to the Bluetooth module. The Bluetooth module's return values are received by the core board and forwarded to the serial monitor for printing. This module offers good compatibility and a relatively long transmission distance, enabling wireless transmission of data from the Arduino to the mobile device. On the App side: Upon receiving the data, the mobile app can display the wearer's fall status in real time. If a fall occurs, the app will trigger an alarm and display key information such as the location and time of the fall, helping family members or caregivers respond quickly. The Bluetooth connection and data transmission are illustrated in Figure 7.

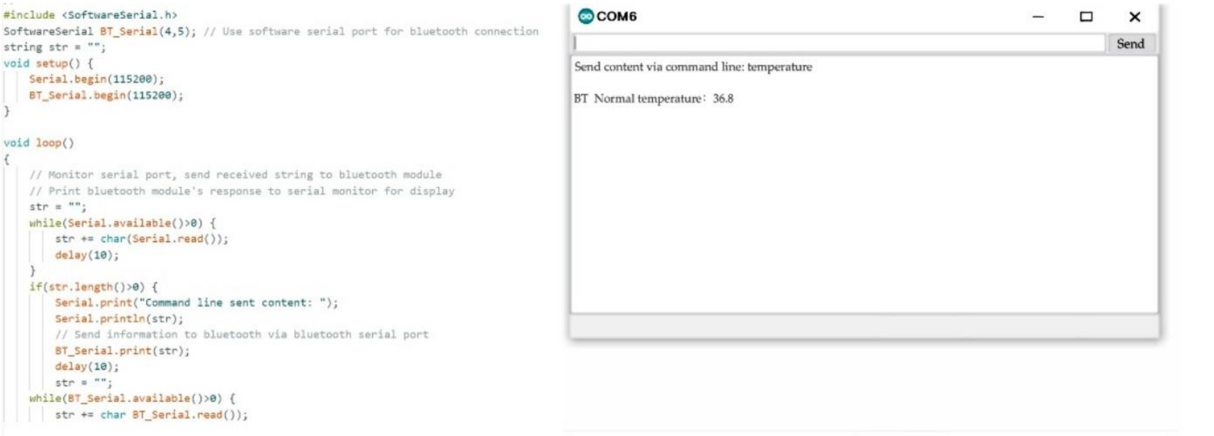

Figure 7. Bluetooth connection and data transmission back to the device

DESIGN OF THE SOFTWARE COMPONENT

The software component is the soul of the entire system, primarily responsible for data acquisition, processing, and analysis, as well as determining whether the wearer has fallen through algorithms. We implement data acquisition and processing by writing Arduino programs, and use Python scripts to assist in data analysis and optimization.

Data Acquisition and Processing

The Arduino collects data from the accelerometer and gyroscope, and combines it with a preset algorithm to determine whether the wearer has experienced a fall. The algorithm judges whether a fall event has occurred by calculating the changes in acceleration and angular velocity and checking if they exceed set thresholds.

Fall Detection Algorithm

The core of the fall detection algorithm is to identify fall events through changes in acceleration and angular velocity data. The specific criterion is: if the acceleration exceeds a set threshold, it indicates that the wearer has experienced sudden and vigorous movement, possibly a fall; if the angular velocity exceeds a set threshold, it indicates that the wearer has undergone rotation or tilting, possibly a fall. The advantage of this algorithm is its simplicity and efficiency, enabling real-time detection of fall behavior.

Optimization and Challenges

Optimization: The data sampling rate used in the algorithm is high to ensure real-time performance. Additionally, by continuously optimizing the thresholds for acceleration and angular velocity, the accuracy of fall detection can be improved.

Challenges: Different wearers may fall in different ways and with varying degrees of intensity. Setting reasonable thresholds to avoid false positives or missed detections remains an area that needs further optimization in this project.

EXPERIMENTAL PROCESS AND EXPERIMENTAL DATA

Project members established a right-hand coordinate system with the waist as the origin, considering the angular changes around the x, y, and z axes as the degrees of forward bending, lateral bending, and rotation, respectively. By calculating the changes in acceleration and angular velocity based on the numerical changes in the marker point coordinates, they determined whether a fall had occurred. According to the survey, different levels of intensity in behavior exhibited corresponding variations in the marker point coordinate changes. When team members performed daily activities, the changes in marker points were relatively small; when the experimenters simulated the process of falling, the changes in marker points were significantly larger. The observed data is shown in Figure 8.

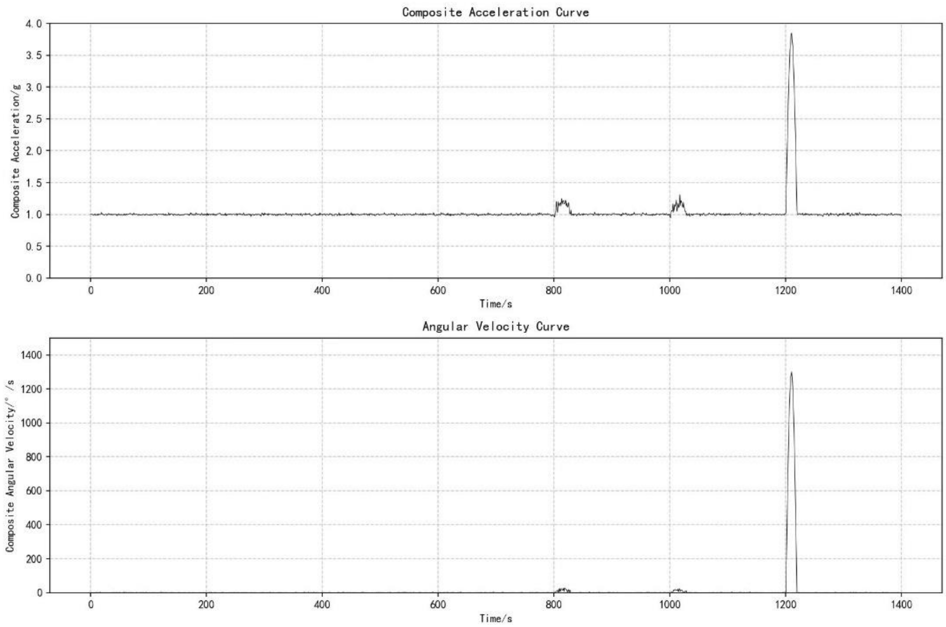

Figure 8. Coordinate change curve of marker points during daily activities

From the coordinate change curve of marker points in Figure 8, we can conclude that static and dynamic behaviors can be distinguished based on the magnitude of acceleration changes and angular velocity amplitudes according to the intensity of the behavior. When project members simulated falling behaviors, the acceleration changes and angular velocity amplitudes were significantly different from those during walking and sitting, characterized by large amplitudes, high frequencies, and rapid changes. Furthermore, based on the coordinate change curve of marker points during daily activities shown in Figure 8, team members conducted numerous fall simulation experiments, collected and summarized data samples of marker point acceleration and angular velocity amplitudes for each group for analysis, and determined the range of acceleration changes during falls. After processing by the algorithm, this data was stored in a database. When the detection system is in operation, the data transmitted back by the sensors is compared with the existing data in the database to determine whether a fall has occurred. Experiments have shown that the product has a high fall detection rate, and the airbag can effectively deploy when a fall occurs, reducing the injury from the fall.

FUTURE PROSPECTS

Although this project has initially realized the basic functions of an anti-fall device for the elderly, there are still many areas that can be optimized. For example, in terms of sensor selection, higher-precision sensors can be used to improve data accuracy; in terms of algorithms, more machine learning methods can be introduced to enhance the system's ability to recognize fall events. Furthermore, with the development of artificial intelligence technology, we can also consider integrating more intelligent functions into the device, such as real-time health monitoring of the wearer and classification of fall events.

CONCLUSION

This paper proposes a design scheme for fall detection for the elderly. In terms of hardware design, a triaxial accelerometer and a biaxial gyroscope are used to detect acceleration and its changes in scenarios such as tilting, movement, vibration, and impact force. Additionally, a Kalman filter is employed to reduce noise interference and improve detection accuracy. In terms of the fall detection algorithm, a threshold algorithm is adopted and a support vector machine model is established to enhance the accuracy of fall detection. Furthermore, a location data module is incorporated to promptly send the location information of the elderly person's fall to family members and medical institutions, reducing rescue time and mitigating the harm caused by falls. Experimental results demonstrate that this design can accurately distinguish between daily activities and fall events, and can deploy the airbag within 1 second of detecting a fall. This design provides a new research approach for the development of fall detection products for the elderly and represents a beneficial exploration in promoting the development of the elderly smart healthcare industry against the backdrop of an aging society.

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