PRIVACY-PROTECTED ELDERLY MONITORING SYSTEM USING WI-FI AND WEARABLE SENSORS

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1 Introduction

1.1 Problem

China is undergoing a significant demographic transformation entering an aging society. Nearly a third population will be over 60 years old by 2050 as projected by "National Development Bulletin on Ageing 2020,". Already, over 264 million Chinese citizens are aged 60 and above, making up approximately 18.7% of the nation's total population. [1] This demographic shift has led to an increased demand for elderly care services, placing Elderly Care Centers at the forefront of providing essential care and safety for this vulnerable group. Yet, these centers face substantial challenges in monitoring and responding to emergencies, such as falls or medical crises, without compromising the privacy and dignity of the elderly, as traditional methods of monitoring the elderly, such as hiring professional caregivers, have the main disadvantage of high manpower costs and cannot be extended to most elderly institutions. On the other hand, monitoring with a caregiver or visual recognition program reduces costs, but the demand for surveillance equipment undoubtedly violates the privacy of the elderly to a certain extent. Considering the harm to the psychological health of the elderly, the market urgently needs a monitoring program that can solve the above issues. [2]

A survey among Elderly Care Centers in China revealed a significant lack of advanced mechanisms for detecting emergencies while preserving privacy.[3] This inadequacy in care provision highlights an urgent need for innovative solutions that balance efficient emergency detection with the preservation of privacy and dignity. [4] Developing such systems is essential not only for enhancing elderly care but also for adapting to China's changing demographic landscape, making it imperative to invest in technologies that ensure safety and respect for the elderly simultaneously.[5]

1.2 Solution

To bridge this gap, we propose an Emergency Detection System specifically designed for elderly individuals. This system combines two innovative components to ensure both efficacy and privacy. The first component is Wi-Fi Emergency System: Utilizing advanced signal processing and deep learning techniques, this system interprets Wi-Fi signal disruptions caused by human movement within its coverage area. By analyzing these disruptions, the system can identify unusual patterns indicative of falls or other emergencies without the need for visual surveillance, thereby maintaining privacy. [3]

The second component is Wearable Devices that complements the Wi-Fi Emergency System. These devices are equipped with motion and health sensors. They are designed to be lightweight, unobtrusive, and capable of providing real-time data on the wearer's physical state. In the event of an abnormality, the device can trigger an immediate alert to caregivers for prompt response.

1.3 Visual Aid

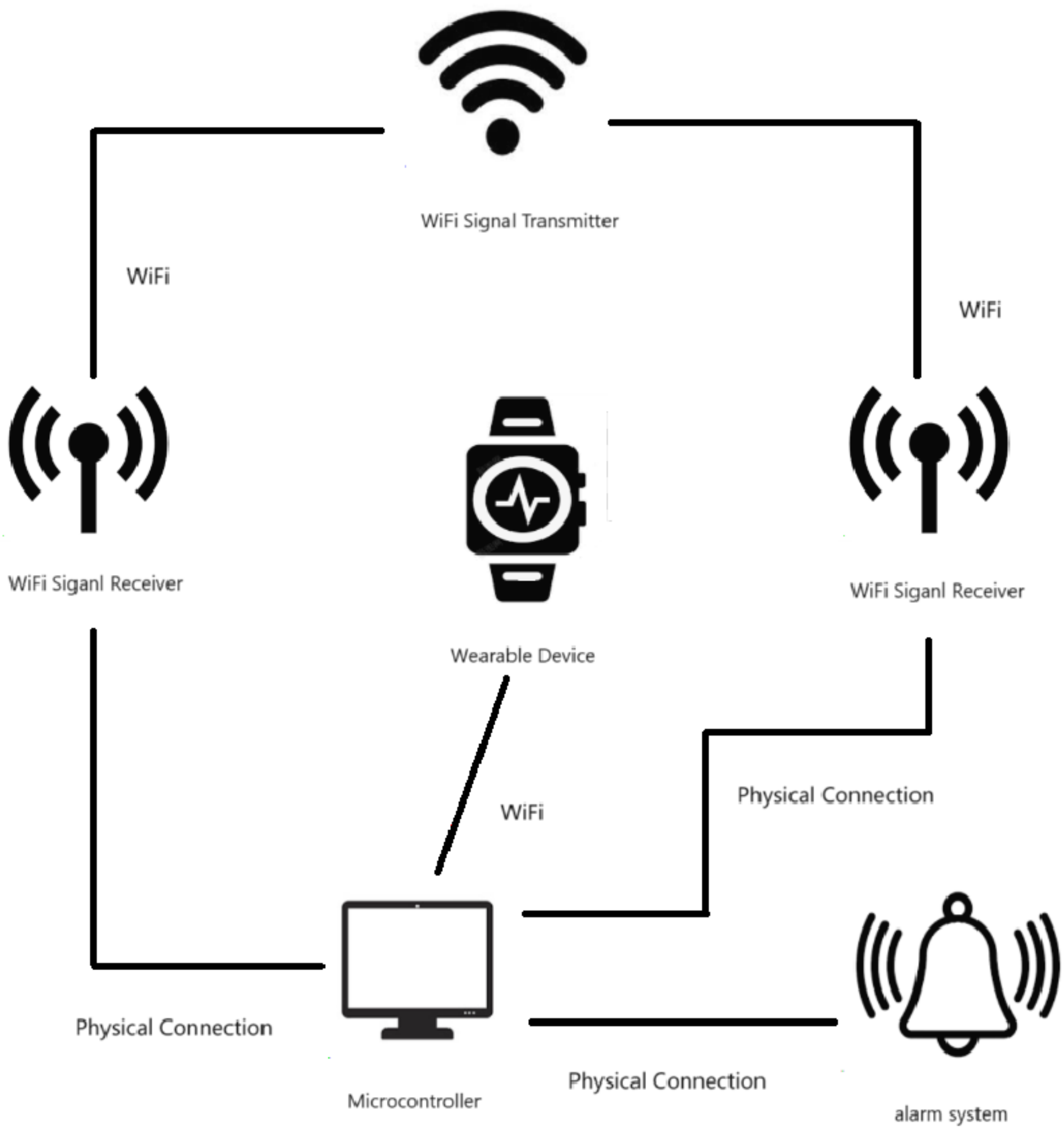

Figure 1: Visual Aid

1.4 High-level Requirements Lists

- For the recognition of the action of falling, the correct rate should be 100%, the probability of false alarms should be maintained at less than 20%, and the probability of miss should be maintained at least at less than 5% and 0 miss should be the target.
- The complete system should be able to operate in a 20 square meter scenario and maintain above recognition accuracy. Real-time signal monitoring should be maintained within this area
- The system alarm should be triggered within 500 ms after the falling action.

2 Design

2.1 Block Diagram

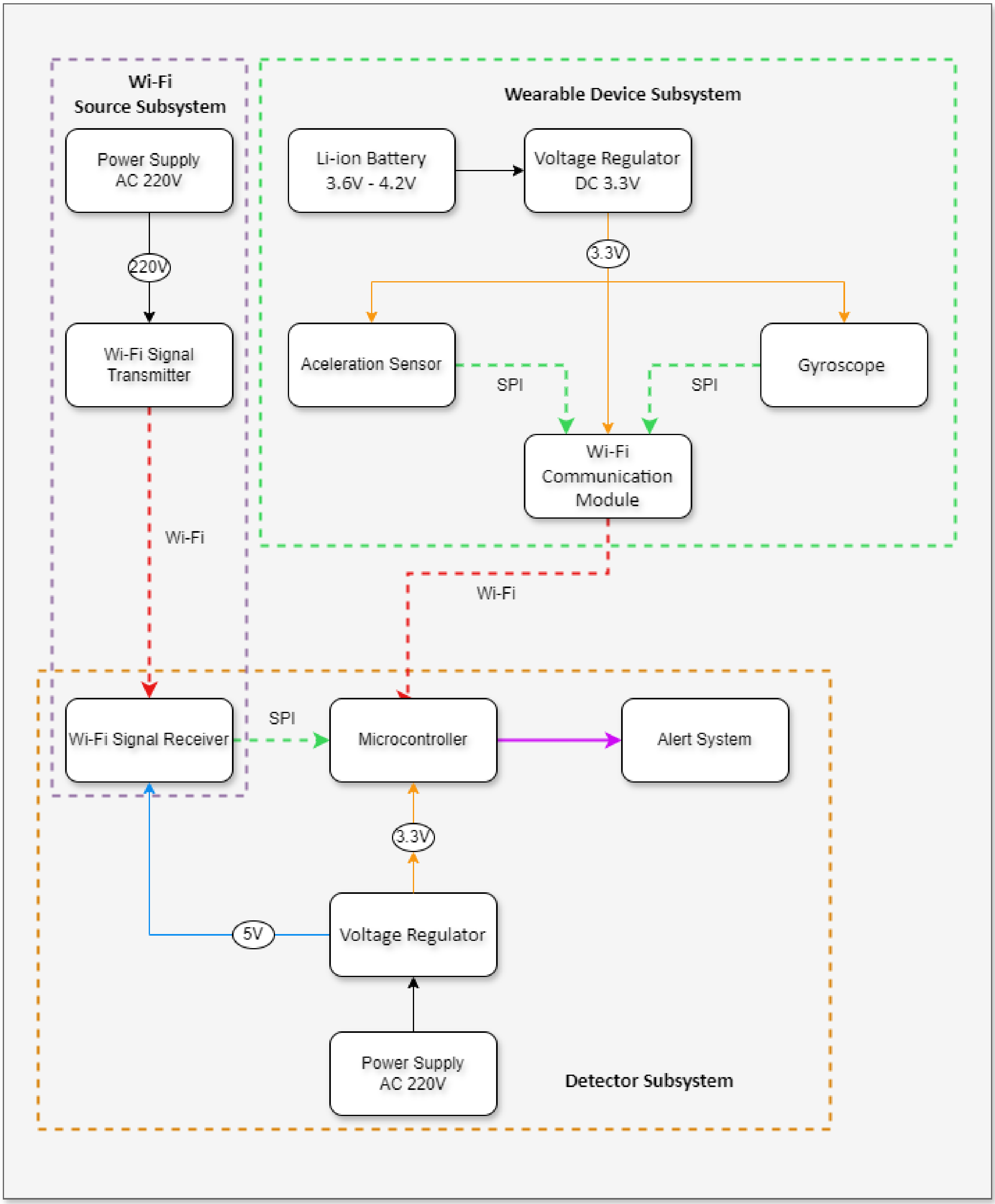

Figure 2: Block Diagram

2.2 Physical Design

2.3 Subsystem Overview

The Wi-Fi Source Subsystem will be a high-performance Wi-Fi router capable of dual-band signaling (2.4GHz and 5GHz), providing extensive coverage and penetration through various obstacles commonly found in residential settings. It should be capable of sustaining multiple device connections simultaneously without degradation of service quality. The router will have high-gain antennas to ensure the signal's strength is maintained even at the edges of the coverage area. The Wi-Fi signal will be received by the Detector Subsystem and used to determine the current movement of the tester.

The Wearable Device Subsystem is designed to collect acceleration as well as angle information while being worn on the tester's wrist and send it to the software processing section. The subsystem needs to consist of at least one acceleration sensor module and one gyroscope module to collect enough information. The information is sent to the software processing section via a transmission module. The entire subsystem should be powered by a separate power supply module that can provide 3-5V voltage. Similarly, the acceleration and angular data collected by the sensors in three dimensions will be received by the Detector Subsystem and used to determine the current movement of the tester.

The Detector Subsystem is a standalone module with its own dedicated casing, designed to be lightweight and compact, potentially the size of a small router or a large smartphone to be placed within the living space of the elderly person. It requires a stable power source, typically 5V supplied via a USB connection or wall adapter, and must have an internal voltage regulator to provide a clean 3.3V power supply for its internal electronics, with at least 500mA current capacity to support its operation.

The core of this subsystem is a high-performance microcontroller or a microprocessor with a fast clock speed, sufficient to process data from both the wearable sensors and the Wi-Fi signal strength information. It should possess robust communication interfaces like SPI and I2C to interface with the Wi-Fi module and possibly additional UART interfaces for debugging and future expansions.

The Wi-Fi module should be capable of operating in dual-band (2.4GHz and 5GHz) to ensure comprehensive coverage and the ability to analyze signal strength with a high degree of accuracy. The SPI or UART interface with the microcontroller must support high data rate transfer to prevent any data bottleneck.

Moreover, the Detector Subsystem should feature onboard memory (RAM and flash) to log events and store the necessary analysis algorithms, ensuring that a transient loss in connectivity does not result in data loss. The received Wi-Fi signal and sensor data will be used in this sub-system to determine the tester's movements and cross validate for improved accuracy.

2.4 Wi-Fi Source Subsystem

In the realm of behavior recognition using Wi-Fi signals, the precision of data collection heavily depends on the capabilities of the Wi-Fi equipment employed. The following outlines the detailed requirements and verification processes for selecting Wi-Fi devices aimed at gathering data compatible with specific datasets, including UT-HAR, NTU-HAR, and Widar. These datasets have distinct characteristics in terms of frequency bands, bandwidth, subcarrier numbers, and environmental adaptability, necessitating a careful selection of Wi-Fi hardware to ensure the collected data's accuracy and reliability.

UT-HAR and Widar: These datasets demand devices that operate on a 5GHz band, with a focus on capturing data from 30 subcarriers. This requirement ensures the collection of fine-grained Wi-Fi Channel State Information (CSI) necessary for accurate behavior analysis.

NTU-HAR: This dataset ups the ante with a need for Wi-Fi devices capable of operating with 40MHz bandwidth under the 5GHz band, accommodating up to 114 subcarriers. Such specifications are critical for enabling large-scale, lightweight Wi-Fi sensing via CSI compression, allowing for efficient data processing and analysis.

Requirements	**Verification**
1. Frequency and Channel Requirements: Requirement: The Wi-Fi device must operate on the 5GHz frequency band to align with the operational frequency Quantitative Detail: The device should support configuration for at least 30 subcarriers, essential for compatibility with UT-HAR and Widar datasets. For adherence to NTU-HAR requirements, the capability to handle up to 114 subcarriers is necessary. Moreover, specific channel operation, such as channel 165 (5.825 GHz) as indicated for the Widar dataset, must be configurable. 2. Bandwidth Requirements: Requirement: Essential bandwidth configuration of 40MHz under the 5GHz frequency band to meet the specifications listed for the NTU-HAR dataset. Quantitative Detail: The device must provide an option to select and operate under a 40MHz bandwidth, ensuring the collection and analysis of Wi-Fi signals are conducted under precise and stipulated conditions. 3. AP Support: Requirement: The system should integrate seamlessly with at least two TP-Link N750 APs or equivalent models to establish a network environment as per the NTU-HAR dataset's setup. Quantitative Detail: Ensure the Wi-Fi device's compatibility with specific Access Point (AP) models and support simultaneous connections,	1. Frequency and Channel Verification: Equipment: Utilize a spectrum analyzer or Software Defined Radio (SDR) for direct measurement. Procedure: Configure the device to operate on the specified channels and frequencies. Measure and record the frequency and subcarrier distribution using the SDR or spectrum analyzer. Result Presentation: Graphical representation of the frequency spectrum and subcarrier allocation. 2. Bandwidth Verification: Equipment: Network analysis tools (e.g., Wireshark). Procedure: Set the device to the 40MHz bandwidth mode. Use network analysis tools to capture and analyze the Wi-Fi traffic, verifying the operational bandwidth. Result Presentation: Summary report detailing bandwidth utilization and configuration adherence. 3. AP Support Verification: Equipment: TP-Link N750 APs or equivalent, multiple Wi-Fi enabled devices. Procedure: Connect the Wi-Fi device to the APs set in the required configuration. Test the stability and throughput with multiple connected devices under various conditions.

facilitating a robust network framework for data collection. 4. Hardware Interface and Compatibility: Requirement: Provision of comprehensive hardware interface options, including USB, Ethernet, or Wi-Fi, to ensure seamless connectivity with a variety of operating systems (Windows, Linux, macOS) and programming environments. Quantitative Detail: Define clear compatibility metrics and interface standards (e.g., USB 3.0, Ethernet 10/100/1000 Mbps) to facilitate straightforward integration into the existing data collection and analysis infrastructure. 5. Environmental Adaptability: Requirement: The Wi-Fi device must exhibit high performance and reliability across diverse environments – indoor, outdoor, varying temperatures, and humidity levels. Quantitative Detail: Establish operational parameters, such as operating temperature range (-10°C to 50°C) and humidity tolerance (10% to 90% non-condensing), ensuring device resilience and consistent data collection quality across environments. 6. Data Precision and Stability: Requirement: Achieve high precision and stability in data collection across different environmental and operational conditions, crucial for accurate behavior recognition and analysis. Quantitative Detail: Set specific performance metrics, like a maximum data variance threshold of ±5% under predefined conditions, to ensure reliability and accuracy in data capture and processing.	Result Presentation: Performance metrics report, including throughput rates, connection stability, and device compatibility confirmation. 4. Hardware Interface and Compatibility Verification: Equipment: Various computing platforms with different OS. Procedure: Connect the WiFi device using its provided interfaces to the computing platforms. Test compatibility through data transmission tasks. Result Presentation: Compatibility matrix and performance analysis across different platforms. 5. Environmental Adaptability Verification: Equipment: Environmental test chamber or equivalent setup. Procedure: Operate the device within an environmental test chamber set to varying conditions. Monitor performance and data integrity. Result Presentation: A detailed report highlighting performance metrics under each tested condition. 6. Data Precision and Stability Verification: Equipment: Standardized test environments and data analysis software. Procedure: Collect data using the Wi-Fi device under controlled conditions. Analyze the data for precision and stability metrics. Result Presentation: Statistical analysis report, including variance and error rates, with comparisons against predefined performance thresholds.

2.5 Wearable Device Subsystem Requirement

2.5.1 Sensor Module

The sensor module should be able to measure and output three-way acceleration and three-way rotational angular velocity data with a certain degree of accuracy under the power supply module, and transmit the data in real time in a certain format to the Wi-Fi data transmission module, which means that the module should at least contain acceleration sensors and gyroscopes to complete the measurement of the data, and should support the I2C or TCP protocols to transmit the data to the corresponding module. Based on the above requirements, we believe that the IMU sensor (MCU6050) can meet the needs.

Requirements	Verification
Accelerometers should have a range of at least ±2g, gyroscopes should have a range of at least ±360°	We will use the MCU6050 IMU sensor and test it, while it is fixed on the wrist and other parts of the test personnel in the normal adult male standard larger test movements and real-time data recording to determine the required maximum range of range maintains a more stable condition.

2.5.3 Power Module

The power module will be used to power the sensor module and the Wi-Fi data transmission module. Considering the size requirement of wearable devices: no more than twice the size of a common watch and the portability requirement: as little as possible obstruction of the test movement while wearing it, we ruled out the option of powering it through a power cord and initially planned that the power module should contain a power supply module that acts as a voltage regulator that converts an input voltage of 3.7V-5V into an output voltage of about 3.3V. The power supply module should contain a voltage regulator that converts the 3.7V-5V input voltage into an output voltage of about 3.3V for the sensor module and about 5V for the Wi-Fi data transmission module. The power supply will be powered by a battery pack that holds up to two common Li-ion 5 or 7 batteries, which we expect to be able to provide an output voltage of at least 6V at an expected output voltage of 7.4V and an input current of up to 1A to meet the input requirements of the power supply module.

Requirements	Verification
According to the need to output about 3.3V (3V-3.6V) and 5V (4.7V-5.3V) more stable voltage. Output current no higher than 1A.	A multimeter is used to measure the battery and power supply module before official operation under simulated real load conditions, and the overall circuit is regularly monitored during the test to ensure that the power supply module maintains a more stable condition.

2.5.4 Wi-Fi Communication Module

The Wi-Fi data transmission module, powered by the power supply module, will receive the data transmitted from the sensor module in real time and perform operations such as formatting, after which the module will send the processed data to the processor subsystem. This requires that the module should support common Wi-Fi protocols such as IEEE 802.11b/g/n Wi-Fi protocol and have a suitable processor chip to perform the potentially required data processing operations. Based on the above requirements, we believe that the ESP8266 wireless Wi-Fi module can meet our needs.

Requirements	Verification
1. Delays due to data processing operations should be less than 200 ms. 2. The packet loss rate for data transmission over the Wi-Fi protocol should be no more than 1 per cent.	1. After writing the data processing code on the finished processor, we try to calculate the time required using the timing-related libraries in the environment, and if the results do not meet the requirements, we evaluate the parts that must run on that processor and transfer the code that can be moved to the processor part to reduce the transfer latency 2. After the subsystem docking test, we will conduct a transmission stability test of no less than 2 hours, where the tester wears a wearable device to move around the room and simulate a normal life situation, and the processor subsystem part will be added in advance to monitor the packet loss rate and stability and alert the police if it exceeds the stipulated limits.

2.6 Detector Subsystem Requirement

2.6.1 Wi-Fi Signal Processing Module

CSI Data Acquisition: Continuous monitoring and collection of Channel State Information (CSI) from Wi-Fi devices provide the raw data necessary for analysis. The system utilizes the fine-grained temporal fluctuations in CSI caused by the respiratory movement of a person's chest and abdomen to detect breathing patterns.

Signal Processing and Filtering: The raw CSI data is processed to filter out noise and irrelevant information. Techniques such as band-pass filtering are applied to isolate the frequency bands that are most affected by human respiration, typically within the 0.1 Hz to 0.5 Hz range, which corresponds to normal human breathing rates.

Multi-Domain Analysis: By employing a multi-domain analysis that includes both Doppler shifts (frequency domain) and Angle of Arrival (AoA) (spatial domain), the system can construct a two-dimensional Doppler AoA map (DAM). This map enables the differentiation of respiration signals from multiple individuals in the monitored environment.

Super Resolution Doppler AoA Map Construction: To enhance the resolution of the DAM and improve the accuracy of respiration rate estimation, a super-resolution technique is implemented. This approach is crucial for accurately clustering and identifying individual breathing patterns, especially when the number of Wi-Fi antennas is limited.

Clustering and Respiration Rate Estimation: The peaks within the DAM represent potential respiration signals. A clustering algorithm, such as DBSCAN, groups these peaks based on their proximity, each cluster corresponding to an individual's respiration signal. The centroid of each cluster is used to estimate the respiration rate accurately.

Requirements	Verification
Processor for Signal Processing: A Raspberry Pi 4 or a computer with sufficient processing power to handle real-time signal processing and analysis. Implementation Steps: Signal Acquisition: Set up the Wi-Fi router in a central location within the environment to ensure broad coverage. Use software tools like Linux 802.11n CSI Tool on the receiver to capture CSI data from the Wi-Fi signals. Signal Preprocessing: Implement a high-pass filter using Python or MATLAB on the received CSI data. This can be done by designing a Butterworth filter with scipy.signal.butter in Python, specifying the high-pass frequency cutoff according to the expected minimum movement frequency of humans. Feature Extraction: Write scripts to calculate amplitude variance, phase change rate, and Doppler shift frequencies from the preprocessed CSI data. Use numpy and scipy libraries in Python for efficient computation	Conduct experiments simulating various human movements within the coverage area of the Wi-Fi signals. Capture the CSI data and use a spectrum analyzer software or a MATLAB tool to analyze the frequency and phase accuracy of the processed signals.

2.6.2 Motion Sensor Signal Processing Module

Our algorithm employs machine learning techniques for fall detection by analyzing real-world fall data collected from wearable sensors. The dataset used, known as the FARSEEING database, is the most comprehensive real-world fall dataset to date and consists of acceleration signals recorded by inertial sensors placed on the waist of subjects at risk of falling. The dataset consists of 143 falls by subjects in a variety of environments and conditions, providing a rich basis for developing and testing fall detection algorithms.

To develop the fall detection algorithm, our algorithm pays special attention to features inspired by the multiphase fall model. The model takes into account the different phases of a fall, including pre-impact, impact, and post-impact phases, which allows for a more detailed analysis of the fall features. Acceleration data from the sensors were processed to identify these phases and extract relevant features such as lower peaks, upper peaks, wavelet-based coefficients, post-impact periodicity, and post-impact standard deviation.

Machine learning models were then trained and tested on the processed dataset to accurately recognize falls. The study tried various classifiers including Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, k-Nearest Neighbor (KNN) and Random Forest to compare their effectiveness in fall detection. Among them, the SVM, which uses a radial basis function kernel and is trained on the features of a multiphase fall model, is the most promising. It has a sensitivity higher than 80%, a false alarm rate of 0.56 per hour, and an F-measure of 64.6%, which indicates that it performs well in detecting real-world falls with a very low false alarm rate.

The approach to training and testing these algorithms is comprehensive, with a focus on cross-validation to avoid overfitting and to ensure that the models generalize well to unseen data. Our algorithms use a subject-based five-fold cross-validation strategy to ensure that data from a single subject is limited to a single fold. This approach helps reduce the risk of the model learning subject-specific features rather than general fall patterns.

Requirements	Verification
Noise Reduction: Implement a low-pass filter in the data processing script to remove unwanted high-frequency noise from the sensor data. The filter can be implemented similarly to the Wi-Fi signal preprocessing step. Feature Identification: Develop algorithms to identify features indicative of a fall from the motion sensor data, focusing on parameters such as peak acceleration and impact duration.	Perform controlled drop tests with dummies equipped with motion sensors to simulate falls. Record the sensor data and analyze it to verify the accuracy of feature identification and the effectiveness of noise reduction.

2.6.3 Predicting Falls: Ensemble Method Module

This module requires Central Processing Unit: A computer or a high-performance computing device like NVIDIA Jetson Nano for running complex machine learning models. and Software Tools: Python programming environment with libraries such as scikit-learn for machine learning, numpy for numerical computations, and pandas for data manipulation.

Requirements	Verification
Model Training: Preprocess the collected Wi-Fi and motion sensor data and split it into training and testing sets. Use scikit-learn to train SVM models on the Wi-Fi data and Random Forest models on the motion sensor data. Optimize the models using grid search for hyperparameters. Ensemble Integration: Implement a weighted voting system in Python where each model's vote is weighted by its accuracy on a validation set. The	Test the ensemble method on a diverse dataset that includes both fall and non-fall scenarios not seen during training. Use k-fold cross-validation to ensure the model's generalization capability and document the system's performance in terms of sensitivity, specificity, and false alarm rate.

ensemble method should output a fall detection result based on the combined votes. Fall Detection: Integrate the ensemble method into the system's central processing unit. The system should analyze incoming data in real-time and trigger an alert if a fall is detected.	

2.6.4 Alert System

This module requires Bluetooth Module: A Bluetooth Low Energy (BLE) module like the HC-05, connected to the central processing unit. And Emergency Notification Device: A smartphone or a device capable of receiving Bluetooth notifications. Alert Configuration: Program the central processing unit to send a wireless signal to the Bluetooth module when a fall is detected by the ensemble method.

Notification: Pair the Bluetooth module with the emergency notification device. Develop an application or use existing services on the device to receive alerts and notify caregivers or emergency services.

By meticulously implementing these steps and adhering to the specified requirements, developers can create a robust and reliable emergency detection system capable of identifying falls in real-time. This system leverages the complementary strengths of Wi-Fi signal processing, motion sensor data, and advanced machine learning techniques to provide timely alerts and potentially lifesaving interventions for the elderly or individuals at risk of falls. Here's how to proceed with the implementation, focusing on integrating the alert system and ensuring the system's operational readiness.

Requirements	Verification
Programming the Microcontroller: Write a script for the microcontroller that sends a predefined message to the Bluetooth module whenever the ensemble method detects a fall. This message can include details like the time of the fall and the location if known. Developing the Notification App: Create a simple mobile application that listens for Bluetooth messages from the paired Bluetooth module. Upon receiving a message, the app should display a notification, sound an alarm, or even send an SMS to a predefined contact list, depending on the severity of the alert and user preferences.	Conduct extensive testing to ensure the Bluetooth module reliably connects to the notification device and that the alert system activates correctly under fall conditions. Simulate various environments and distances to ensure the system's robustness.

2.7 Tolerance Analysis

2.7.1 Wi-Fi Source Subsystem Analysis

The subsystem must sustain a consistent signal strength with a variance not exceeding ±2 dBm to ensure the Detector Subsystem can accurately assess Wi-Fi signal strength. It should also feature adaptive channel selection to avoid congestion and interference with other household devices, maintaining a signal-to-noise ratio (SNR) above 25 dB for optimal performance.

Security measures will be tested to ensure compliance with current standards, and the UPS will undergo rigorous testing to validate its 24-hour minimum operational capacity.

As the risk of this subsystem ceasing to function due to equipment damage could result in a complete loss of the Wi-Fi signal, it was considered that this tolerance could be consolidated into the processor and alarm system to be handled centrally.

2.7.2 Wearable Device Subsystem Analysis

The accuracy of the data collected and the miniaturization and robustness of the device structure are priorities for the wearable device subsystem. Given that the errors of existing sensors are negligible compared to the magnitude of the test movements, the tolerance analysis will focus on ensuring that the wearable device minimizes the impact on daily movements when worn on the wrist. Additionally, it must remain fixed and maintain normal function during more amplified test movements. During the initial testing of the wearable, the body will be confined and secured in a closed box no larger than twice the size of a normal watch. The device is then worn by a tester in a series of larger test motions to assess its size and robustness.

2.7.3 Detector Subsystem Analysis

For the Detector Subsystem, accurate fall detection is critical and dependent on the precision and reliability of the received data. The tolerance analysis will focus on ensuring the processing latency and the integrity of the data. For instance, the subsystem must be able to handle potential data transmission errors, which can be mitigated through cyclic redundancy checks (CRC) or similar error-detection schemes.

The voltage regulation must have a tolerance of ±5%, ensuring the microcontroller and associated electronics function optimally even with fluctuations in power supply. The Wi-Fi module's sensitivity should be high enough to discern signal strength variations corresponding to different locations within the home, with a minimum detectable signal change of -3 dBm to ensure spatial resolution.

To ensure robust operation, the subsystem's design must include electromagnetic compatibility (EMC) considerations to minimize the impact of noise on the signal integrity. The EMC tests should verify that the subsystem is compliant with regulatory standards, indicating a high tolerance to potential interference.

Through rigorous testing and simulation, we can establish the operational tolerances for each component within the Detector Subsystem to ensure reliable and accurate performance in the context of elderly fall detection.

3 Cost and Schedule

2.1 Cost

Our fixed development cost is ￥40/hour for four people for 10 hours per week.[7] We believe that

Within the semester (10 weeks), we will have completed all the final design, so the estimate of our labor cost is:

$$\frac{￥40}{hr} \times \frac{10hr}{wk} \times 10wk \times 4 = ￥16000$$

Our parts and manufacturing prototype costs are estimate as ￥749.64 each:

Parts	Cost (Prototype)
Breadboards, Dupont cables, data cables, etc. (Taobao; generic)	￥20
IMU sensor module (Taobao; MPU6050)	￥10.4
Wi-Fi module (Taobao; ESP8266)	￥36.5
Battery box and power supply module (Taobao; 18650/RunesKee)	￥26.24
Wi-Fi router (Taobao; TP-LINK AX1500)	￥159
Microcontroller (Taobao; Raspberry PI 5)	￥479
Bluetooth module (Taobao; HC-02)	￥18.5

2.2 Schedule

Week	Jincheng Zhou	Junyue Jiang	Pu Lin	Zizhao Cao
3/4/24	Meet with the Sponsor to identify the project topic and review relevant papers.	Meet with the Sponsor to identify the project topic and review relevant papers.	Meet with the Sponsor to identify the project topic and review relevant papers.	Meet with the Sponsor to identify the project topic and review relevant papers.
3/11/24	Confirm the overall idea of the project and delineate the subsystems for which each is responsible. Responsible for the algorithm part	Responsible for receiving control and alarm components	Responsible for the Wi-Fi signal transmitter section	Responsible for wearable device subsystems
3/18/24	Review of relevant	Review of relevant	Review of relevant	Review of relevant

	literature to identify algorithm implementations with required environments and datasets	literature and budget to determine required component types	literature and budget to determine required component types	literature and budget to determine required component types
3/25/24	Perform the required model training	Perform building the circuit for the processor section	Perform the Wi-Fi router portion of the deployment	Perform building the circuit for the wearable device part
4/1/24	Finish the required model training	Finish building the circuit for the processor section	Finish the Wi-Fi router portion of the deployment	Finish building the circuit for the wearable device part
4/8/24	Testing the effectiveness of model training	Test the normal functioning of the processor section for compliance	Test the Wi-Fi router to see if it delivers compliant data	Test wearable device circuits for proper functioning and providing correct data
4/15/24	Accuracy of the test model on the data obtained from the measurements	Test that the model can be successfully deployed on the processor and that it runs as fast as required	Test that the data provided by the Wi-Fi router meets the model requirements	Test that the wearable part of the device measures and correctly transmits compliant data
4/22/24	Optimize changes in response to changes suggested by TA and Sponsor	Optimize changes in response to changes suggested by TA and Sponsor	Optimize changes in response to changes suggested by TA and Sponsor	Optimize changes in response to changes suggested by TA and Sponsor
4/29/24	In conjunction with the sub-systems, conduct overall deployment tests to test the accuracy of judgement on pre-programmed actions	In conjunction with the sub-systems, conduct overall deployment tests to test the accuracy of judgement on pre-programmed actions	In conjunction with the sub-systems, conduct overall deployment tests to test the accuracy of judgement on pre-programmed actions	In conjunction with the sub-systems, conduct overall deployment tests to test the accuracy of judgement on pre-programmed actions
5/6/24	Preparing Final Demo, Starting Final Report	Preparing Final Demo, Starting Final Report	Preparing Final Demo, Starting Final Report	Preparing Final Demo, Starting Final Report

4 Ethics & Safety

Our Emergency Detection System for Elderly Care is designed with a strong commitment to ethical standards and safety, drawing guidance from the IEEE Code of Ethics and the ACM Code of Ethics. Key ethical considerations include the protection of privacy and confidentiality, as outlined in the ACM Code, and the imperative to avoid harm, a fundamental aspect of the IEEE Code.[6] We prioritize these ethical principles by implementing data encryption, anonymization, and employing system designs that minimize the risk of false alarms and missed emergencies.

Proactive measures to avoid ethical breaches include regular reviews by an ethics board, comprehensive team training on ethical conduct, and strict data protection measures. Potential safety concerns, such as device malfunction and data breaches, will be mitigated through rigorous testing, the development of clear emergency response protocols, and advanced cybersecurity measures.

Our approach ensures that the Emergency Detection System not only enhances the safety and care of the elderly in care facilities but does so with utmost respect for their dignity and privacy, embodying the principles of ethical responsibility and safety compliance.

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