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Design of an Abnormal Behavior Monitoring System for Elderly Living Alone Indoors

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Abstract: Aiming at the prominent indoor safety hazards and the difficulty in timely detecting abnormal behaviors of elderly living alone against the backdrop of accelerating population aging, an abnormal behavior monitoring system for elderly living alone indoors, integrating multi-sensor technology and intelligent algorithms, is designed. The system adopts a four-layer architecture of "perception layer–processing layer–communication layer–application layer," integrating hardware modules for visual collection, environmental sensing, physiological monitoring, and posture perception, and realizing collaborative data processing through embedded processors and edge computing devices. At the algorithm level, it optimizes target detection, behavior classification, posture fusion, and multi-modal discrimination models to achieve real-time identification of risks such as falls, posture abnormalities, and physiological abnormalities. The communication link combines short-range and long-range technologies, coupled with a multi-terminal early warning mechanism to ensure efficient transmission of abnormal information. The system balances detection accuracy, privacy protection, and user acceptance, providing technical support for the home safety of elderly living alone. The relevant design ideas can serve as a reference for the development of similar intelligent elderly care equipment.

Keywords: Abnormal behavior monitoring; Multi-sensor fusion; Multi-modal early warning; Intelligent elderly care

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1. Introduction

With the acceleration of China's population aging process, data from the Seventh National Population Census shows that the proportion of the population aged 60 and above reaches 18.70%, and the proportion of the population aged 65 and above is 13.50%. Meanwhile, the miniaturization of family structures has led to an average annual increase of 8.2% in the number of elderly living alone [1]. In the daily life of elderly living alone, abnormal behaviors such as falls, gait abnormalities, and sudden changes in physiological parameters are often accompanied by serious safety risks. Statistics from the World Health Organization indicate that the average annual fall rate of the elderly over 65 years old is 28.7%, and falls have become the primary cause of accidental injury and medical treatment for this group. Moreover, due to the lack of immediate care in the living alone state, the disability rate of the elderly who do not receive timely treatment after falls is 37% higher than that of non-living alone elderly [2]. In addition, hidden behavioral changes of the elderly, such as gait abnormalities and prolonged immobility, often indicate health crises such as cardio-cerebrovascular diseases, which urgently require intelligent technologies to achieve “early detection and early intervention” [3].

Existing indoor abnormal behavior monitoring technologies for the elderly are mainly divided into two categories: non-visual detection and visual detection. Non-visual detection technology relies on wearable sensors or environmentally deployed sensors. Although it can protect user privacy, wearable devices have discomfort (the actual acceptance rate of the elderly is only 62%), and the deployment cost of environmental sensors is relatively high. Visual detection technology is based on deep learning algorithms such as YOLO and OpenPose, which do not require contact deployment and have a wide detection range. However, it is easily affected by lighting conditions (the accuracy can drop to 75% in low-light environments) and has the risk of privacy leakage [4]. Current research mostly focuses on the optimization of a single technical path, such as only improving target detection algorithms or data processing methods of a single sensor, lacking the full-link integration of “hardware selection–algorithm design–communication architecture–application implementation,” and there is still room for improvement in multi-scenario adaptability and compatibility with actual home scenarios [5].

Based on the above problems, this paper designs an abnormal behavior monitoring system for elderly living alone indoors. The core goal is to balance detection accuracy, privacy protection, and user acceptance through the integration of multi-modal hardware and optimization of intelligent algorithms. In the system design process, priority is given to selecting low-power, low-cost, and easy-to-deploy hardware modules to avoid interfering with the daily life of the elderly; at the algorithm level, multi-model fusion is used to reduce the limitations of a single technical path; the communication and application layers adopt a “local-remote-cloud” collaborative architecture to ensure real-time transmission of abnormal information and convenient operation [6]. The following will elaborate on the design scheme in detail from two aspects: related technologies and hardware foundation, and overall system design, focusing on explaining the functional positioning, hardware selection basis, algorithm design ideas, and collaborative logic between modules of each level.

2. Related technologies and hardware foundation

2.1. Core algorithm technologies

The system algorithm design focuses on the goals of “high-precision recognition-low false positive rate-real-time response,” integrating four core technologies: target detection, behavior classification, posture fusion, and multi-modal discrimination. The design ideas and key functions of each technology are as follows:

The optimized YOLOv5s target detection algorithm is the core of visual monitoring. To address the problems of low accuracy and large model size of traditional YOLOv5s in low-light environments, two improvements are made: first, the standard Conv module in the backbone network is replaced with the GhostConv module. Through a lightweight structure of “basic convolution + linear transformation,” the number of parameters is reduced by 60% while ensuring the feature extraction capability, and the model inference speed is increased to 27 fps; second, the Coordinate Attention (CA) mechanism is embedded to enhance the feature extraction capability of human regions. Especially in low-light (5 lux) and partial occlusion scenarios, the human detection accuracy can be increased to over 92% [7]. At the same time, the algorithm combines the lightweight OpenPose model to extract 17 key human joints (including neck, hips, knees, ankles, etc.), and calculates features such as human aspect ratio, spine angle, and height ratio between head and ankles through joint coordinates to provide a basis for fall behavior discrimination.

The multi-modal data fusion discrimination algorithm is the core of the system's abnormal judgment, aiming to integrate the advantages of visual, pressure, and posture data. In the algorithm design, weights are assigned according to the detection performance of each modality in different scenarios: the weight of visual data (optimized YOLOv5s output) is 0.4, because it has significant advantages in large-scale behavior monitoring; the weight of pressure data (SVM classification result) is 0.3, benefiting from its high accuracy in short-range behavior discrimination; the weight of posture data (complementary filtering result) is 0.3, which can quickly respond to sudden changes in human posture.

2.2. Hardware selection and functional design

The system hardware design follows the principles of "low power consumption, low cost, easy deployment, and low interference," and is selected according to the "perception layer–processing layer–communication layer–application layer" levels. The functional positioning, selection basis, and collaborative logic with algorithms of hardware at each level are as follows:

As the source of data collection, the perception layer needs to achieve multi-dimensional coverage of "vision-environment-physiology-posture" and avoid interfering with the daily life of the elderly. The visual collection unit selects a Hikvision 2K infrared camera with a resolution of 2560×1440, a frame rate of 25 fps, and supports infrared fill light in the range of 0.1–10 m. It can be installed hidden in the corners of the bedroom and living room ceiling, which can not only ensure that the monitoring range covers key activity areas but also solve the problem of low-light environment detection through infrared fill light. The output video stream is directly used for target detection of the optimized YOLOv5s algorithm; the environmental sensing unit adopts a customized flexible pressure sensor array. After being embedded in the carpet, it is laid in fall-prone areas such as beside the bed and bathroom shower area, which can not only collect real-time human pressure distribution data but also not affect the normal walking of the elderly. The collected pressure matrix provides input for the SVM classification algorithm; the physiological monitoring unit includes a MAX30102 heart rate and blood oxygen sensor and a DS18B20 temperature sensor. The MAX30102 supports heart rate measurement of 30–240 beats per minute and blood oxygen measurement of 0–100% with an accuracy of ± 2%. The DS18B20 has a measurement range of -55°C–125°C and an accuracy of ± 0.5°C (-10°C–85°C). Both are integrated into the smart bracelet and communicate with the processor through the IIC interface to collect physiological parameters in a non-invasive manner. When the data exceeds the threshold of 35°C–38.5°C (body temperature) and 30–120 beats per minute (heart rate), the auxiliary early warning is directly triggered; the posture sensing unit adopts MPU6050 six-axis inertial sensor. It is also integrated into the smart bracelet, and the output acceleration and angular velocity data are used for the complementary filtering posture fusion algorithm.

The processing layer is responsible for data preprocessing and algorithm operation, and needs to balance local real-time processing and edge computing capabilities. The local processing core selects STM32F103C8T6 microcontroller, which is based on the ARM Cortex-M3 core, with a main frequency of 72 MHz, Flash capacity of 64 KB, and RAM capacity of 20 KB. It supports multiple communication interfaces (IIC, UART, SPI), and can realize pressure data denoising, physiological parameter threshold judgment, lightweight operation of SVM classification algorithm, and complementary filtering posture calculation, meeting the needs of local rapid data preprocessing; the edge computing device selects NVIDIA Jetson NX, which is equipped with 128-core Maxwell GPU and 6-core ARM Cortex-A57 CPU, with strong parallel computing capabilities. It is mainly used to deploy the optimized YOLOv5s model, process the video stream collected by the camera, and complete target detection and skeleton extraction, avoiding detection delays caused by insufficient computing power of the local microcontroller. The two realize data interaction through the UART interface, and the key data after local preprocessing (such as pressure features, posture angles) is uploaded to the edge device, which participates in multi-modal fusion discrimination collaboratively with the visual detection results.

The communication layer is responsible for data transmission at all levels, and needs to meet the requirements of "local short-range reliability–remote real-time upload." Short-range communication adopts TI CC2530 Zigbee module; long-range communication selects Air724UG 4G module; the positioning module adopts ATGM336H GPS/Beidou dual-mode module. It can obtain the real-time position information of the elderly, especially when a fall abnormality occurs, the positioning data is transmitted with the early warning instruction to assist the guardian in quick positioning.

The application layer provides data display and early warning functions for users, and needs to take into account both local and remote usage scenarios.

3. Overall system design

3.1. System architecture design

The system adopts a four-layer architecture of "perception layer–processing layer–communication layer–application layer." Each layer realizes data interaction and functional collaboration through standardized interfaces.

3.2. Core module design

3.2.1. Data acquisition and preprocessing module

This module is responsible for the collection, denoising, and feature extraction of multi-source data, providing high-quality data support for subsequent abnormal discrimination. The main functions implemented by the code are: (1) Visual fall discrimination; (2) Classification of stress behaviors; (3) Abnormal posture discrimination; (4) Identification of physiological abnormalities; (5) Multi-modal fusion judgment.

In the module design, visual data preprocessing eliminates environmental interference through scaling and normalization, pressure data highlights behavioral differences through filtering and feature extraction, physiological and posture data ensure measurement accuracy through calibration and verification, and all preprocessing operations balance real-time performance and lightweight, adapting to the computing power of the processing layer hardware [8].

3.2.2. Abnormal discrimination module

This module is the core decision-making unit of the system, integrating visual, pressure, and posture multi-modal data to achieve accurate discrimination of abnormal behaviors through multi-algorithm collaboration.

The main functions implemented by the code are: (1) Visual fall discrimination; (2) Pressure behavior classification; (3) Posture abnormality discrimination; (4) Physiological abnormality discrimination; (5) Multi-modal fusion judgment.

3.2.3. Communication and early warning module

This module is responsible for data transmission and multi-terminal early warning, ensuring real-time transmission of abnormal information through multi-path redundancy design. The main functions implemented by the code are:

(1) Data encapsulation; (2) Local communication and early warning (Zigbee); (3) Remote communication and early warning (4G+MQTT); (4) Communication confirmation and retransmission.

4. Summary of system design

The abnormal behavior monitoring system for elderly living alone indoors, designed in this paper, constructs a four-layer architecture of “perception-processing-communication-application” with the core design concept of “multi-modal fusion, low-interference deployment, and high-reliability early warning.” At the hardware level, it integrates four types of sensors: visual, environmental, physiological, and posture, selects a combination of low-power, easy-to-deploy modules, and reduces interference with the daily life of the elderly through hidden installation and flexible design; at the algorithm level, it optimizes target detection, behavior classification, posture fusion, and multi-modal discrimination models, solving the limitations of a single technical path and improving the accuracy of abnormal recognition in complex environments; at the communication and application level, it combines short-range and long-range technologies, coupled with local and remote multi-terminal early warning to ensure efficient transmission of abnormal information.

The design highlights of the system are reflected in three aspects: first, multi-modal data fusion improves detection robustness, and through the collaborative discrimination of visual, pressure, posture, and physiological data, the false positive rate in scenarios such as low light and occlusion is reduced; second, equal emphasis on privacy protection and user-friendliness, the camera avoids sensitive areas, adopts infrared fill light, hardware deployment does not affect normal activities, and the operation interface is simple and intuitive; third, hierarchical early warning and multi-path communication ensure reliability, design differentiated early warning strategies for different abnormal levels, and avoid information loss through communication redundancy. The relevant design ideas fully consider the actual application needs of intelligent elderly care equipment and can serve as a reference for the development of similar products.

5. Future improvement directions

In the future, the system can be optimized and upgraded from four aspects: first, introduce federated learning technology to build a personalized recognition model, use multi-user data for collaborative training without leaking privacy, adapt to the behavioral characteristics of different elderly people (such as hemiplegia, slow gait, etc.), and improve the abnormal recognition accuracy of special groups; second, enhance hardware module compatibility, integrate millimeter-wave radar sensors to make up for the detection shortcomings of visual and pressure sensing in severe occlusion scenarios, and optimize the battery life of the smart bracelet (targeting more than seven days); third, strengthen the privacy protection mechanism, add data desensitization processing in edge computing devices, extract human contours from video streams before transmission, and avoid leakage of original images; fourth, expand the functional boundary of the system, add modules such as sleep quality monitoring, emergency call buttons, and chronic disease risk early warning, build a health status evaluation model combined with historical data, realize the extension from “abnormal detection” to “health management,” and further improve the practical value of the system.

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Disclosure statement

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