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Design and Application of Intelligent Medical Care Beds Empowered by EEG Technology

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Abstract: With the continuous development of domestic brain-computer interface technology, in response to clinical pain points such as high nursing labor consumption and high risk of pressure ulcers for long-term bedridden patients, this paper designs an Intelligent medical bed system empowered by EEG. The system adopts an edge intelligent decision-making architecture composed of embedded control and brain electroencephalogram (EEG) rehabilitation upper-level modules. At the control level, non-invasive electrodes are used to collect single-channel EEG signals from the frontal lobe, and an OptimizedCNN deep learning model is employed to decode the patient's movement intentions of 'resting/left turn/right turn' in real-time, driving the bed's segmented motors to achieve closed-loop turning control. At the nursing assistant level, a catheter length prediction model is built based on BMI and height measurement data to assist with precise PICC placement. Simulation test results show that the system's accuracy in recognizing turning intentions reaches 68.0%. Combined with a triple safety fuse mechanism, it significantly improves nursing efficiency and patient safety, achieving a shift from experience-based care to data-driven and intelligent nursing.

Keywords: Brain-Computer Interface; Intelligent Nursing Bed; Deep Learning; Pressure Ulcers; PICC Catheter.

1. Introduction

1.1. Background

The global population structure is currently undergoing a transformation centered around aging, which poses a very serious challenge to the healthcare system. According to data released by the United Nations, in 2023, the proportion of the elderly population aged 65 and above worldwide was 10%, and by 2050, this proportion is expected to rise further to 16% [1]. In our country, the aging process is even more rapid. Data from the seventh national population census and predictions by experts show that the current number of people aged 60 and above is close to 300 million, and it is expected that this number will surpass 400 million around 2035. By the middle of this century, the elderly population will reach approximately 500 million, with the proportion of very old seniors exceeding 10% [2].

As the aging process deepens, the number of disabled and semi-disabled elderly individuals continues to grow, and the demand for long-term bedridden care is increasing. At the same time, the burden of disease is also intensifying. According to statistics, new cancer cases in China account for 24% of the global total, and cancer-related deaths make up 30% of the global total[3]. Among these, many cancer patients require long-term bed rest due to chemotherapy, postoperative recovery, and other reasons, and must undergo peripherally inserted central catheter (PICC) treatment. This prolonged bedridden state poses numerous serious risks of complications, with pressure ulcers being a common and preventable example. Studies indicate that the incidence of pressure ulcers among long-term bedridden patients can reach 20% to 50%, especially among elderly patients who are bedridden for extended periods, with incidence rates exceeding 30%[4].

1.2. Research Significance

Faced with the dual challenges of a surge in nursing demands and a high incidence of complications, the development of brain-computer interface (BCI) technology and edge computing has made it possible to directly convert patients' brain electrical signals into device control commands. This paper designs an intelligent medical bed system empowered by EEG, aiming to alleviate the pressure on caregiving through technological means, reduce the risks of pressure ulcers and infections, and achieve a shift from 'passive care' to a new mode of 'active interaction'.

1.3. Research Objectives

The main research objectives of this article include:

1. Design an edge intelligence decision-making architecture based on 'embedded control + EEG rehabilitation upper computer'.
2. Developed an EEG intention recognition algorithm based on the OptimizedCNN deep learning model, capable of real-time decoding of three states: 'resting,' 'turning left,' and 'turning right.'
3. Build a PICC catheter length prediction model based on BMI and height data to assist in precise care.
4. Verify the safety, stability, and clinical auxiliary application value of the system through simulation and pre-testing.

2. Overview of System Design

2.1. Basic Principles of EEG Technology

Electroencephalogram (EEG) signals are weak electrical signals generated by neuronal activity in the brain, characterized by monitorability and real-time capabilities. In the medical field, EEG technology is commonly used for epilepsy monitoring, sleep analysis, and rehabilitation training. This system employs single-channel frontal lobe EEG signal acquisition, primarily utilizing frequency band variation features under different mental states to detect the patient's intention to turn over:

- **Alpha rhythm (8-13Hz):** Dominates the state of rest and relaxation.
- **Beta band (13-30Hz):** Enhanced during the movement preparation phase, corresponding to the intention to turn over.
- **Gamma band (30-80Hz):** bursts related to fine motor coordination, assisting in distinguishing left and right movements.

2.2. The Current Situation of Smart Medical Beds

Traditional intelligent medical beds mostly use buttons, voice, or gesture control, which present interaction barriers for patients with severe disabilities who cannot move their limbs. This study addresses these issues by combining an embedded control system with a brainwave rehabilitation upper computer—forming an edge intelligent decision-making center—and integrating deep learning to enhance the system's robustness and clinical practicality.

2.3. Application of Deep Learning in EEG Decoding

Convolutional Neural Networks (CNNs) and their variants (such as EEGNet) perform excellently in extracting features from EEG signals. When combined with Long Short-Term Memory networks (LSTM), they can effectively capture dependencies in time series data. Additionally, attention mechanisms like CBAM can significantly highlight key signal segments. The OptimizedCNN model used in this paper integrates various advanced structures to better adapt to complex and variable clinical environments.

2.4. Hardware Perception and Control Implementation

The hardware system selects the STM32F103C8T6 as the core, equipped with a PICC catheter assistance module and integrated with the TGAM brainwave module (single-channel frontal EEG collector). It also includes a DC reduction motor driven by the TB6612 driver module, forming a four-layer architecture of 'perception - control - transmission - execution.'

3. Analysis of Smart Bed Functional Requirements

3.1. User Needs Analysis

Based on surveys of medical staff and long-term bedridden patients, the main needs are focused on the following aspects:

1. **Turning care:** Regularly or as needed, turning to prevent pressure ulcers and reduce the burden on caregivers.
2. **Interactive convenience:** For patients with disabilities, it is necessary to provide interaction methods that do not require significant physical movement (such as brainwave control).
3. **Treatment assistance:** For procedures such as PICC placement, precise positioning support and length prediction are required.
4. **Safety:** The system must have mechanisms to prevent accidental activation, emergency stop, and protection against abnormal conditions.

3.2. Functional Module Planning

Based on the above requirements, the system plans the following core functional modules:

1. **Electroencephalogram (EEG) Intent Recognition Module:** Collects EEG signals to decode the patient's turning intention.
2. **Intelligent motion control module:** drives the partition motor to achieve back elevation, left and right turning, and bed/chair switching.
3. **Vital signs and physiological parameter monitoring module:** integrates height, weight, BMI measurement, and heart rate and blood oxygen monitoring.
4. **PICC catheterization assistance module:** predicts catheter length based on physiological parameters, non-contact collection, and provides sterile operation support.
5. **Safety protection module:** includes confidence gating, physical emergency stop, and timeout protection.

3.3. Improved Scenario Analysis

Compared to traditional medical beds, the intelligent improvements in this design include:

- **Interaction upgrade:** introducing blink count-based state switching (two blinks to enter control mode, three blinks to return to idle) and direct motor control based on EEG intent.
- **Data-driven nursing:** automatically calculating catheter placement length based on BMI and height data, contactless data collection, and providing sterile operation support.
- **Closed-loop control:** forming a closed loop between intent recognition and motor execution, combined with safety fuse logic to ensure reliable operation.

4. System Design Framework

4.1. Overall Architecture Design

The system adopts a layered decoupling design, divided from bottom to top into the hardware communication layer, signal preprocessing layer, deep learning layer, predictive control layer, and user interaction layer. The core architecture is based on an 'embedded control + EEG rehabilitation upper computer' edge intelligent decision-making center:

1. **Host Computer:** Responsible for high-computation tasks, including single-channel EEG signal acquisition from the prefrontal cortex, feature extraction, and inference using the OptimizedCNN deep learning model to decode the patient's movement intentions in real-time.
2. **Embedded Controller:** Based on the STM32F103 microcontroller, responsible for receiving data from various sensors (height, weight, vital signs), as well as executing motor drive commands and safety fuse logic.
3. **Communication Link:** Utilizes Bluetooth and 433M dual wireless communication schemes. Bluetooth is primarily used for real-time data exchange

with a mobile app, while 433 MHz is used for remote manual control. This ensures communication redundancy and stability in complex hospital environments.

4.2. Mechanical Structure System Design

1. **Segmented bed surface:** Divided into head, back, hip, thigh, and lower leg sections based on human anatomical structure. The back section can be elevated from 0° to 75°, allowing the back to be raised within this range. To reduce skin tension on the thigh when the patient's center of gravity shifts, the thigh section can be flexed independently, thereby reducing the risk of pressure ulcers.

2. **Left and right turning mechanism:** An independent left and right turning system is installed beneath the bed surface. It recognizes the patient's turning intention through EEG signals, and uses a motor to drive support linkages to lift one side of the bed, creating a 10°–30° lateral tilt angle, utilizing gravity to assist passive turning.

3. **Integrated bed and wheelchair system:** The bed can switch between 'flat bed' and 'wheelchair' modes within 30 seconds, reducing the risk associated with multiple transfers during ICU transport and CT scans.

4. **PICC auxiliary components:** Includes an integrated telescopic sterile operating table, a sharps disposal box, and an adaptive flexible infusion stand, which can automatically make fine adjustments of ±10° to the upper limb angle every 30 minutes.

4.3. Software Architecture Design

The software system is divided into upper computer inference software and lower computer control firmware. The upper computer is developed using Python/PyTorch and mainly handles model loading and inference-related tasks; the lower computer uses the C language to advance the development process and is responsible for real-time control logic. Communication between the two is achieved through a serial communication protocol to synchronize commands and statuses.

5. EEG Signal Processing Algorithm Design

5.1. Signal Acquisition and Preprocessing

The system collects patients' EEG signals through a single-channel TGAM module, with a sampling rate set to 512 Hz. The data is filtered with a 0.5-45 Hz bandpass filter to remove baseline drift and high-frequency noise. Features are calculated in real-time within an independent background thread, supporting a wavelet denoising switch and local Z-Score normalization, which both reduce the load on the main thread and enhance feature robustness.

5.2. Feature Extraction and Model Construction

Construct a 5-dimensional physiological feature vector, including channel envelope value, focus normalization value, α/β power ratio, signal mobility, spectral entropy, etc. The model adopts a cascaded structure of 'residual denoising + EEGNetBlock + CBAM attention + multi-scale TCN dilated convolution + LSTM temporal modeling' (OptimizedCNN):

1. **Residual noise suppression module:** constructs a 'main path feature extraction + noise path suppression mask' structure, increasing the effective signal-to-noise ratio (SNR) by approximately 4 dB.

2. **CBAM 1D attention mechanism:** applies weighting across channel and temporal dimensions to highlight key segments such as action initiation/termination and eye movements.

3. **TCN and LSTM:** use dilated convolutions with dilation rates of 1/2/4 to expand the temporal receptive field, and encode the dynamic evolution of actions through LSTM. The model has approximately 218,000 parameters, with a single inference delay of about 187 ms on a standard CPU.

5.3. Model Training Strategy

Model training is based on the PyTorch framework. To address the class imbalance problem where 'resting' samples are more prevalent than 'left turn over/right turn over' in EEG intention recognition, the Adam optimizer and Focal Loss function are used.

$$Loss = -\alpha_t(1-p_t)^{\gamma}log(p_t)$$

Where p_t is the model's predicted probability, γ is the focusing parameter, and α_t is the class balancing coefficient. Compared to traditional cross-entropy loss, Focal Loss forces the model to pay more attention to hard-to-distinguish reversal action samples. The dataset is divided into training, validation, and test sets in a 7:1.5:1.5 ratio. Regularization is applied using Dropout (0.5) and L2 weight decay.

6. Hardware Implementation of Intelligent Medical Beds

6.1. Core Controller

The hardware system is built around the STM32F103C8T6 as the core, establishing a four-layer architecture of 'perception - control - transmission - execution.' This microcontroller features low power consumption and high stability, making it well-suited for medical embedded environments.

6.2. Perception Module

1. PICC catheter placement auxiliary module:

Height measurement: The head and foot ends are equipped with HC-SR04 ultrasonic distance sensors and SHT11 temperature and humidity sensors. Considering that environmental temperature and humidity can affect the speed of sound, the real-time calibration of the speed of sound v is performed using Zhang Andong's compensation formula:

$$v = v_0\sqrt{\left(1+\frac{t}{T_0}\right)\left(1+0.3192g\frac{P_w}{P}\right)}$$

Where v_0 is the standard sound speed (331 m/s), t is the ambient temperature, T_0 is the reference temperature controlled by the device (273.15 K), and $\frac{P_w}{P}$ is the relative humidity. Height measurement error is controlled within 5% after compensation [5].

Weight and BMI calculation: Integrates HX711 pressure sensor, uses median filtering to calculate the patient's weight in real-time, and combines height data to generate BMI index for subsequent PICC catheter length prediction.

2. Multimodal vital sign collection: Combines TGAM EEG module (single-channel frontal EEG collector), heart rate and blood oxygen module, and motion sensors. For the EEG sensor, a dry electrode design is used to improve comfort during wear.

6.3. Execution and Communication Modules

In terms of the actuator, a DC reduction motor is used in conjunction with a TB6612 driver module, utilizing PWM signals to adjust speed and direction. Additionally, a flyback diode and current detection circuit are designed to protect against motor overload and overheating. Regarding the communication link, the Bluetooth module is used for interaction with a mobile app, while the 433MHz wireless module is employed for remote manual control, ensuring redundancy in communication.

7. Software System Development and Testing

7.1. Software Development Environment

The upper computer software runs in a Windows environment and uses PyTorch for model inference. The lower computer firmware is developed with Keil MDK. The user interface (UI) can display patient status, bed angle, vital signs, and catheterization recommendations.

7.2. Active Learning and Safety Controls

1. **Active learning layer:** integrates user intent conflict detection and uncertainty sampling strategies. When the user's declared true action conflicts with high-confidence predictions, it is marked as a high-value correction sample, and the model is updated online accordingly.
2. **Triple Safety Circuit Breaker Mechanism:**

- **Confidence Gate:** Confidence < 0.6 persists for 2 seconds, soft stop.
- **Physical Emergency Stop:** Button trigger immediately terminates.
- **No Data Timeout Protection:** If no data is received for 2 consecutive seconds, the safety lock engages.

7.3. Virtual Simulation Verification

In order to verify the confidence and stability of the EEG control system in actual use, preliminary validation was conducted using the VirtualTaurusEEG v9 virtual EEG device simulator before officially conducting real-person experiments. This was used to assess the robustness of the model under ideal environmental conditions as well as in noisy environments.

8. Application Cases and Effect Analysis

8.1. Experimental Data Collection

During data collection, the subject wore a single-channel frontal EEG device and performed three types of actions in a specified order: rest, intention to turn left, and intention to turn right. For each action, 30 samples were collected, totaling 91 valid samples.

8.2. Evaluate the Indicators

To comprehensively evaluate the model's performance, the following metrics are used:

1. **Accuracy:** the proportion of correctly predicted samples out of the total samples

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP + TN}}{\boldsymbol{TP + TN + FP + FN}}$$

2. **Precision:** The proportion of samples predicted as positive that are actually positive.

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}}$$

3. **Recall:** The proportion of actual positive samples that are correctly predicted.

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}$$

4. **F1 Score:** The harmonic mean of precision and recall

$$\boldsymbol{F1\_Score} = \boldsymbol{2} \times \frac{\boldsymbol{Precision \times Recall}}{\boldsymbol{Precision + Recall}}$$

5. **(Confusion Matrix):** Visualize the misjudgment between categories

8.3. Model Training Results

The training results are shown in Figure 1. After 60 epochs of training, the model achieved an overall accuracy of 68% on the test set. The training loss eventually converged to 0.2679, and the validation loss stabilized at a similar level, indicating that the model has good generalization ability with no obvious overfitting observed.

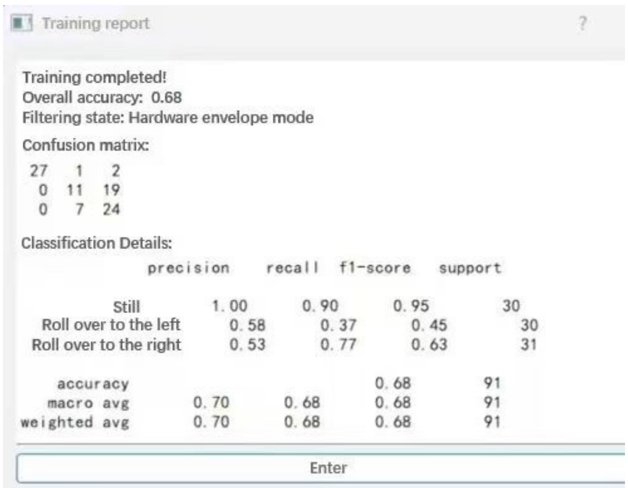

Figure 1. Brainwave Control Model Training Report

8.4. Performance Metric Evaluation

The model performance metrics are shown in Table 1:

Detection of the stationary state is better than detection of turning left or right. Even though there are occasional misjudgments, the number of incorrect samples is relatively small and within an acceptable range. The recognition performance for the turning left action is not very good: precision is 0.58, recall is 0.37, and the F1 score is 0.45. Among the three actions, this category has the poorest recognition performance. The recognition of turning right is relatively more stable, with a precision of 0.53 and a recall of up to 0.77. Although precision isn't very high, recall is strong, indicating that the model can capture the turning-right action reasonably well.

8.5. Analysis of PICC Nursing Auxiliary Effects

Based on the PICC placement prediction model validated through clinical trials by the Fengfeng team[6], the system incorporates a predictive algorithm that combines BMI and height. The display can simultaneously show the key anatomical distances from the puncture site to the sternoclavicular joint and also provides a recommended catheter length (with an additional safety margin of 6 to 10 centimeters added in practice). Throughout the data collection process, a contactless method is used, providing support for sterile procedures. This feature can effectively assist nurses in performing precise PICC placements.

Table 1. Classification Performance Indicators of EEG Intention Recognition

Action Recognition	Precision	Recall	F1_Score	Support
Still	1.00	0.90	0.95	30
Turn left	0.58	0.37	0.45	30
Turn right	0.53	0.77	0.63	31
Macro Avg	0.70	0.68	0.68	91
Weighted Avg	0.70	0.68	0.68	91

9. Conclusion

This article focuses on the issues of nursing staff shortages and the high incidence of pressure ulcers among long-term bedridden patients in the context of an aging population. It designs an intelligent medical bed empowered by EEG technology. The device adopts an 'embedded control + EEG rehabilitation upper computer' architecture, enabling a transition from purely 'passive care' to an interactive 'active interaction' mode. In terms of EEG control, it relies on collecting single-channel frontal lobe EEG signals and applying the OptimizedCNN deep learning model. Currently, it has successfully achieved recognition of intentions such as 'resting,' 'turning left,' and 'turning right,' with an accuracy rate of 68%, providing a practical foundation for further research. Additionally, the device incorporates a BMI catheterization prediction model to assist with precise PICC placement, allowing non-contact data collection to support sterile clinical operations. To ensure safety during daily use of the smart bed, the system employs a triple safety fuse mechanism to effectively safeguard the bed in non-command states, demonstrating preliminary clinical auxiliary application value.

However, this study still has limitations. In terms of recognition accuracy, the differentiation of the turning left and right actions in experiments conducted with real people still needs improvement; additionally, the current experimental sample size is small, and the model's generalization ability needs further validation. Future efforts can explore multi-channel EEG collection methods and improved transfer learning algorithms to enhance the model's accuracy; to improve the model's generalization ability, the scale of clinical trials should be expanded and validated. It is hoped that this smart bed can alleviate caregiving pressures in the future, reduce the risks of pressure ulcers and infections, and provide a new paradigm for intelligent nursing.

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