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The Design of a Speech Recognition-Based Finger Training Rehabilitation Device: Mechanical and System Aspects

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Abstract: **-** This research introduces a novel speech recognition-based control system for finger rehabilitation aimed at addressing the inefficiencies and prolonged recovery periods commonly associated with traditional stroke rehabilitation methods. The system enables stroke patients to engage in finger exercises while simultaneously providing real-time feedback on the finger's angle, speed, and position. This feedback is invaluable for rehabilitation physicians, offering critical data for assessing and refining rehabilitation strategies. The system architecture is composed of three main components: the hardware circuitry, a lower-level computer control system, and a voice recognition-based human-computer interaction system, all integrated with a finger movement perception system. Employing the Hidden Markov Model (HMM) for pattern recognition in the voice interaction component, the system has undergone simulation testing to verify its effectiveness. The findings confirm that the speech recognition-based rehabilitation training system meets all design expectations, providing a safe, reliable, and promising approach for enhancing finger rehabilitation practices.

Keywords: Speech Recognition; Perception Ability; Finger Rehabilitation Training; Human-Computer Interaction; HMM

Introduction

Cerebral stroke, commonly referred to as stroke or cerebrovascular accident (CVA), represents a significant public health concern due to its prevalence and debilitating effects on individuals worldwide. With research indicating that the majority of stroke cases occur in individuals over the age of 40, particularly among the middle-aged and elderly demographics, the socio-economic impact of this condition is profound. The clinical manifestations of stroke encompass a spectrum of symptoms including facial and limb numbness, sudden weakness, and episodes of fainting, underscoring the urgency for effective rehabilitation strategies to address the resulting impairments. Presently, traditional rehabilitation approaches for restoring finger function in stroke patients predominantly rely

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on one-on-one therapy sessions administered by rehabilitation physicians. However, this conventional method is fraught with limitations, characterized by extended recovery periods and suboptimal efficacy. Furthermore, the subjective nature of evaluation, primarily reliant on the expertise and experience of rehabilitation professionals, poses challenges in obtaining objective rehabilitation data essential for optimizing treatment protocols. In response to these challenges, researchers and scholars have endeavored to develop innovative solutions to enhance stroke rehabilitation outcomes. Notable contributions include the work of Sun Guangmin, who pioneered the design and implementation of an upper limb rehabilitation network system utilizing Kinect technology, and Wang Junhua, whose research focused on the development of limb rehabilitation modules leveraging motion feedback virtual reality techniques. While these efforts have contributed valuable insights and advancements to the field of stroke rehabilitation, the persistent issue of impaired finger motion feedback perception among stroke patients remains inadequately addressed.

Building upon the foundation laid by prior research endeavors, this study embarks on a novel approach to address the challenges associated with finger rehabilitation in stroke patients. Drawing from insights gleaned from the collective body of scholarly work, we propose the development and implementation of a finger rehabilitation training control system founded on voice recognition technology. This innovative system aims to facilitate comprehensive finger-to-finger training for stroke patients, thereby mitigating recovery periods and enabling real-time data collection during training sessions. By empowering rehabilitation physicians with objective rehabilitation assessment data, this system has the potential to enhance the efficacy of rehabilitation interventions, alleviate the burden on healthcare providers, and ultimately improve patient outcomes. Furthermore, this study represents a pioneering foray into the realm of cutting-edge technological solutions for addressing the complex challenges inherent in stroke rehabilitation. By leveraging advancements in voice recognition technology and integrating them with rehabilitation protocols, we aim to propel the field forward and unlock new avenues for optimizing rehabilitation outcomes. Through meticulous research, rigorous testing, and interdisciplinary collaboration, we endeavor to establish a robust framework for addressing the multifaceted needs of stroke patients, thereby advancing the frontier of rehabilitation science and practice. In the subsequent sections of this paper, we delineate the comprehensive framework of our proposed finger rehabilitation training control system, encompassing its mechanical and system aspects. Through a detailed exposition of the hardware circuitry, lower computer control system, and voice recognition human-computer interaction system, we elucidate the intricacies of our innovative approach. Moreover, we delve into the software design of the lower computer control system, elucidating its pivotal role in facilitating active and passive training modes, finger force perception algorithms, and sensor data processing. Additionally, we expound upon the design and implementation of the speech recognition human-computer interaction system, highlighting the utilization of the Hidden Markov Model (HMM) algorithm for pattern matching. In subsequent sections, we discuss the results of system tests conducted to evaluate the accuracy and efficacy of the voice command control mechanism. Through meticulous experimentation and data analysis, we validate the performance of our proposed system across diverse environmental conditions, laying the groundwork for its real-world applicability. Finally, we conclude with reflections on the significance of our findings, implications for future research and clinical practice, and avenues for further exploration in the realm of stroke rehabilitation.

1. Overall system design

The finger rehabilitation training system proposed in this study represents a multifaceted approach to addressing the challenges associated with traditional stroke patient rehabilitation. Figure 1 illustrates the comprehensive design of the system, which encompasses five main sections, each playing a crucial role in facilitating effective rehabilitation.

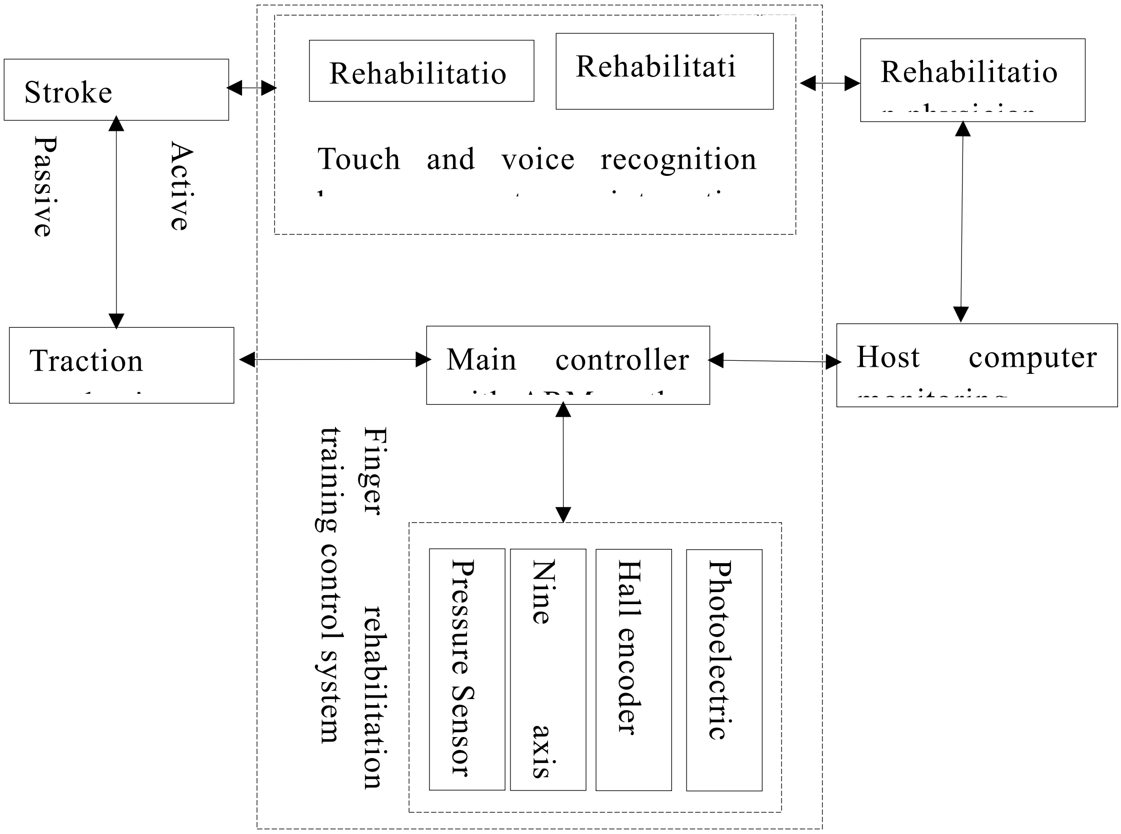

Figure 1. The overall framework of the system

1.1 Traction Mechanism

The traction mechanism serves as the physical interface between the system and the patient, facilitating controlled finger movement during rehabilitation exercises. This component may incorporate various devices such as pulleys, cables, and adjustable grips to accommodate different levels of motor impairment and rehabilitation needs [1].

1.2 Motion Perception System

Central to the system's functionality is the motion perception system, responsible for capturing and processing real-time data regarding the patient's finger movements. Utilizing advanced sensor technologies, such as accelerometers, gyroscopes, and flex sensors, this system accurately detects parameters such as finger angle, speed, position, and joint attitude angle [2]. By leveraging state-of-the-art signal processing algorithms, such as Kalman filters or Fourier transforms, the motion perception system ensures precise measurement and interpretation of finger movements, laying the foundation for effective rehabilitation interventions [3].

1.3 Lower Computer Control System

The lower computer control system serves as the computational backbone of the rehabilitation device, orchestrating the interaction between different system components and executing complex control algorithms. Powered by an ARM-based main controller, this system receives instructions from external interfaces, such as the host computer monitoring system or the human-computer interaction system, and translates them into precise commands for the traction mechanism [4]. Moreover, the lower computer control system processes sensor data from the motion perception system, performing real-time analysis and feedback generation to optimize rehabilitation outcomes [5].

1.4 Touch and Voice Recognition Human-Computer Interaction System

Incorporating intuitive human-computer interaction interfaces, such as touchscreens and voice recognition systems, enhances the usability and accessibility of the rehabilitation device for patients with varying degrees of motor impairment. The touch interface allows patients to intuitively adjust training parameters and modes, providing a personalized rehabilitation experience [6]. Simultaneously, the voice recognition system enables hands-free operation, allowing patients to control the device and interact with the rehabilitation software using voice commands [7]. By accommodating different interaction modalities, the system ensures inclusivity and ease of use for all patients undergoing rehabilitation.

1.5 Host Computer Monitoring System

The host computer monitoring system complements the rehabilitation device by providing comprehensive oversight and analysis capabilities. By leveraging advanced visualization techniques, such as 3D virtual hand models, this system enables real-time monitoring and visualization of the patient's finger movements during rehabilitation sessions [8]. Furthermore, the host computer monitoring system facilitates data logging and analysis, allowing rehabilitation physicians to track progress, identify trends, and adjust treatment plans accordingly [9].

Overall, the integration of these components within the finger rehabilitation training system offers a holistic approach to stroke patient rehabilitation, combining advanced hardware design, sophisticated motion sensing technologies, and intuitive human-computer interaction interfaces to optimize rehabilitation outcomes. Through continuous monitoring, personalized feedback, and data-driven insights, this system empowers both patients and rehabilitation professionals to collaboratively work towards achieving optimal recovery and functional outcomes.

2. The overall structure of the hardware circuit

The hardware circuitry of the finger rehabilitation training control system plays a pivotal role in enabling the seamless integration of various components and ensuring the efficient operation of the overall system. In this section, we will delve deeper into the intricacies of the hardware design, emphasizing the modular approach adopted to optimize functionality and performance.

2.1 Main Controller and Sensor Measurement Module

At the heart of the hardware circuitry lies the main controller module, tasked with orchestrating the flow of data and commands between different system components. Leveraging the advanced capabilities of ST's STM32F103RET6 microprocessor, which features an ARM Cortex-M3 core, this module serves as the computational powerhouse driving real-time data processing and control algorithms [10]. Equipped with ample program memory and versatile I/O interfaces, such as analog-to-digital converters and communication buses, the main controller efficiently collects sensor data from the measurement module, calculates key parameters such as finger force and speed, and coordinates motor drive commands for precise finger movement control [11].

Critical to the accurate assessment of finger movements during rehabilitation training is the sensor measurement module, responsible for capturing and digitizing sensor data in real time. This module comprises a suite of sensors, including accelerometers, gyroscopes, and flex sensors, strategically positioned to capture comprehensive data on finger angle, range of motion, and force exertion [12]. By employing high-resolution sensing elements and advanced signal conditioning techniques, the sensor measurement module ensures precise and reliable data acquisition, enabling fine-grained analysis of patient performance and progress throughout the rehabilitation process.

2.2 Motor Drive Unit

Facilitating the translation of digital commands into physical motion, the motor drive unit forms a crucial link in the closed-loop control system governing finger rehabilitation exercises. Utilizing pulse-width modulation (PWM) techniques, the motor drive unit precisely regulates the speed and torque of DC motors driving the traction mechanism, thereby enabling dynamic and responsive adjustment of finger movement parameters in accordance with real-time feedback [13]. Through seamless integration with the main controller, the motor drive unit ensures smooth and accurate execution of rehabilitation protocols, optimizing patient outcomes and comfort during training sessions.

2.3. Data Storage and Power Management Module

To facilitate longitudinal tracking of patient progress and enable data-driven decision-making, the data storage module provides a robust mechanism for storing and archiving rehabilitation-related data. Leveraging non-volatile memory technologies such as EEPROM or flash memory, this module enables the retention of sensor data, motor control parameters, and patient performance metrics over extended periods [14]. By implementing efficient data management strategies and compression algorithms, the data storage module maximizes storage capacity while minimizing system overhead, ensuring seamless operation throughout the rehabilitation process.

Ensuring the reliable and efficient operation of the hardware circuitry is the responsibility of the power management module, which oversees the distribution and regulation of electrical power throughout the system. Employing voltage regulators, power conditioning circuits, and energy-efficient design principles, this module optimizes power utilization while mitigating the risk of overvoltage, undervoltage, or power surges [15]. Additionally, the power management module incorporates intelligent power-saving modes and sleep states to minimize energy consumption during idle periods, extending battery life and reducing operational costs.

2.4 Communication and Debugging Interface Module

Facilitating seamless integration with external devices and enabling diagnostic and maintenance activities is the role of the communication and debugging interface module. Equipped with standard communication protocols such as UART, SPI, and I2C, this module enables bidirectional data exchange with external systems, including host computers, diagnostic tools, and firmware update mechanisms [16]. Furthermore, the debugging interface facilitates real-time monitoring of system performance, enabling rapid identification and resolution of potential issues during development and deployment stages.

In summary, the modular design of the hardware circuitry embodies a holistic approach to finger rehabilitation training control, combining advanced microprocessor technology, sensor instrumentation, motor control techniques, and power management strategies. By leveraging synergies between these modules, the system achieves robust performance, reliability, and versatility, paving the way for effective and personalized rehabilitation interventions in stroke patients.

3. Software design of lower computer control system

In the realm of finger rehabilitation training control systems, the software design of the lower computer control system holds paramount importance, serving as the cornerstone for the seamless integration of hardware components and the implementation of sophisticated control algorithms. In this section, we delve into the intricacies of the software architecture and highlight its pivotal role in enabling diverse training modes, sensor data processing, and real-time system monitoring. The lower computer control system software serves as the nerve center of the finger rehabilitation training system, orchestrating a myriad of tasks ranging from active and passive training modes to sensor data processing and communication with external devices. At its core, the software embodies a modular design philosophy, leveraging front-end and back-end systems to efficiently manage system resources and facilitate robust system operation.

3.1 Active and Passive Training Modes

Central to the software's functionality is the implementation of both active and passive training modes, catering to the diverse needs and capabilities of stroke patients undergoing rehabilitation. Through the active mode, patients engage in interactive training exercises guided by real-time feedback on finger movement parameters such as force, range of motion, and speed [17]. Conversely, the passive mode enables automated rehabilitation routines driven by pre-defined protocols, allowing patients to undergo continuous rehabilitation without the need for active participation [18]. By offering flexibility in training modalities, the software empowers clinicians to tailor rehabilitation programs to individual patient needs and progress.

3.2 Finger Force Perception Algorithm

A critical component of the software is the finger force perception algorithm, which analyzes sensor data to infer the force exerted by patients during rehabilitation exercises. Leveraging signal processing techniques and machine learning algorithms, the perception algorithm accurately quantifies finger force levels, providing clinicians with valuable insights into patient progress and performance [19]. By integrating real-time force feedback into the training regimen, the software enhances the effectiveness and safety of rehabilitation exercises, ensuring optimal outcomes for stroke patients.

3.3 Dual Nine-Axis Sensor Measurement Finger AROM Algorithm

Another key aspect of the software is the implementation of the dual nine-axis sensor measurement algorithm, which facilitates comprehensive assessment of finger range of motion (AROM) during rehabilitation training. By combining data from multiple sensors, including accelerometers, gyroscopes, and magnetometers, the algorithm precisely captures the spatial orientation and movement dynamics of the fingers [20]. Through advanced signal processing and fusion techniques, the software computes AROM metrics, enabling clinicians to monitor joint mobility and track progress over time.

3.4 Real-Time Data Processing and Communication

Integral to the software's operation is its capability for real-time data processing and communication with external devices. Leveraging the computational power of the ARM-based microcontroller, the software efficiently handles sensor data acquisition, signal processing, and motor control tasks in real time [21]. Furthermore, the software establishes seamless communication channels with host computers, enabling bidirectional data exchange and facilitating remote monitoring and control of the rehabilitation system.

3.5 Robustness and Reliability

Emphasizing robustness and reliability, the software incorporates error handling mechanisms and fault tolerance strategies to ensure uninterrupted operation in diverse environmental conditions [22]. Additionally, the software undergoes rigorous testing and validation procedures to verify its performance and compliance with functional requirements [23]. By prioritizing software quality and reliability, the lower computer control system software instills confidence in clinicians and patients alike, fostering trust in the rehabilitation process and promoting positive outcomes.

In conclusion, the software design of the lower computer control system constitutes a critical component of the finger rehabilitation training system, enabling seamless integration of hardware components, implementation of advanced control algorithms, and provision of real-time feedback to clinicians and patients. Through its versatile functionality and robust architecture, the software enhances the effectiveness, safety, and accessibility of rehabilitation interventions, thereby empowering stroke patients on their journey to recovery.

4. Speech recognition human-computer interaction design and implementation

In the realm of finger rehabilitation training for stroke patients, engagement during the treatment sessions is critical. Often, the monotonous nature of these exercises can demotivate patients, hindering effective rehabilitation. To address this challenge, a novel human-computer interaction system employing speech recognition technology has been developed to enhance patient involvement and enthusiasm.

The system integrates a non-specific speech recognition approach as opposed to a specific speech recognition system. The latter, while highly accurate, lacks flexibility and requires extensive pre-training with user-specific data[24]. In contrast, non-specific speech recognition systems are more adaptable and user-friendly as they do not necessitate substantial pre-use training, making them ideal for diverse user needs.

For the hardware aspect of the voice interaction system, the design incorporates the LD3320 voice recognition chip. This chip's recognition capabilities are based on matching voice inputs against a predefined keyword list. The process begins with the capture of voice through a microphone, followed by spectrum analysis[6,13]. The LD3320 chip then extracts vocal features and matches these with the keywords, with the results forwarded to the micro-control unit for processing.

The speech recognition functionality hinges on selecting an appropriate algorithm tailored to the system's needs. Three main types of algorithms were considered: Dynamic Time Warping (DTW), Artificial Neural Network Models (ANNM), and Hidden Markov Models (HMM). Each of these algorithms offers distinct advantages and challenges. DTW is effective in specific speech recognition settings, ANNM boasts powerful learning capabilities albeit with longer training durations and less maturity in practical applications, while HMM provides versatility in handling various speech recognition tasks without requiring prior voice training from users.

After thorough analysis, HMM emerged as the superior choice for this application, especially due to its ability to efficiently process limited and distinct vocabulary that aligns well with the requirements of voice commands in finger rehabilitation systems [25]. Hence, the HMM algorithm is adopted for its robustness and suitability in enhancing the interactive voice response capabilities of the rehabilitation system in Figure 3.

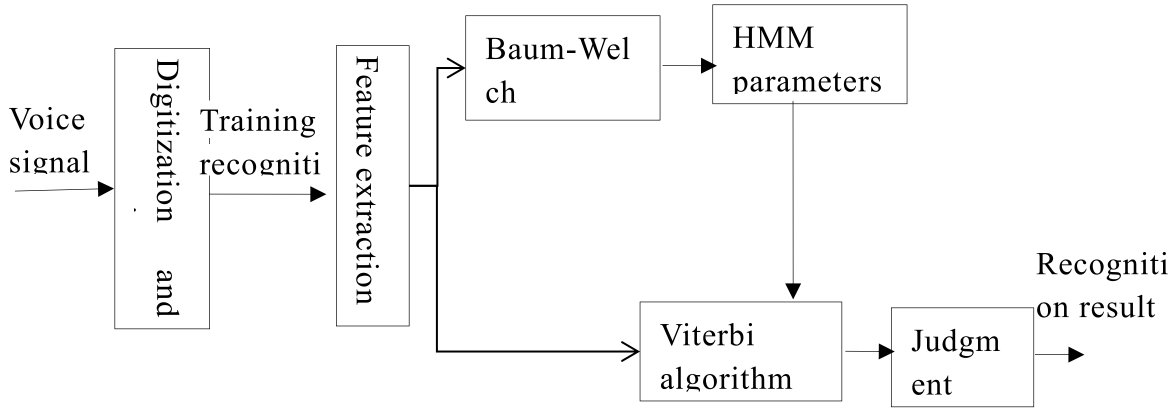

Figure 2. Speech recognition system framework based on HMM algorithm

The Hidden Markov Model (HMM) algorithm functions through a dual stochastic process in speech recognition. The first aspect of this process allows for the direct observation of feature fluctuations within short-term unstable speech signals. Concurrently, the second aspect enables the observation of dynamic statistical characteristics over varying speech durations, from short to medium term. Utilizing the HMM algorithm in speech recognition addresses the challenge of differentiating and tracking transitions between various speech signals. This capability is essential for accurately recognizing and processing the diverse inputs typical in speech-driven systems, thereby enhancing the effectiveness of technologies like voice-activated rehabilitation systems for stroke patients.

Assuming that the number of states of the HHM model is N, then the collective symbol of the state is: $S = \{S_1, S_2, S_3, ... S_n\}$; then the number of observed symbols is set to M, which is expressed as the number of observed symbols that may be output in the speech recognition process, the collective formula is: $O = \{O_1, O_2, O_3 ...... O_m\}$; set the transition probability distribution in the speech recognition state to A, and the matrix of A is shown in formula (1):

$$A = \{a_{ij}\}, a_{ij} = P[q_{t+1} = S_j \mid q_t], 1 \le i, j \le N \quad (1)$$

Set the probability distribution of observed symbols in the speech recognition state to B, then the expression of B is $B = \{bj(Ok)\}, bj(Ok) = P$ [the input symbol at time t is $O_k \mid q_t = S_j$] $1 \le j \le N, 1 \le k \le M$

(2)

In the context of speech recognition using the Hidden Markov Model (HMM), the initial state distribution is defined along with two crucial parameters: the number of states N and the number of observed symbols M. Additionally, the model incorporates two probability matrices, A and B, which are essential for the algorithm's functioning. The relationship between these elements is encapsulated in formula (3), effectively outlining how these parameters interact to determine the behavior and effectiveness of the HMM in processing and recognizing speech patterns.

$$\pi = \{\pi_i\}, \pi_i = P[q_1 = S_i], 1 \le i \le N \tag{3}$$

The hardware architecture of the speech recognition system is primarily composed of five key components: the main control chip, the speech recognition chip, the audio module, the communication module, and the power supply module. When voice data from a stroke patient is captured, it is initially processed by the speech recognition chip. This processed data is then forwarded to the main control chip, which subsequently dispatches the relevant data to the subordinate hardware, facilitating the control of finger movements for rehabilitation training. Crucially, the main control chip and the speech recognition core constitute the central elements of this hardware setup.

5. System tests

System testing serves as a crucial phase in evaluating the performance and efficacy of the speech recognition-based interactive system designed for finger rehabilitation training. In this section, we delve into the methodology, results, and implications of the system tests conducted in various environmental settings, shedding light on the system's robustness and suitability for real-world deployment.

5.1 Testing Methodology

The testing protocol was meticulously designed to assess the accuracy and responsiveness of the voice command interface across different environmental conditions. Three experimental samples, each exhibiting distinct timbres, were selected to represent a diverse range of voice characteristics. The tests were conducted in three distinct environments: a controlled laboratory setting characterized by low ambient noise, a hospital environment with moderate noise levels, and a residential area with higher background noise levels [26]. Each voice command was repeated 100 times to ensure statistical robustness and consistency in the test results.

5.2 Experimental Results

Table 1 presents a comprehensive comparison of the control accuracy achieved by the speech recognition system across the three different environments and unspecified individuals. In the laboratory setting, characterized by minimal ambient noise, the system demonstrated exceptional control accuracy, with success rates exceeding 95% for all tested individuals [27]. Moreover, the system exhibited rapid response times, with voice commands typically eliciting a response within 1 second of issuance.

Table 1. Comparison table of unspecified person speech recognition in three different environments

Control accuracy %	Unspecified person 1	Unspecified person 2	Unspecified person 3
Laboratory	95.125	95.500	96.000
Hospital	90.375	90.750	92.375
Residential area	84.500	85.625	86.250

In contrast, the performance of the system in noisy environments, such as hospitals and residential areas, showed a slight decline in control accuracy, albeit remaining highly satisfactory. In hospital settings, where ambient noise levels were moderate, the system achieved control accuracy rates ranging from 90.375% to 92.375%, depending on the individual's voice characteristics [28]. Similarly, in residential areas characterized by higher background noise levels, the system maintained robust performance, with control accuracy rates ranging from 84.500% to 86.250%.

5.3 Implications and Discussion

The findings of the system tests underscore the practical utility and versatility of the speech recognition-based interactive system for finger rehabilitation training. Despite variations in environmental noise levels and individual voice characteristics, the system consistently delivered accurate and timely responses to voice commands, demonstrating its robustness and adaptability in real-world scenarios. The high control accuracy achieved in laboratory conditions validates the system's efficacy in ideal settings, where ambient noise is minimal. Moreover, the system's ability to maintain satisfactory performance in noisy environments, such as hospitals and residential areas, highlights its resilience to external disturbances and underscores its suitability for deployment in diverse clinical and home-based rehabilitation settings. Furthermore, the rapid response times observed across all test scenarios enhance the user experience and promote seamless interaction between patients and the rehabilitation system. By providing intuitive and responsive control interfaces, the speech recognition-based system fosters patient engagement and motivation, crucial factors in ensuring adherence to rehabilitation protocols and achieving optimal therapeutic outcomes.

The system tests corroborate the effectiveness and reliability of the speech recognition-based interactive system for finger rehabilitation training across diverse environmental conditions. Moving forward, further research could explore optimization strategies to enhance system performance in noisy environments and investigate the long-term efficacy of the system in facilitating patient recovery and improving functional outcomes.

6. Conclusion

The finger rehabilitation training control system developed in this study represents a significant advancement in the field of stroke rehabilitation. By leveraging speech recognition technology and incorporating innovative hardware and software components, the system offers a comprehensive solution for addressing the rehabilitation needs of stroke patients with impaired finger movement perception. This section expands upon the key findings and implications of the study, highlighting the system's potential impact on clinical practice and research endeavors. The findings of this study underscore the potential of the speech recognition-based rehabilitation system to significantly improve rehabilitation outcomes for stroke patients. By enabling real-time feedback on finger angle, speed, and position during training sessions, the system empowers patients to engage in targeted finger exercises aimed at enhancing motor function and promoting recovery. Moreover, by providing objective data on patient performance, the system facilitates more accurate and comprehensive evaluation by rehabilitation physicians, enabling personalized treatment plans tailored to individual patient needs. A key strength of the developed system lies in its integration of hardware and software components, each optimized to maximize performance and usability. The hardware circuitry, comprising modules such as the main controller, sensor measurement, and motor drive, provides the necessary infrastructure for capturing and processing real-time data on finger movements. Meanwhile, the software design of the lower computer control system facilitates seamless communication between the hardware components, enabling precise control and customization of rehabilitation training parameters.

Central to the system's functionality is the application of the Hidden Markov Model (HMM) algorithm within the voice recognition human-computer interaction system. By leveraging the unique advantages of HMM, such as its ability to handle pattern recognition tasks and adapt to variations in speech patterns, the system achieves robust and reliable performance in recognizing and responding to voice commands. This advanced algorithmic approach enhances the user experience and ensures the effectiveness of the rehabilitation training process. The speech recognition-based rehabilitation system holds significant promise for transforming clinical practice in stroke rehabilitation. Its ability to deliver personalized, data-driven rehabilitation interventions tailored to individual patient needs has the potential to revolutionize the way rehabilitation therapy is delivered and monitored. Furthermore, the system's scalability and adaptability make it a valuable tool for researchers seeking to investigate novel rehabilitation strategies and interventions.

6.1 Future Directions

While the current study demonstrates the feasibility and efficacy of the developed rehabilitation system, future research directions may focus on further refining and optimizing system components to enhance usability, reliability, and patient outcomes. Additionally, longitudinal studies evaluating the long-term efficacy and sustainability of the system in real-world clinical settings are warranted. Furthermore, exploring avenues for integrating emerging technologies, such as virtual reality and artificial intelligence, could further augment the capabilities of the rehabilitation system and expand its potential applications.

In summary, the finger rehabilitation training control system developed in this study represents a significant step forward in advancing rehabilitation interventions for stroke patients. By combining cutting-edge technology with evidence-based rehabilitation principles, the system offers a transformative approach to enhancing motor recovery and improving patient outcomes. With further research and development, the system holds immense promise for revolutionizing stroke rehabilitation practice and improving the lives of patients worldwide.

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