Control schemes in soft hand rehabilitation exoskeleton

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Abstract. In recent years, rehabilitation exoskeletons have become a rapidly developing technology for rehabilitating and aiding people with various types of hand functional disabilities. However, one of the intractable problems is the lack of methods that can effectively convert the intentions of wearers to the motions of exoskeletons. In order to systematically understand the working principles and operation methods of some advanced control strategies, and to explore their potential. This review introduces three existing and modern control schemes in soft robotic hand exoskeleton from the perspective of their target, analysis methods and operating ways, with practical applications in every strategy. Then, the remaining context explores individual advantages and drawbacks to discuss the opportunities and challenges met in some state-of-the-art patterns that relate the bio-signal to the movement of robotic hand exoskeletons. Finally, the conclusion deduces that the prospective control schemes are the development of hybrid control architectures that synergistically integrate complementary advantages from multiple methodologies. Such hybrid approaches are expected to enhance the rehabilitation efficacy of robotic prosthetic devices significantly, optimizing patient-specific functional recovery outcomes and providing flexible rehabilitation plan.

Keywords: Rehabilitation Robot, Soft Robotic Hand, PID Control, Fuzzy Control, Sliding Mode Control.

1. Introduction

Today, significant advancements have been made in the field of prosthetic hands over the years. Many universities and research labs are actively funding this area, recognizing its importance and the potential opportunities for the rehabilitation of patients. Persistent hand impairment affects an estimated 50 million survivors of stroke and spinal cord injury globally [1]. Modern scientists are excited about the applications, which can lead to logical and effective rehabilitation training after conditions like dyskinesia or paralysis, as well as the development of better-fitting prosthetic limbs.

Currently, advancements in soft materials and tendon-driven designs are enhancing the external structure of prosthetic devices. ETH Zurich has designed a fully wearable assistive soft hand exoskeleton called the RELab Tenoexo, which has one hybrid architecture that combines soft and rigid structures to be lightweight and improve accuracy, while Harvard University has published a portable soft robotic glove with outstanding wearing comfort [1, 2]. These innovations reduce the burden on patients and increase flexibility. While the external design of these devices is relatively advanced, the control scheme design remains a significant challenge.

The prosthetic hands control process first decodes the user's movement with intent by extracting bioinformation via bio-signal, coordinate changes and torque applied et al., then converts this information into executable commands for prosthetic hand actuation following rule bases and translating equations. But most rehabilitation prosthetic hands have technical obstacles in the operation system, causing limited performance. Besides grabbing and moving objects, more complex actions are unable to be done perfectly and smoothly.

The difficulties in design slow down the hand-assist robot development process. To increase the intelligence of robotic hands and the smoothness of action completion, researchers are developing a growing number of learning-based analysis systems. These systems aim to interpret the rich informational content from patients to assist in the rehabilitation plan for the robot hand. Recognizing the critical role of this data-driven approach, this review provides a systematic examination of three kinds of control strategies. Specifically, this article reviews the core techniques for Proportional-integral-derivative (PID), Fuzzy and Sliding Model control, explaining their targets, rule bases and operating functions for hand rehabilitation, with a focus on how machine learning models to control the rehabilitation robot hand flexibly and accurately. Then, this review discusses and compares various control strategies in rehabilitation robots, analyzing the advantages and drawbacks. By synthesizing this knowledge, this paper finally aims to offer a clear overview of the state-of-the-art, identify current challenges, and point toward future research directions.

2. Proportional-integral-derivative control

2.1. Working principle

The control strategies play an important role in the signal process and generation to regulate the movement of the hand exoskeleton. The Proportional-integral-derivative (PID) control strategy is commonly used in the realm of rigid exoskeleton hands because of its precision on the prediction of linear motion of rigid bodies and systems. For soft hand exoskeletons, the PID control strategy is an effective tool for simplification such that providing an acceptable way for analysis and study under a limited condition. The equation of PID control is displayed below [3].

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)\, d\tau + K_d \frac{de(t)}{dt} \tag{1}$$

Where K_p is the proportional gain, K_i is the integral gain, and K_d is the derivative gain. The terms $e(t)$ and $e(\tau)$ are the errors, respectively. The PID method is highly dependent on the closed-loop control that is essentially based on the feedback errors as illustrated in Figure 1.

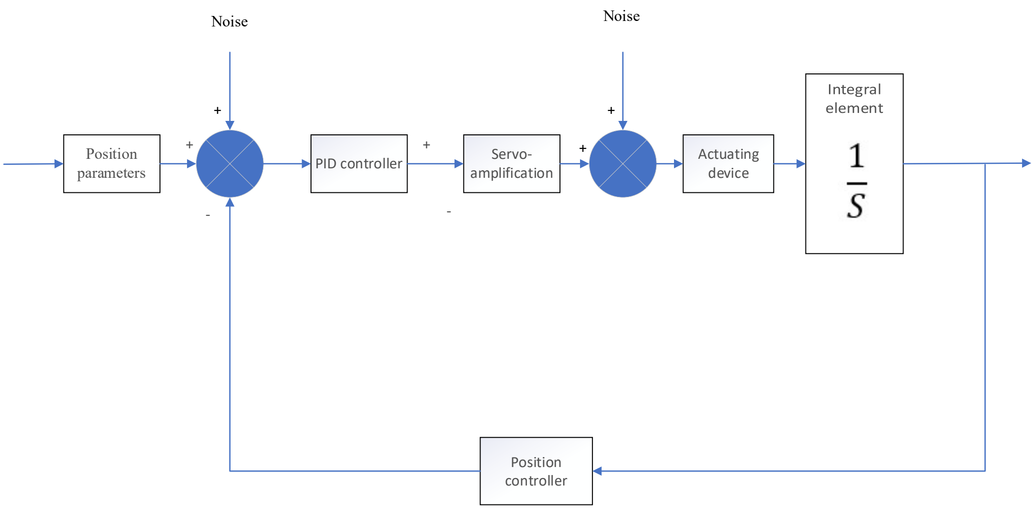

Figure 1. Basic loop of PID control strategy (Picture credit: Original).

The design of PID control can be classified into two types, model-based and model-free. The model-based design allows researchers to implement advanced features and reduces hardware, to optimize structure and improve control accuracy, while the model-free one achieves a simplification of a complex system and an efficiency for tuning and iteration procedures.

2.2. Rehabilitation Exoskeleton based on proportional-integral-derivative control

Kaplanoglu et al. proposed a wearable, tendon-driven, continuum robot (TCDR), which was a complicated system with more than 12 degree-of-freedom (DOF), for finger rehabilitation with PID controllers [4]. They determined the PID parameters, K_p, K_i and K_d, are 50, 20 and 10, respectively, by using the Ziegler-Nichols open-loop tuning method, a classic heuristic approach, through simulation only. The signal input of this system targets reference angles for each finger joint, the direct output is the actuating force, while the theoretical joint angle movement is the measured output signal. Their design, which was mainly targeted at the kinematic evaluations of the distal interphalangeal (DIP), metacarpophalangeal (MCP) and proximal interphalangeal (PIP) joints, achieved an accuracy and effectiveness of joints that followed the reference trajectories, especially within an error of ±0.7 ° for the MCP joints from graphical analysis.

Tejada et al. utilized PID controllers and an open-loop to form a system [5]. The team embedded a PID controller in each pneumatic finger with a flexion sensor in the hardware that consisted of five solenoid valves and pressure pumps, to capture the bending angle. Specifically, the team chose to use the pole assignment method, which is based on the real-world prototype and then derived the data from the physical model. What they innovated was that the feedback error could be collected from the actual bending percentage instead of the pneumatic signal. Their experimental results showed that the model achieved a mean absolute error (MAE) of 4.58%, which demonstrated the potential of PID control could work with myoelectric control and then apply broadly, as shown in Figure 2 and Figure 3.

Figure 2. Illustration of the glove exoskeleton[5].

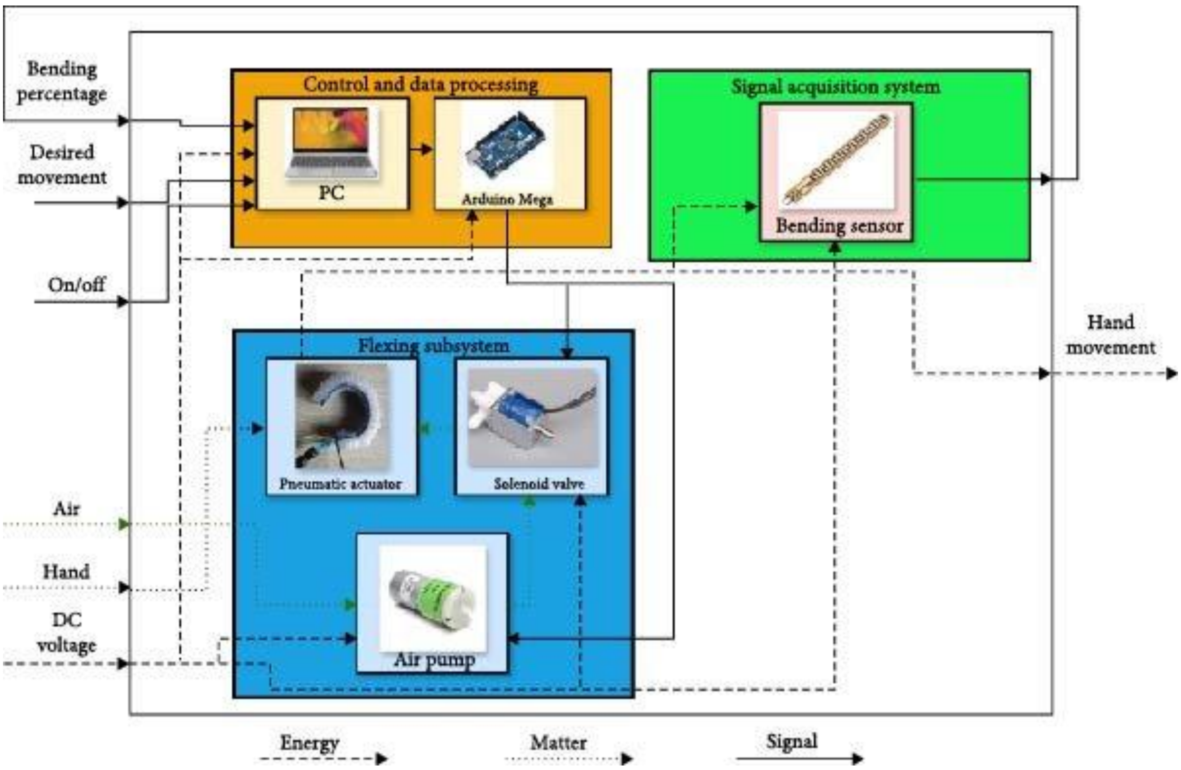

Figure 3. Structure of the control circuit for each finger. [5]

Ismail et al. presented the design, construction, and testing of a soft, wearable robotic glove that relied on the proportional-integral (PI) control [6]. The PI control, which is a branch of PID control, can be viewed as a simpler version of PID control with K_p and K_I items only, then it has less complexity and a good resistance to noise. This model used the real-time signal that came from EMG directly or the potentiometer on the remote control, and the aim is to control the extension and flexion of fingers from the output, as shown in Figure 4.

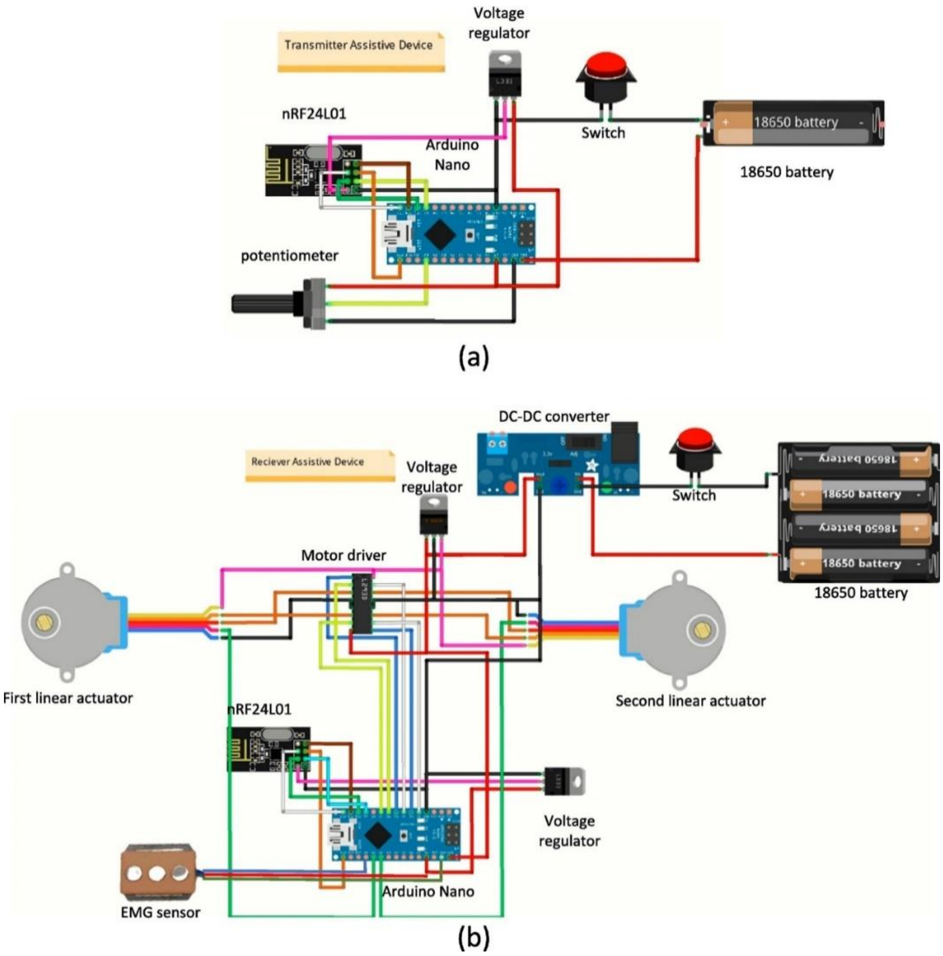

Figure 4. Schematic diagram of (a) remote control, (b) soft exoskeleton gloves. [6]

3. Fuzzy Control

3.1. A Fuzzy Logic-Based Pain Detection Approach

For rising safety and effectiveness during treatment, Abdallah et al. applicate a pain-sensing mechanism to regulate the magnitude of rehabilitation and personalized treatment methods.

Rehabilitation robot control, understanding fuzzy concepts involves uncertainties and subjective factors such as pain situation and individual endurance. For direct control decision-making for three key reasons: First, the machine hardly captures the continuum of human feeling. Second, they fail to represent the clinician's qualitative judgment of patient capability. Third, they lack adaptability to individual patient recovery patterns. As shown in Fig. 5, this fundamental limitation motivates the application of fuzzification, which transforms crisp numerical metrics into linguistic variables that better align with both clinical assessment paradigms and the inherent variability of neurorehabilitation. Then, fuzzy inference stimulates the decision process of the plan, evaluating the feeling to reveal the stiffness evaluation and translate it into parameters.

The pain represents fuzzy and approximation content, and the control method depends on EMG value and muscle contraction. Four key activity features, EMG_RMS, EMG_V-Order, EMG_SSI and

EMG_LOG are obtained by sensors during use. The root mean square value evaluates muscle contraction and constant force. And the EMG_SSI represents the magnitude of the EMG signal. The remainder considers the estimation of applied force. Then, a two-stage fuzzy inference system analyzes these inputs along with range-of-motion data to classify pain levels. Finally, different actions will be performed, achieving personalized rehabilitation by continuously monitoring physiological responses and modulating intervention intensity accordingly [7].

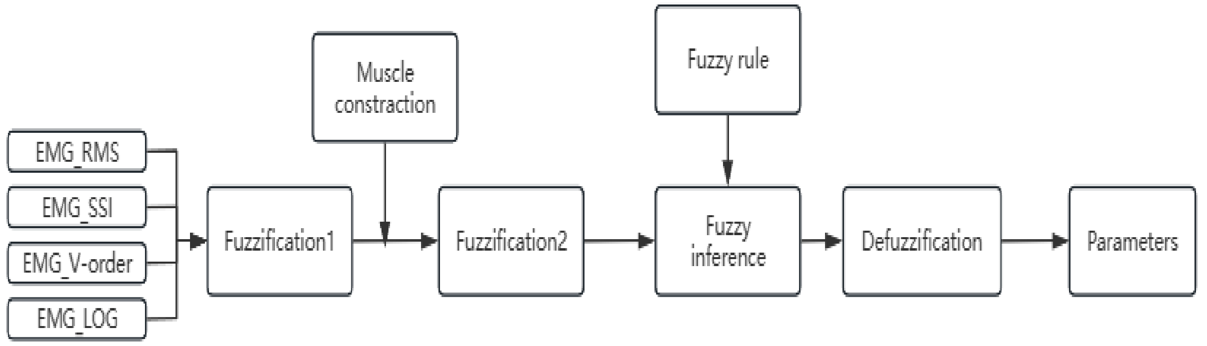

Figure 5. Fuzzy process in Fuzzy Logic-Based Pain Detection Approach [7].

4. Sliding Mode Control

4.1. Basic Sliding Mode Control

SMC is a non-linear control method for automatic control systems. It can adapt dynamically based on the system's state to force the state trajectory onto a sliding surface. A basic form for this surface is defined by the equation $s(t) = \lambda e + \dot{e}$, where the term e is a tracking error and $\dot{e}$ is its change of rate. When the condition $s(t) = 0$ is met, the system is constrained to follow a desired trajectory, which is known as the sliding surface [8]. The SMC control process is divided into two phases, which are shown in the control law equation below.

$$\tau(t) = \tau_{eq}(t) + \tau_r(t) \tag{2}$$

In this formula, $\tau_{eq}(t)$ represents Equivalent Control. It calculates the force required to maintain the system moving along the sliding surface based on known conditions (such as inertia, gravity, etc.). $\tau_r(t)$ represents Reaching Control. Its function is to apply a discontinuous corrective torque when the system state deviates from the sliding surface due to disturbances, thereby forcing the state trajectory to converge back to the surface. Specifically, the fundamental switching principle of the Reaching Control function is defined as:

$$u(t) = \begin{cases} u^{+}(t), & S(t) > 0 \\ u^{-}(t), & S(t) < 0 \end{cases} \tag{3}$$

The equation discontinuously switches between two different control laws $u^{+}(t)$ and $u^{-}(t)$ according to the sign of the switching function S(t). This discontinuous switching can generate a strong error correction force, ensuring that the system can resist uncertainty and external interference and maintain strongly on the sliding surface [9].

4.2. Non-Singular Terminal Sliding Mode Control

The NSTSM control strategy defines a nonlinear slide surface, which dictates the desired error dynamics.

The NSTSM surface is typically formulated as:

$$s = e + \Omega \epsilon^{\frac{a}{b}} \tag{4}$$

The key improvement over basic SMC is the nonlinear term ε^(a/b), where a and b are positive odd integers with a > b. The fractional power term serves to drive the tracking error to zero within a finite time. Concurrently, the parameters a and b are specifically chosen to preclude mathematical singularities during the system's approach to the sliding surface. Another improvement of NSTSM is the Reaching Control function in control law, which replaced the conventional 'sign' function with the saturation 'sat' function to mitigate the chattering effect [10].

4.3. Non-Singular Terminal Sliding Mode Control

The basic SMC has the advantages of a quick response and high robustness to parameter variations and disturbances [8]. Terminal Sliding Mode (TSM) control ensures finite-time state convergence to equilibrium. However, this is achieved through a negative fractional power term in its control law, which leads to the issue of singularities. Thus, Pratap et al. applied NSTSM control to their hand exoskeleton to deal with all these problems [10].

The overall architecture of the NSTSM control system is depicted in the block diagram in Figure 6. This diagram illustrates how the desired trajectory, feedback error, the sliding surface, and the control law interconnect to form a closed-loop system that controls the exoskeleton.

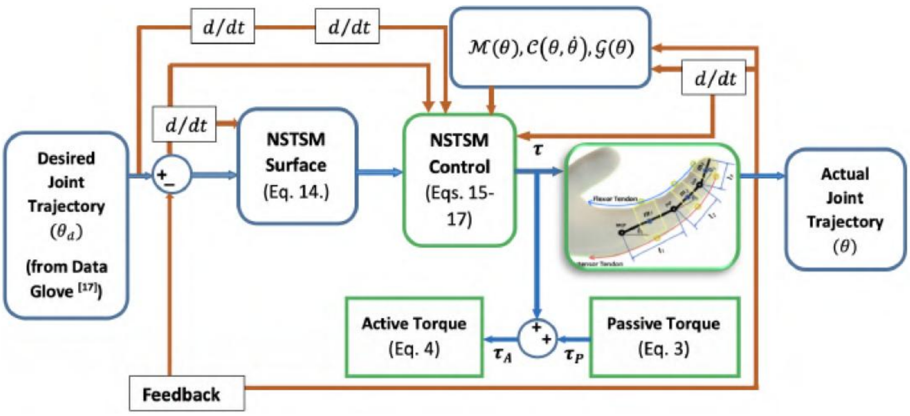

Figure 6. NSTSM control architecture [10].

To evaluate the performance of the NSTSM controller, a comparative simulation was conducted against a conventional PID control system. A uniformly lower RMS error in trajectory tracking across all finger joints demonstrated the performance advantage of the NSTSM controller. This difference was most pronounced at the metacarpophalangeal (MCP) joint, where the NSTSM controller's error (0.003 rad) was six times lower than that powered by the PID controller (0.018 rad). Higher performance was also presented in the other joints: for the PIP joint, the error under NSTSM control was approximately 0.004 rad, compared to 0.005 rad for PID, and the DIP joint showed a marginal improvement, with its error decreasing from about 0.017 rad to 0.016 rad. This series of simulation results provides practical evidence of the NSTSM strategy's superiority in handling uncertainties and achieving high-precision control, offering a more powerful and reliable solution for rehabilitation robotics than traditional PID [10].

5. Discussion

The PID control works mathematically on the feedback error from the output, and the parameters K_p, K_i and K_d in the linear equation can be iterated from physical models or through tuning [4,5]. Given this factor, the PID control strategy relies on the performance of the model or the system design under laboratory conditions. On the contrary, traditional PID control strategy has a lack of robustness, which is crucial in real-world situations. While PID control remains a fundamental building block for low-level execution, it is no longer the core of the system; instead, it is directed by a more intelligent, high-level brain, as shown in Figure 7.

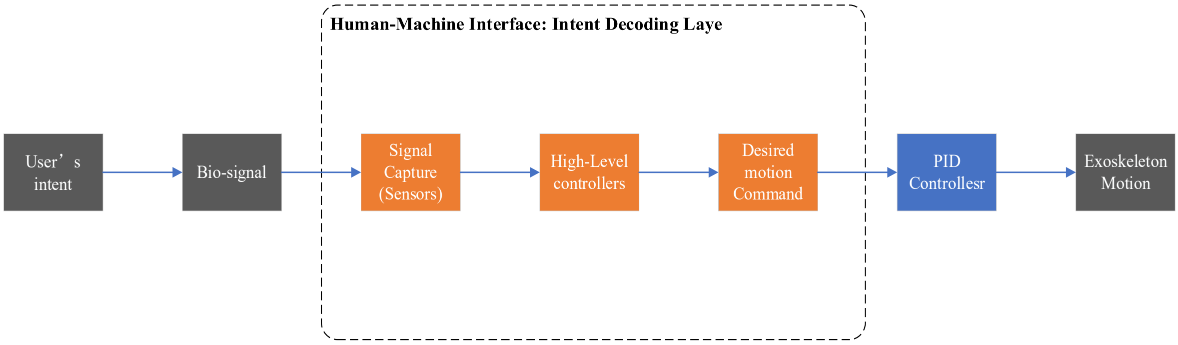

Figure 7. Bio-signal-driven Exoskeleton Control Architecture (Picture credit: Original).

Researchers now engage in the synergy between the EMG signal and the PID strategy system. The general trend is that control systems are becoming more intelligent and humane. The research focus has shifted from simple signal conversion to more advanced intention understanding and human-robot interaction. Nevertheless, difficulties come from aspects such as the noise and instability, lack of a stable setpoint, non-linearity and individual variability, creating challenges before commercializing this concept.

The PID control strategy works as an inner loop controller to guarantee the precise motion of the exoskeleton. With the addition of EMG-EEG fusion control, the rehabilitation device based on the basis of PID control shows its potential to broaden the application scenarios and a good performance. The authors also mentioned the series elastic actuators (SEA) to alleviate the impacts of noise. Another method to integrate EMG signal into the input of the PID control loop innovated by Abas et al. is to use an artificial neural network (ANN) as the high-level controller in the entire loop instead [11]. With the fully actuated form. The ANN could be simplified to be viewed as a translator that commands the PID controllers with the predicted joint angles. It is still a viable way to correlate the typical PID control to using the EMG signal as an input form. To raise the accuracy, the team equipped each finger with one PID controller, increasing the complexity and weight of the whole system. Thus, there are still some great challenges and urgent issues that need to be overcome when trying to realize PID control in exoskeletons for patients.

For fuzzy control, its outstanding ability to handle nonlinear and complex systems without a precise mathematical model’s requirement excels in rehabilitation planning design under variable patient responses [7]. Fuzzy logic prefers interpreting ambiguous or subjective inputs, such as pain levels or muscle activity, and translating them into actionable control signals. The whole process highlights fuzzy control's capacity to enhance patient-specific therapy. However, fuzzy control is not without limitations. Its performance heavily depends on the design of membership functions and rule bases. In Abdallah and Bouteraa's work, the fuzzy classifier's accuracy relied on carefully selected EMG features and pain estimation rules, and these are under expert knowledge or extensive tuning [7]. Additionally, fuzzy control systems face computational challenges when processing high-dimensional inputs or operating under strict time limits. This limitation arises because fuzzy logic relies on evaluating multiple rules and membership functions simultaneously, which increases computational overhead as the input space grows, so that delays during the process are hard to avoid. Despite these challenges, fuzzy control's benefits outweigh its drawbacks in rehabilitation contexts. Hu et al. emphasized the importance of motor learning and patient initiative. They employ fuzzy rules to modulate assistance forces based on task performance and impulse in rehabilitation. And their results showed improved subject engagement and reduced slacking during training. The application underscores fuzzy control's versatility in addressing diverse rehabilitation challenges [12]. Recently, Ni et al. revealed an exoskeleton rehabilitation design, which is a hybrid architecture of fuzzy control within Impedance control based on PSO-BP neural networks. During the fuzzification, the other control actively inserts the random disorder variance to train the networks, declaring the interference. The design integrates the interpretability of fuzzy logic with the learning capacity of neural networks and enables automatic optimization of both rule bases and membership functions through continuous interaction with patient data. Architecture's self-learning capabilities make the system nonlinearities and patient variability with higher robustness demand controllers evolve alongside the rehabilitation process [13].

For SMC and its advanced variants, such as NSTSM. They provide a robust approach to controlling rehabilitation robots, offering resilience against uncertainties arising from the patient and external disturbances. Unlike PID control, which relies on empirical tuning, or rule-based fuzzy control, SMC is mathematically guaranteed to be robust against parameter variations and external disturbances through its discontinuous switching control law. This is a crucial advantage for rehabilitation devices that must operate stably in complex and variable real-world situations. However, SMC also has some limitations, as its design involves a trade-off between robustness and control smoothness. A primary challenge is the chattering problem associated with classical SMC. The high frequency switching of the control signal contradicts the goal of smooth human interaction required for rehabilitation exoskeletons and must be suppressed. Although methods such as the saturation function used in the study by Pratap et al. can effectively mitigate this issue, this is often achieved at the expense of some robustness. Furthermore, advanced control schemes like NSTSM rely on the accurate modeling of the system, which is complex and hard to create and validate. Any deviation between the model and reality will impact control performance and limit its generalizability across different users.

The evolution of SMC within rehabilitation robotics is now trending towards hybrid control strategies that merge the precise trajectory tracking of SMC with the compliant characteristics of impedance control. This hybrid framework ensures safe, compliant interaction during exoskeleton movement. For instance, Hu et al. proposed an Impedance Sliding-Mode Control method for rehabilitation robots [14]. In their research, a sliding mode control is added to the traditional impedance control law to reduce system instability, which is caused by uncertainties such as patient limb shaking. Concurrently, their system can automatically regulate its stiffness based on the interaction force exerted by the patient, thus achieving adaptive rehabilitation. This research demonstrates a promising development path forward that hybrid strategies could be the next-generation myoelectric control systems.

6. Conclusion

The evolution of bio-signal control for soft wrist rehabilitation robots is fundamentally driven by the need for controllers that can manage the complexities of compliant hardware and human-robot interaction. However, the conversion of complex bio-signals into stable and reliable machine instructions remains a core challenge in this field. This review focuses on three bio-signal control strategies for soft rehabilitation robotic hands that offer distinct solutions to this reliability issue: PID control, Fuzzy control, and NSTSM control. PID control is a classical linear feedback approach, widely used as a performance benchmark. Fuzzy control is a rule-based strategy to handle subjective user inputs without a precise system model. NSTSM is a model-based control strategy that provides high robustness against model uncertainties and external disturbances. This review demonstrates that every control strategy has its own strengths and limitations, and a suitable method must be selected based on the specific application needs. In the future, some hybrid control schemes will become a promising development pathway. For example, the combination of Admittance Control and PID Control can create an accurate and intuitive human-robot interaction system. In future studies, researchers can focus on such hybrid methods that merge the advantages of different control strategies, allowing rehabilitation robotic hands to better assist patients, and even be a helpful assistant in everyone's life.

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Authors Contribution: All the authors contributed equally and their names were listed in alphabetical order.

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