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Advancements in Enhancing Degrees of Freedom for Upper-Limb Prostheses: Mechanisms, Control, and Sensory Feedback

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Abstract. Upper-limb amputation seriously affects a person's daily life. Traditional commercial myoelectric prostheses have only 2-6 degrees of freedom (DOFs) and are not yet capable of fine-motor manipulation. This paper reviews representative progress from 2014 to the first half of 2026 in three main directions: mechanism design and actuation, intelligent control and intention decoding, and sensory feedback and closed-loop interaction. The reviewed studies show that advanced mechanical configurations can add more active DOFs while reducing weight; deep learning decoding and shared semi-autonomous control can improve the accuracy and ease of control; and bidirectional neural interfaces, such as the e-OPRA system, have demonstrated the feasibility of closed-loop interaction. The analysis indicates that increasing the effective DOFs of prostheses requires the systematic integration of mechanisms, control and sensory feedback, rather than simply adding more joints.

Keywords: upper-limb prosthesis, degrees of freedom, myoelectric control, sensory feedback, neural interface

1. Introduction

Losing a hand through upper-limb amputation profoundly disrupts daily living. Although the human hand has over 20 degrees of freedom (DOFs), most clinically used myoelectric prostheses have only 2-6 active DOFs and are not very dexterous. Adding more joints does not automatically add function; all active DOFs must be properly coordinated by control channels, actuation devices and feedback loops [1, 2]. This paper reviews representative developments from 2014 to the first half of 2026 in mechanism design and actuation [1, 3], intelligent control and neural interfaces [4, 5], and sensory feedback and closed-loop interaction [6]. Chinese- and English-language literature on upper-limb prostheses published between 2014 and 2026 was collected from Web of Science, PubMed and IEEE Xplore. Studies on lower-limb prostheses, exoskeletons and brain-computer interfaces for non-prosthetic applications were excluded.

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2. Basic theory and performance evaluation of upper-limb prosthesis degrees of freedom

2.1. Definition and classification of degrees of freedom

A DOF is one independent movement that a joint can perform. The human hand alone has 21 DOFs, and the upper limb exceeds 27 DOFs when the wrist and forearm are included. According to the actuation method [7], prosthetic hands can be divided into three categories. Fully actuated designs provide a separate motor for each joint; they are relatively dexterous but are generally heavy and power-hungry. Underactuated designs use fewer motors than joints and transmit the driving force through linkages or other mechanisms, achieving a lightweight and energy-efficient structure at the cost of independent control of every DOF. Passive designs have no active components and offer the lowest level of functionality. Active DOFs are directly controlled by the user, whereas passive DOFs respond to external contact [2], as illustrated in Figure 1; they improve grasp adaptability but cannot be controlled voluntarily.

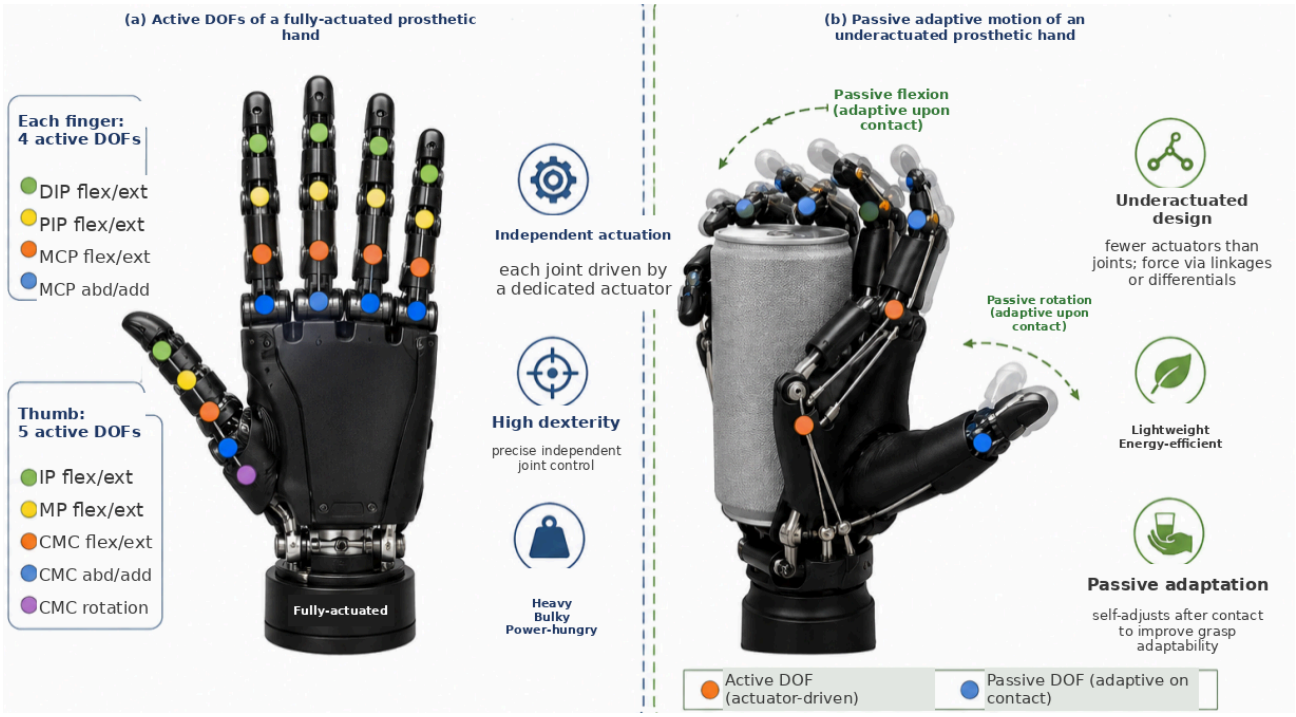


Figure 1. Schematic comparison of active and passive degrees of freedom

2.2. Relationship between degrees of freedom and dexterity

Dexterity is the ability to perform fine motor movements with the hands. The Cutkosky grasp taxonomy classifies human grasping into 16 patterns, from power grasps to precision pinches [8]. A prosthesis with more DOFs can theoretically reproduce more grasp patterns, but the relationship is not linear: without parallel improvements in control and feedback, extra DOFs raise cognitive load and reduce usability, and a few frequently used grasp patterns already cover most daily needs [9]. Mechanism design sets the upper bound on the achievable DOFs, intelligent control determines which DOFs can be controlled effectively, and sensory feedback determines which DOFs are actually usable in practice; this pathway is illustrated in Figure 2.

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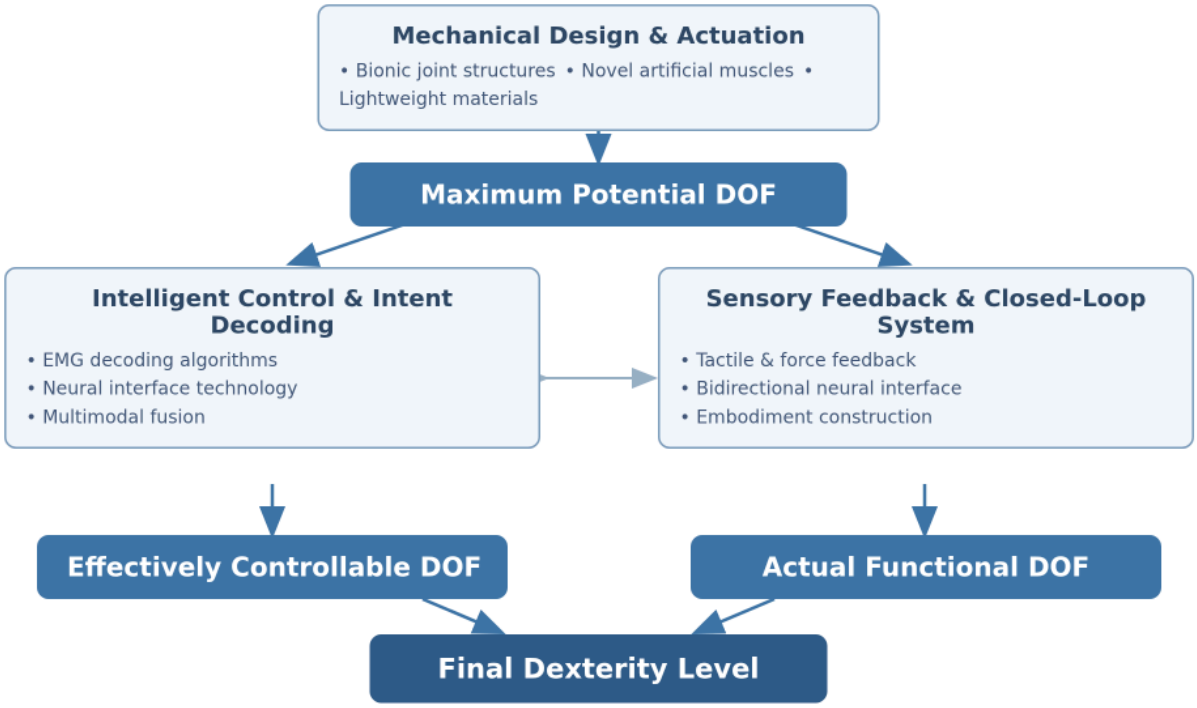


Figure 2. DOF Transformation pathway for upper-limb prostheses

2.3. Standardized functional assessment system and comparative analysis of mainstream high-DOF prototypes

Several standardized assessment protocols have been developed to evaluate prosthetic hand performance, including the Southampton Hand Assessment Procedure (SHAP), which uses 26 tasks to assess hand function [10]; the Box and Block Test for gross manual dexterity [11]; and the Action Research Arm Test (ARAT) and Functional Independence Measure (FIM) for upper-limb function and independence in daily living [12, 13]. Table 1 summarizes the main parameters of several high-DOF prosthetic hands and commercial products and shows how they balance DOFs, actuation, weight and control difficulty.

Table 1. Comparison of parameters of representative high-DOF upper-limb prostheses

Prosthetic Hand	Total DOFs	Active DOFs	Actuation Technology	Control Source	Feedback Mechanism	Weight (g)	Year
Shadow Hand C6	24	20	DC motors with gearboxes	sEMG/TMR	None (optional tactile)	1900	2015
USTC Lightweight Dexterous Hand (2025)	19	19	SMA wires with integrated cooling	Voice recognition	Joint angle sensing	370	2025
JHU Rigid-Soft Hybrid Hand (2025)	15	10	Pneumatic soft joints + rigid skeleton	sEMG	Three-layer neuromorphic tactile sensing	420	2025
Chalmers e-OPRA	7	6	DC motors	Implanted electrodes (osseointegration)	Intraneural stimulation	580	2020

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Table 1. (continued)

i-Limb Quantum	14	6	DC motors	sEMG	Vibrotactile feedback	520	2015
SoftHand Pro	19	1	DC motor with differential mechanism	sEMG	None	380	2018

Table 1 should not be interpreted solely in terms of the absolute number of DOFs. For example, the University of Science and Technology of China (USTC) hand achieves 19 active DOFs at only 370 g and is controlled by voice [14], whereas the SoftHand Pro has only one active DOF yet covers most daily activities through mechanical adaptability. The goal of prosthetic design is therefore not that "more active DOFs are better" but rather the rational selection of "effective DOFs".

3. High-DOF biomimetic mechanisms and actuation technologies

3.1. Anthropomorphic bionic joints and underactuated adaptive structures

Highly biomimetic prosthetic hands aim to imitate the shape and movement of the human hand [1]. The Shadow Hand C6 has 24 DOFs and a joint range of motion close to that of a human hand. The thumb is the most difficult part to replicate, as it is essential for opposition and precise grasping; recently, a 5-DOF thumb mechanism has been developed that closely imitates human thumb motion, as shown in Figure 3.



Figure 3. Comparison of biomimetic thumb opposition mechanisms

Underactuation is an effective way to reduce the number of motors and make prostheses lighter [2, 7]. The SoftHand Pro, developed at the University of Pisa, uses a single motor and a tendon-driven differential system spanning 19 joints, allowing it to perform many daily activities with only

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one active DOF [15]. The i-Limb Quantum uses six motors to control 14 joints and offers good independent control and adaptability [16].

3.2. Mainstream novel artificial muscle actuation schemes (SMA / pneumatic soft / dielectric elastomer actuators)

Traditional prosthetic hands are driven by DC motors and gearboxes; they tend to be heavy, noisy and limited in power density. Shape-memory alloy (SMA) wires contract when heated and expand when cooled; they provide muscle-like linear actuation, a high power-to-weight ratio, silent operation and a compact form factor. Zhang Shiwu's team at USTC reported a 19-DOF lightweight SMA dexterous hand in Nature Communications, weighing only 370 g with closed-loop control of all active DOFs [14]. After about half a day of training, amputees could use the hand to comb their hair, write and even make sign language gestures. However, SMA actuation suffers from large hysteresis and slow heat dissipation, so a control compensation algorithm is required.

Pneumatic and hydraulic soft actuators produce bending and twisting motions under fluid pressure; they are light, inexpensive and inherently safe but require external pumps or compressors. A team at Johns Hopkins University developed a rigid-soft hybrid prosthetic hand in Science Advances, featuring a rigid endoskeleton and soft pneumatic joints [17]. A three-layer neuromorphic tactile sensor enables the hand to sense the hardness and texture of objects and grasp them safely without complex force control.

Dielectric elastomer actuators (DEAs) are electroactive polymers that deform under an electric field, offering high energy density, fast response and high efficiency; finger prototypes driven by DEA pairs in an agonist-antagonist configuration have been shown to produce strains and force outputs close to those of biological muscles [18]. However, DEAs require operating voltages of several kilovolts, raising safety and practicality concerns for wearable devices, and they remain at the prototype stage.

3.3. Lightweight materials and modular system design

Weight is a major concern in prosthetic design: excessive weight causes fatigue and long-term health problems. Many prosthetic hands are now made of materials such as carbon fiber, titanium and PEEK. Carbon fiber offers an excellent strength-to-weight ratio and is widely used in structural components [1]. Modular designs use interchangeable finger and wrist modules that can be combined to suit different needs and also facilitate low-cost repair [19].

4. Intention decoding and high-DOF coordinated control technologies

4.1. Inherent limitations of traditional EMG decoding and deep learning optimization approaches

Traditional myoelectric control relies on surface electromyography (sEMG) to record electrical signals from residual limb muscles. The earliest systems controlled one or two DOFs using amplitude thresholds [16]; more advanced systems employ pattern recognition algorithms such as linear discriminant analysis (LDA) and support vector machines (SVM) to map muscle activation patterns to discrete commands and recognize 5-10 gestures [5]. However, these systems offer few independent control channels, weak proportional control, signal drift and a high cognitive load, making it difficult to control more than 6-7 active DOFs.

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Deep learning has achieved promising results in EMG decoding: CNNs extract spatial features from high-density EMG arrays, while RNNs and Transformers model temporal correlations. Benchmark studies have recognized several dozen hand gestures with accuracies of about 90% or higher [20]. Regression models can directly map EMG signals to joint angles or torques, enabling simultaneous and proportional control of multiple DOFs [21], and human-machine co-adaptive online learning can reduce training time and cognitive load [22]. Figure 4 compares the two processing pipelines.

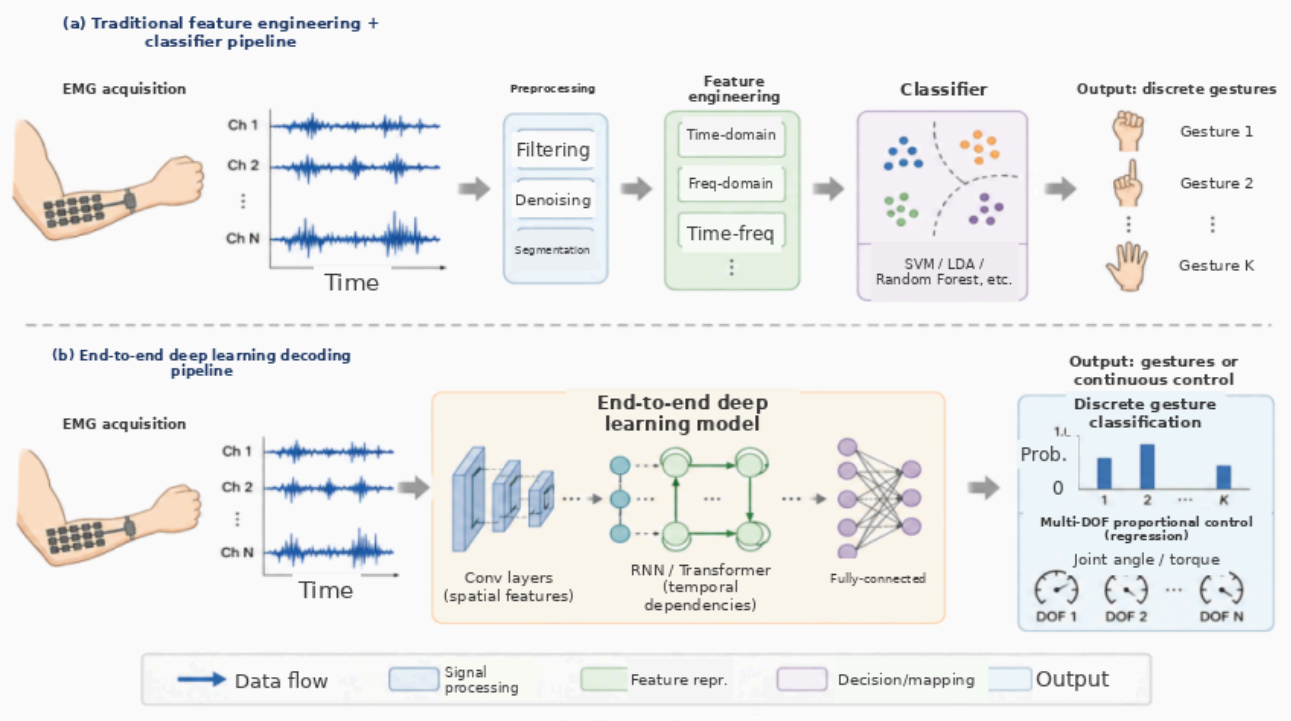


Figure 4. Comparison of traditional and deep learning EMG decoding methods

Most of the high accuracies reported above, however, were obtained in in-session tests. The main obstacle to clinical application is the lack of cross-session stability: signal distributions drift because of electrode displacement, sweat, fatigue and other factors. Deep domain adaptation aligns feature spaces to transfer knowledge from previous sessions to new ones [23], and adversarial training enables "calibration-free" control without new labeled data [24]. Combining EMG with inertial measurement units (IMUs) has also been used to improve the stability of recognition and control [25].

4.2. Shared semi-autonomous control paradigm (vision/voice assistance)

When active DOFs exceed six, both the EMG bandwidth and the number of stable control patterns are limited, so direct one-to-one mapping of more than ten DOFs is not feasible. Shared control shifts the low-level tasks of grasp configuration planning, joint coordination and closed-loop force control from the user to the machine; the user then only needs to provide high-level intentions. Computer vision can detect an object in the camera view and automatically determine its grasp point [26], and voice commands can be used to switch between modes [14].

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4.3. Implantable neural control: TMR and osseointegration technologies

Advances in signal processing cannot overcome the fundamental limitation on the number of independent control signals obtainable from residual limb muscles. The two main surgical approaches are targeted muscle reinnervation (TMR) and osseointegration. TMR redirects severed nerves to denervated muscles near the residual limb, which then act as "biological amplifiers": when the user intends to move the missing limb, these target muscles generate EMG signals that can be picked up by surface electrodes. The surgical principle is illustrated in Figure 5 [27]. TMR greatly increases the number of independent control signals, allowing amputees to control many DOFs intuitively and simultaneously, and can also reduce phantom limb pain [28].

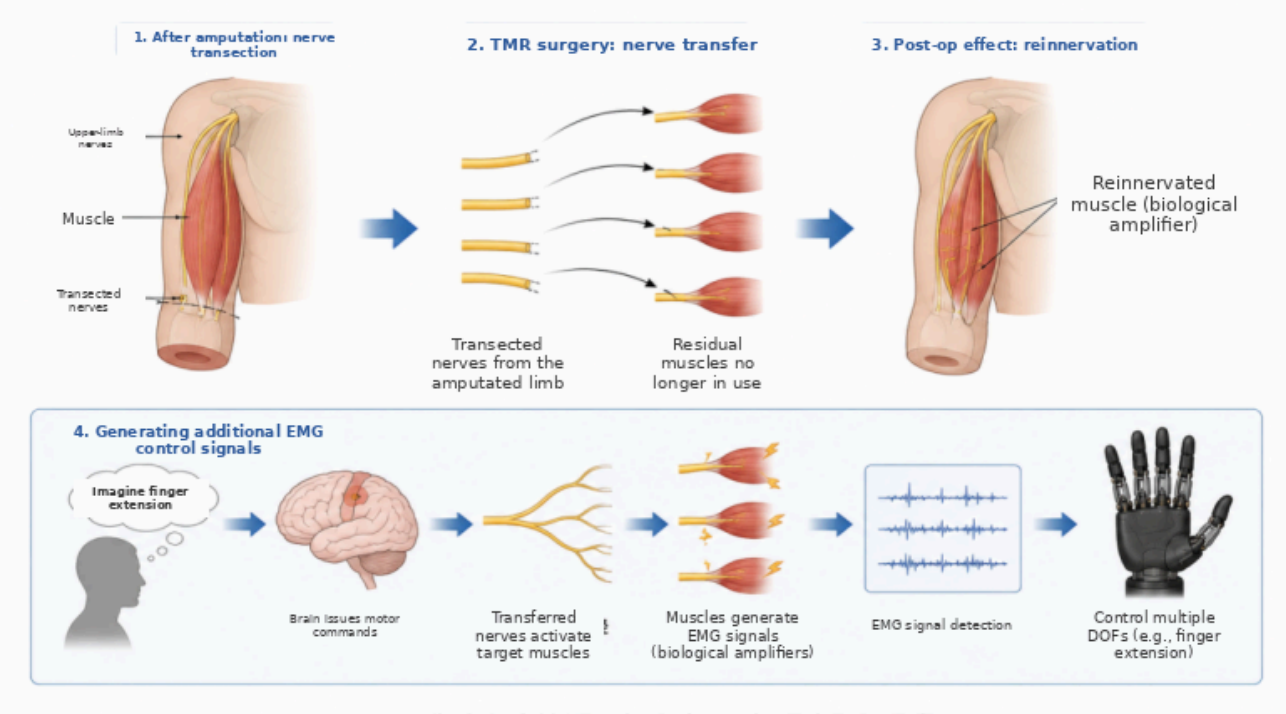


Figure 5. Schematic of the principle of targeted muscle reinnervation (TMR) surgery

Osseointegration refers to the close integration between a titanium implant and the adjacent bone, providing a stable anchorage that eliminates the need for a socket [29]. Implanted electrodes obtain high-quality neural signals. The e-OPRA system connects percutaneously to implanted neuromuscular interfaces and can operate continuously with sensory feedback [30, 31]. Although long-term follow-up has shown improvements in function and quality of life, infection and implant loosening remain concerns. TMR requires no implanted foreign body and suits patients with good residual muscle, whereas osseointegration suits those demanding higher signal quality and wearing stability.

5. Sensory feedback and bidirectional neural closed-loop interaction systems

5.1. Comparison of invasive and non-invasive tactile feedback mechanisms

Current prosthetic hands lack touch, pressure and temperature feedback, so users rely mainly on visual feedback, which is slow and cognitively demanding. Sensory feedback can be delivered by

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external (non-invasive) or internal (invasive) means. Non-invasive feedback can be produced by stimulating the skin of the residual limb [32]: vibration motors convey information about contact and grip force, and electrical stimulation can generate a sense of touch and pressure. These methods are safe and inexpensive and have been adopted in commercial prostheses such as the i-Limb Quantum and Bebionic. The invasive approach stimulates the peripheral nerve directly through implanted electrodes; several designs have been developed for this purpose, including the Utah slanted electrode array (USEA), transverse intrafascicular multichannel electrodes (TIME) and longitudinal intrafascicular electrodes (LIFE) [6, 33]. Cortical stimulation, which targets the somatosensory cortex, offers another route for restoring sensation but remains more invasive and largely experimental. Although non-invasive feedback has gradually reached the market, invasive neural feedback remains at the research and early-clinical stage because of surgical risks and long-term stability concerns.

5.2. Bidirectional neural interface closed-loop architecture and clinical validation cases

Bidirectional neural interfaces can record neural signals to operate a prosthesis and send sensory information back to the nervous system, thereby forming a closed-loop system that functions like a biological limb. Electrodes record neural activity and decode motor intentions; the decoded commands drive the prosthesis, while onboard sensors measure contact forces and motion states that are encoded and transmitted back to the user. This architecture improves control performance and enhances the sense of embodiment [33]. The information flow is illustrated in Figure 6.

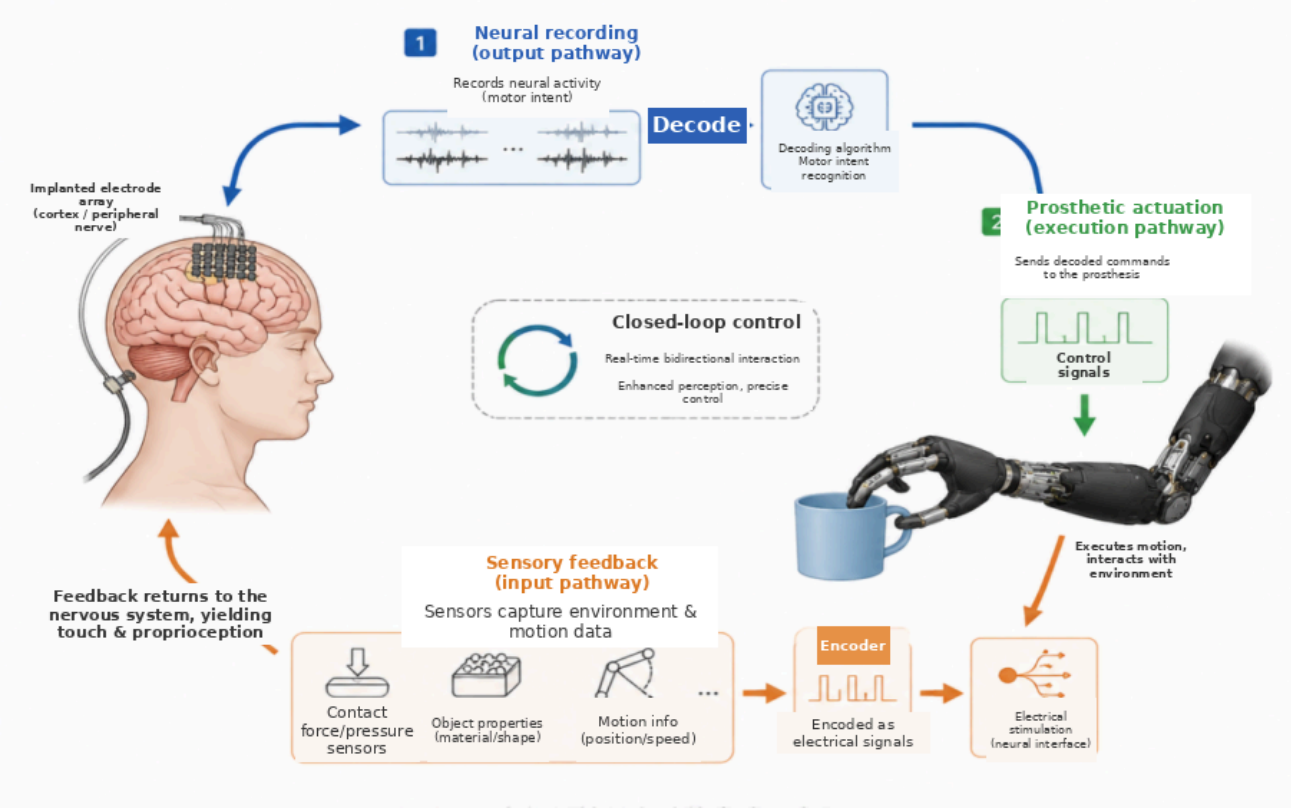


Figure 6. Schematic of information flow in a bidirectional closed-loop neural prosthesis

George et al. developed a bidirectional prosthetic hand that uses intraneural electrodes to record motor intention and provides biomimetic sensory feedback through peripheral nerve stimulation.

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With this hand, a forearm amputee performed fine-motor tasks such as picking up fragile objects with significantly better accuracy and speed than open-loop control, along with a markedly enhanced sense of limb ownership [33]. Another approach to achieving long-term stable bidirectional signal transmission is the regenerative peripheral nerve interface (RPNI) [34]. The e-OPRA system represents a benchmark for long-term clinical application: implant recipients have used it continuously in daily life for several years without serious complications, demonstrating that bidirectional closed-loop prostheses can operate reliably outside the laboratory [30, 31].

6. Conclusion

This paper has reviewed representative achievements from 2014 to the first half of 2026 in three directions for enhancing the effective DOFs of upper-limb prostheses: mechanism design, intelligent control and sensory feedback. The reviewed studies show that lightweight SMA actuation and rigid-soft hybrid structures can already provide 19 active DOFs at about 370 g; that deep learning and multimodal fusion have greatly improved the accuracy and robustness of EMG decoding; that shared semi-autonomous control has addressed the EMG bandwidth bottleneck; that non-invasive feedback technology is now commercially available; and that bidirectional neural interfaces, such as e-OPRA and peripheral nerve stimulation, have shown promise for closed-loop control. Overall, high dexterity is not achieved simply by adding more joints; it requires the integrated development of mechanisms, control and sensory feedback.

This review has some limitations: it draws mainly on representative studies rather than all approaches, and many performance indicators come from different groups without cross-validation against a common benchmark. Future clinical application of neural interfaces will continue to be hindered by long-term interface stability, control-related cognitive load, power consumption and heat dissipation. Industrialization is also constrained by high costs, poor durability, clinical regulatory requirements and the absence of insurance coverage. Looking ahead, miniaturization and wireless operation of bidirectional neural interfaces, rigid-soft integrated structures and regenerative neural interfaces are the most promising directions.

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