Next-Generation Neuroprosthetics: Bridging the Human Mind and Artificial Intelligence

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***Abstract*—*Objective*: This study advances neuroprosthetic design by leveraging neural interface and artificial intelligence (AI) to enable seamless translation of motor intent into intuitive, lifelike control of prosthetic devices. *Methods*: Our approach is founded on three key innovations. First, we develop neuromodulation microchips and devices for acquiring high-fidelity peripheral nerve signals from microelectrode implants. Second, we design and train AI models based on recurrent neural networks (RNN) to decode neural patterns and accurately predict motor intent. Third, we create a prototype neuroprosthetic hand that integrates all components into a portable, self-contained system. *Results*: We demonstrate that acquired nerve signals contain distinct neural signatures for individual hand gestures, which can be decoded by deep learning AI with superior accuracy compared to traditional machine learning techniques. Clinical validation shows the decoder can predict 15 degrees of freedom (DOF) in regression tasks, with a mean squared error (MSE) ranging from 0.001 to 0.01. An optimized classification model achieves 95–96% accuracy in distinguishing movements of the five fingers. When deployed on the prototype neuroprosthetic hand, the AI model enables amputees to control individual prosthetic fingers precisely and intuitively in real time. *Conclusion & Significance*: This work bridges human peripheral nerves with advanced AI to enable precise, intuitive control of prosthetic devices. It represents a transformative step toward next-generation neuroprosthetics, with the potential to significantly improve the quality of life for individuals with motor impairments.**

***Index Terms*—artificial intelligence, deep learning, peripheral nerve, neural decoder, neural interface, neuroprosthesis**

I. Introduction

NEUROPROSTHETICS aims to restore or replace lost or impaired body functions by establishing an efficient connection between the human mind and machines. Among its various applications, restoring upper limb functionality remains one of the greatest challenges due to the complexity of the human hand and its extensive sensory innervation [35]. Advances in robotics and material sciences have enabled the development of prosthetic hands capable of mimicking complex, lifelike movements. Notable examples of state-of-the-art systems include the DEKA Luke Arm [30], [31], the APL ARM [16], and the DLR Hand Arm system [9]. However, a critical gap persists: the absence of an intuitive interface that allows amputees to fully control all degrees of freedom (DOF) of these sophisticated prosthetic hands [3]. Without effective control, even the most advanced prosthetic arms fail to meet the functional needs of users.

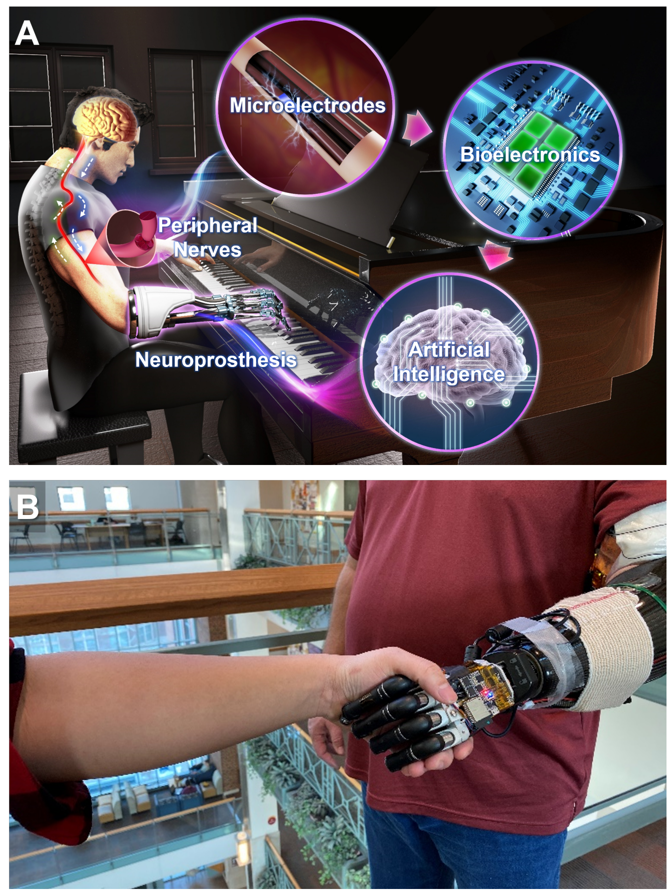

Fig. 1. (A) Concept of a dexterous and intuitive neuroprosthetic hand, facilitated by connecting the human mind with AI through a neural interface. (B) Prototype neuroprosthetic hand developed in this work to realize this concept.

Motor control signals for prosthetic control can be intercepted at various levels: the brain, muscles, or peripheral nerves, each with distinct advantages and limitations. Brain or cortical decoding systems [1], [11], [12], [14] using implanted microelectrode arrays provide sufficient neural information for near-natural, individual finger control. Systems like BrainGate [33] and Neuralink [21] are promising candidates for future commercialization. However, their invasiveness raises concerns about safety, practicality, and long-term reliability. On the other hand, surface electromyography (EMG) signals from

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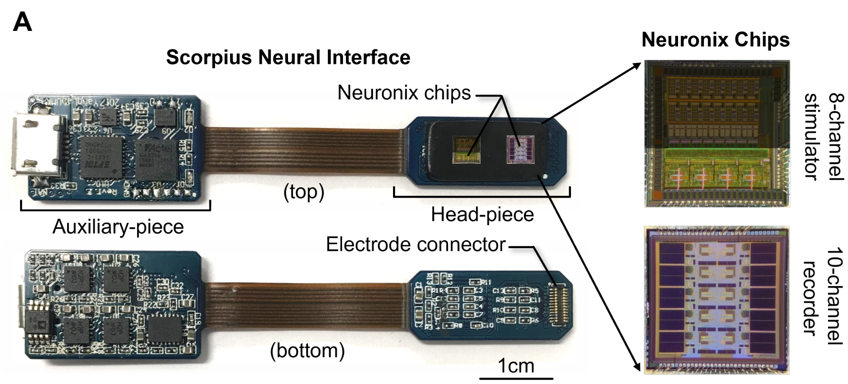


B

Neural Recorder's Specifications

Specifications	RHD2000 (Intan Tech.)	Scorpius (This work)
Chip size (mm)	4.1 x 4.8	3 x 3
System size (mm)	20 x 99 x 155	4 x 12 x 68
System weight (g)	130	3
No. of channels	16-256	10
Samp. rate (kHz)	30	10-80
Bandwidth (Hz)	0.1-10,000	10-5,000
Noise floor (μV)	2.4	2.5
ADC res. (bits)	16	12
System res. (bits)	12.0	11+4.5

Fig. 2. Fully-integrated Neuronix microchips and the Scorpius neuromodulation device enable bidirectional neural interface. (B) Specification comparison between Scorpius and a commercial neuromodulation system.

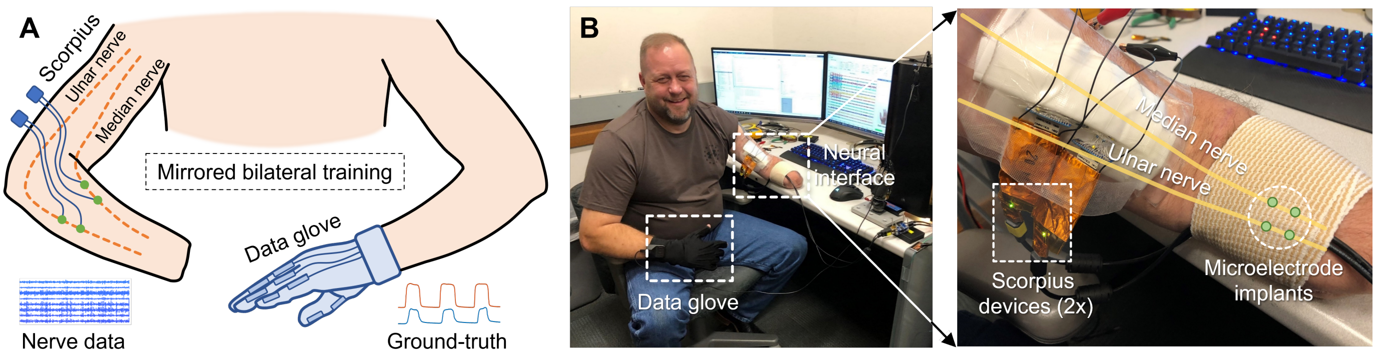


Fig. 3. (A) Overview of the mirror bilateral paradigm to collect training dataset for the AI neural decoder. (B) Photo of the experiment setup with one of the amputees.

residual muscles, commonly used in non-invasive prosthetics, typically allow only sequential control of basic grasp patterns [6]. EMG-based pattern recognition systems [5], [10], [15] can provide limited control, but remain unintuitive, unnatural, and challenging to scale for higher DOF. Targeted muscle reinnervation (TMR) addresses some EMG system limitations, offering more intuitive control, but it requires complex surgery with uncertain outcomes [2].

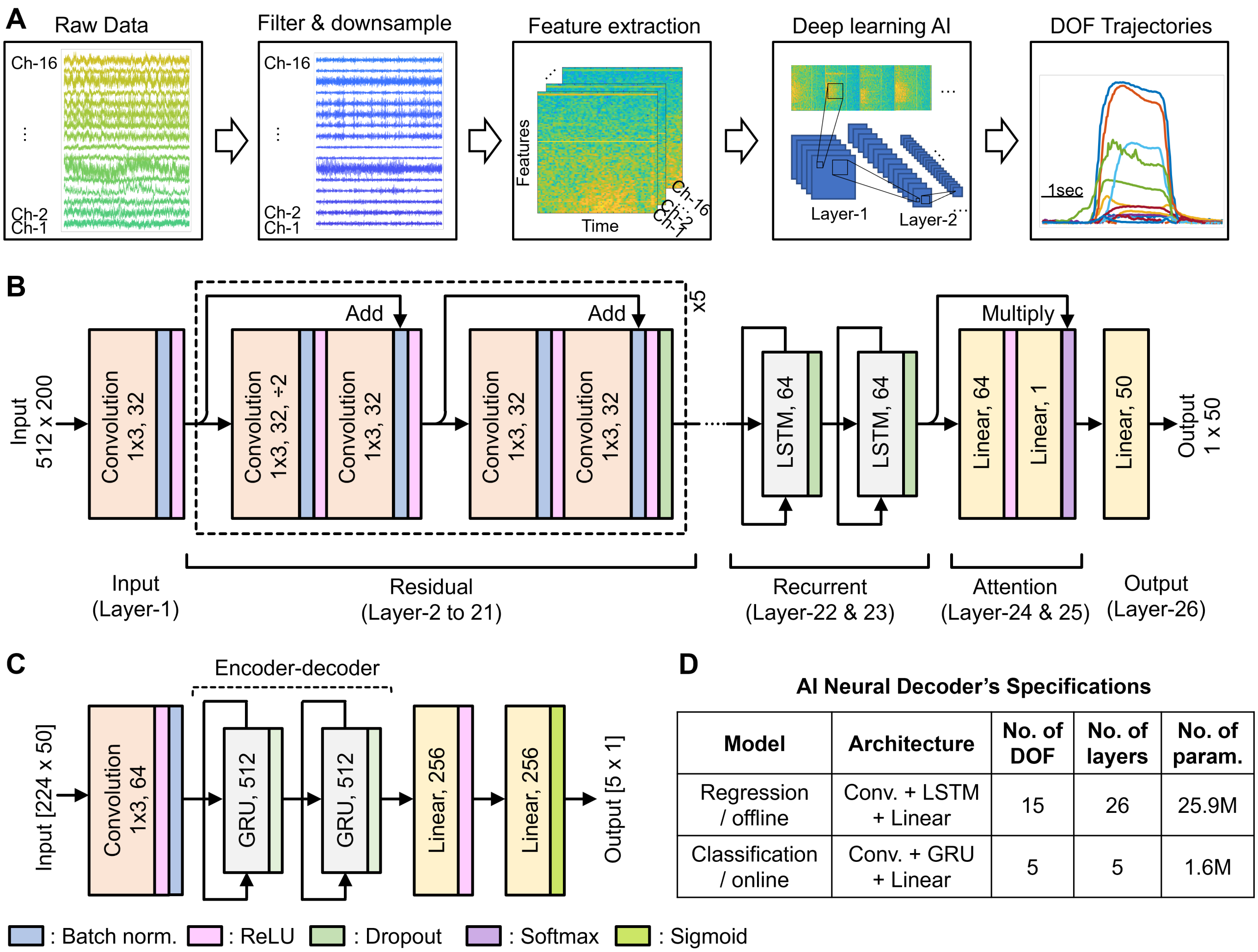
This work focuses on motor decoding signals obtained from the amputee's residual peripheral nerves, a promising approach that strikes a balance between invasiveness and functionality. Peripheral nerve interfaces are less invasive than brain-based systems while still providing sufficient information for control and enabling sensory feedback. However, acquiring and interpreting nerve signals poses significant challenges due to poor signal-to-noise ratio (SNR), stimulation artifacts, and environmental interference. Recent advancements in microelectrodes [29], [32], bioelectronics [28], and machine learning algorithms [20] have addressed many of these challenges, making peripheral nerve interfaces increasingly viable. Previous studies [13], [36], [37] demonstrate that peripheral nerve interfaces can sustain bidirectional communication channels with sufficient bandwidth for prosthetic control. Additionally, machine learning algorithms have proven effective in decoding motor intent from nerve signals [7], [8]. Tactile and proprioceptive feedback delivered through peripheral nerves enhances dexterity and control of prosthetic hands [4], [34].

The remainder of this manuscript is organized as follows: Section 2 describes the design of the neural interface devices, AI neural decoder, and neuroprosthetic hand. Section 3 presents experimental results, including peripheral nerve signal acquisition, motor decoding performance, and real-world testing of the neuroprosthetic hand. Section 4 discusses the implications of this work and potential future directions. Finally, Section 5 concludes the manuscript.

II. Methods

A. Neural Interface Microchips and Devices

Figure 2(A) shows the neural interface microchips-Neuronix and neuromodulation devices-Scorpius that we have developed to enable a high-performance bioelectric neural interface, allowing computers to effectively "talk" to the brain. These hardware systems are built on innovative design techniques pioneered in our work, including the frequency-shaping (FS) amplifier [38], [39], redundant sensing analog-to-digital converter (RS-ADC) [22], [23], super-resolution digital-to-analog converter (SR-DAC) [17], [40], and redundant crossfire (RXF) neurostimulator [27], [41]. The Neuronix microchips integrate high-performance neural recording and high-precision neural



Model	Architecture	No. of DOF	No. of layers	No. of param.
Regression / offline	Conv. + LSTM + Linear	15	26	25.9M
Classification / online	Conv. + GRU + Linear	5	5	1.6M

Fig. 4. (A) Overview of the data processing pipeline to decode motor intent. (B) Architecture of the offline AI neural decoder based on an RNN with LSTM layers. (C) Architecture of the online AI neural decoder, featuring GRU layers and optimized for real-time inference on the Jetson Nano platform. (D) Comparison of specifications between offline and online models.

stimulation functionalities. These chips are capable of acquiring low-noise neural signals from neuronal populations while simultaneously delivering precisely controlled electrical stimulation to modulate the activity of the same neurons. Neuronix chips are embedded into Scorpius devices, which are miniaturized neuromodulation systems designed to interface with microelectrodes, facilitating bidirectional communication between a computer and human peripheral nerves.

Figure 2(B) compares the specifications of the Scorpius system to those of a commercial neuromodulation system. The proposed system features a substantially smaller size and weight, making it ideal for implantable and wearable applications, while also exhibiting enhanced sensitivity and specificity in detecting neural signals. Scorpius devices undergo rigorous validation through extensive in vitro and in vivo animal experiments before deployment in human amputees. The combination of high system resolution, miniaturization, and low-power allow it to isolate weak nerve signals from large-amplitude artifacts and interferences, which is the key to enable in multi-DOF motor decoding using deep neural networks.

B. Deep Learning AI Neural Decoder

Training dataset: Figure 3(A, B) summarizes the human experimental paradigm to collect training data for the AI model. The study involves two transradial amputees and one partial hand amputee. Each amputee have four microelectrode arrays implanted in the median and ulnar nerves, connected to two Scorpius devices via percutaneous connectors.The motor decoding dataset are collected using the mirrored bilateral paradigm. Nerve signals are recorded from the injured hand while ground-truth movements from the able hand. Patients perform different gestures with the able hand while imagining the same movements with the injured/phantom hand simultaneously. The gestures include flexing individual fingers and common gestures such as fist/grip, index pinch, etc., which are combination of muliple fingers. While instrinsic muscles in the injured hand are lost, control signals originated brain are still present strongly and can be captured via residual peripehral

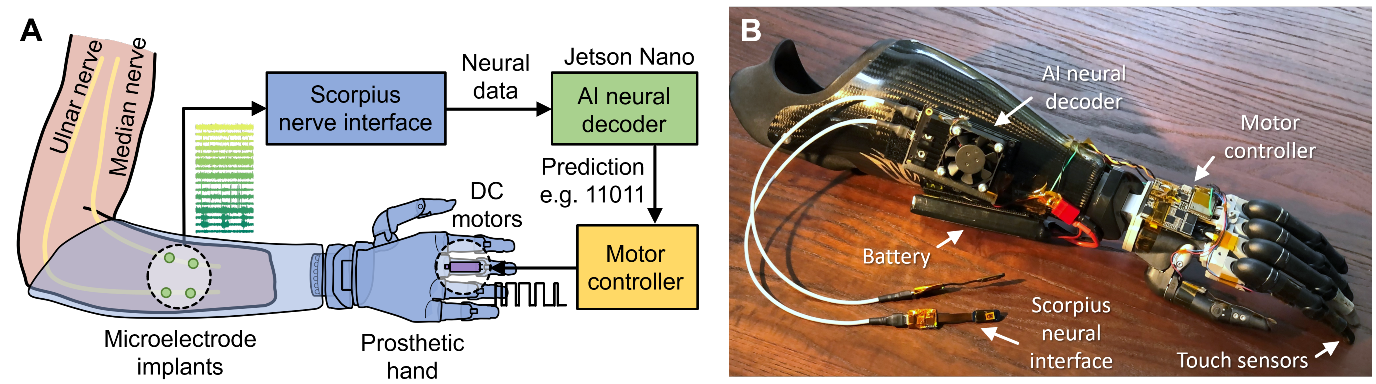


Fig. 5. (A) Overview and (B) implementation of the portable, self-contained prototype neuroprosthetic hand, integrating all key components for real-time control.

nerves with our neural interface. Scorpius system records 16 channels of nerve signals from selected electrodes with highest SNR at a sampling rate of 10 kHz. The dataglove captures 15 DOF including finger flexion/extension, abduction/adduction, and thumb-palm crossing. The dataset is divided into 80% for training and 20% for validation.

Neural decoder: Figure 4(A) provides an overview of the data processing pipeline used to decode motor intents from nerve signals. Initially, raw neural data undergo filtering and downsampling to eliminate unwanted components and focus on the bandwidth that contains relevant neural information. Next, the feature extraction stage serves two critical purposes: reducing the input data dimensionality and emphasizing components with the desired information. Various techniques can be employed at this stage to significantly reduce complexity and enhance the efficiency and accuracy of the subsequent deep neural networks. Finally, the deep learning model processes the extracted features to predict the trajectory of each DOF, which can then be utilized to control the prosthetic hand.

Figure 4(B) shows the architecture of the offline AI neural decoder, which is based on a recurrent neural network (RNN) with long short-term memory (LSTM) layers. RNN were chosen for this task thanks to their proven effectiveness in processing time-series data. This model performs regressive prediction of 15 DOF offline, which allow validating that the acquired nerve signals contain sufficient neural information for dexterous control of multiple DOF. The input to the model is the spectrogram of nerve signals, calculated for frequencies below 3 kHz. The spectrogram serves as a feature extraction step, reducing the input dimensionality while preserving critical neural patterns. The network architecture consists of 21 convolutional layers, two LSTM layers, two attention layers, and an output layer. The architecture is optimized by incrementally adding individual layers and monitoring the decoder's performance using 5-fold cross-validation, until no further improvement is observed and the model shows signs of overfitting.

Figure 4(C) shows the architecture of the online AI neural decoder, optimized for real-time control of a prosthetic hand. We employed several techniques to drastically reduce the model's complexity while maintaining predictive power for practical applications. The model performs classification for the five fingers - the maximum DOF supported by most commercial prosthetic hands. The input data for the online decoder consists of 14 temporal features computed from the neural signals using a sliding window with a 20 ms step. These features are extracted from a narrower frequency band (25–600 Hz), which captures the majority of the neural activity's power. The architecture includes one convolutional layer, two gated recurrent unit (GRU) layers, one attention layer, and an output layer. GRU is used instead of LSTM to improve the runtime efficiency. As shown in Figure 4(D), the optimized model has approximately 16 times fewer parameters than the offline decoder, which is a critical for achieving real-time inference on portable platforms like the Jetson Nano.

We utilize the Adam optimizer to train the models with default parameters ($\beta_1 = 0.99$, $\beta_2 = 0.999$) and a weight decay regularization of $L_2 = 10^{-5}$. The minibatch size is set to 38, with each training epoch comprising 10 minibatches. The learning rate is initialized at 0.005 and reduced by a factor of 10 when the training loss plateaued for two consecutive epochs. For the offline decoding, 15 individual models are trained with the same architecture; each model processes data from all input channels and predicts one DOF. This approach allows us to assess the predictive performance of each DOF independently. For the online model, depending on the specific dataset, a single model is often sufficient to decode all five DOF simultaneously.

C. Portable, Self-contained Neuroprosthetic Hand

Figure 5 shows an overview of the prototype neuroprosthetic hand, designed as a portable, self-contained unit that integrates all essential components: the Scorpius nerve interface, AI neural decoder, motor controller, and battery. Two Scorpius devices are connected to microelectrodes, enabling the recording of 16 channels of nerve signals. The raw nerve signals are transmitted to the Jetson Nano platform via USB cables, where they undergo further processing, including filtering, downsampling, feature extraction, and ultimately feeding into the AI neural decoder. The AI model is pre-trained on an external computer using previously acquired datasets. The trained parameters are then uploaded to the Jetson Nano module,

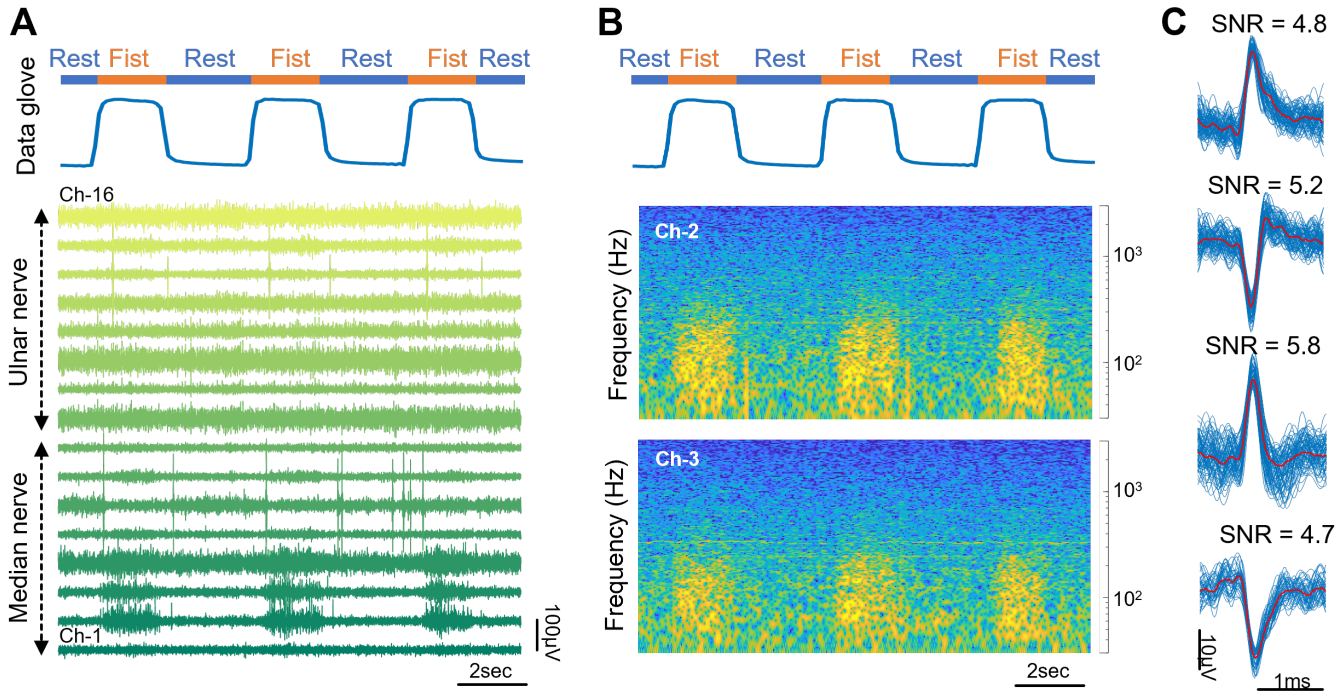


Fig. 6. (A) Sample of mirror bilateral training data, showing nerve signals alongside dataglove movement. (B) Spectrogram of selected channels, highlighting unique neural signatures associated with specific gesture. (C) Examples of spike clusters isolated from the nerve signals.

which performs inference in real-time. A customized carrier board is designed to supply power to the Jetson Nano and provide digital isolation for the Scorpius devices to minimize recording noise. Powered by the Tegra X1 SoC and Maxwell GPU (472 GFLOPs), the Jetson Nano runs the AI model to process neural signal features and predict movements of five fingers in real-time. Predictions are generated every 25 - 50 ms (20 - 40 Hz) with a time latency of 50 - 75 ms and are sent to the motor controller to actuate individual prosthetic fingers, producing the corresponding gestures. A customized motor controller board is designed to replace the internal electronics of the i-Limb hand, providing access to individual DC motors embedded in each finger. The entire system is powered by a 7.4 V, 2200 mAh Li-ion battery pack, enabling approximately 3 - 4 hours of continuous use.

In addition, the prosthetic hand is equipped with touch sensors at the fingertips, which modulate the pattern of electrical stimulation to provide touch sensory feedback. This electrical stimulation is generated by the Scorpius device and delivered back to the amputee's peripheral nerves through the same neural interface, as described in [27], [41]. This bidirectional communication enables a more lifelike and intuitive user experience by not only decoding motor intent but also restoring a sense of touch.

III. Results

A. Nerve Signals Contain Unique Neural Signatures of Individual Hand Gestures

Figure 6(A) presents a sample of mirror bilateral training data, including 16-channel nerve signals and corresponding data glove movement. In this example, the amputee alternates repetitively between fist/grip and rest gestures. Distinct nerve signal patterns are observable across different channels during each gesture. Further analysis of filtered data in low (30–600 Hz) and high (300–3000 Hz) frequency bands reveals diverse waveform components, such as voluntary compound action potentials (vCAPs) and single-axon spike clusters as shown in Figure 6(C). Figure 6(B) shows the spectrogram of selected channels CH-2 and CH-3, where the SNR is most pronounced. Each hand gesture exhibits a unique spectro-temporal signature, closely correlated with finger movements. The signature is complex and not always obvious to the naked eyes, thus, deep learning emerges as the optimal method for implementing the motor decoder. Moreover, our analysis shows nerve activity aligns with human anatomy. Gestures involving flexion of the thumb, index, and middle fingers show prominent activity on channels associated with the median nerve, whereas gestures involving flexion of the ring and little fingers exhibit stronger signals from channels linked to the ulnar nerve. This further underscores the capability of the Scorpius system to capture nerve signals with sufficient detail for decoding the intended movements of individual fingers.

B. Deep Learning AI Outperforms Conventional Machine Learning in Decoding Motor Intent

Figure 7(A, B) shows a performance comparison between the proposed offline AI neural decoder, a convolutional neural network (CNN) with a similar architecture, and three conventional machine learning techniques: support vector machine (SVM), random forest (RF), and multi-layer perceptron

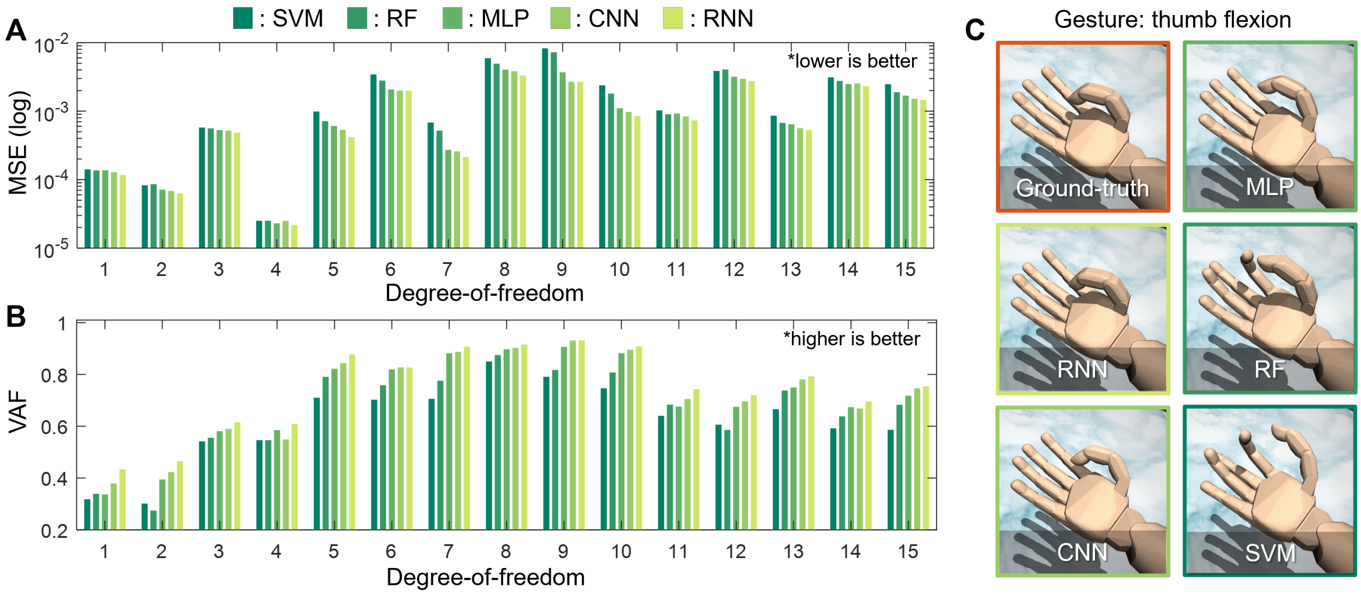


Fig. 7. (A) Mean square error (MSE) and (B) variance accounted for (VAF) metrics demonstrate that the proposed AI neural decoders outperform other methods. (C) Example of 15-DOF predictions mapped onto a virtual hand.

(MLP). Performance is evaluated using two quantitative metrics: mean square error (MSE) and variance accounted for (VAF). The results clearly show that deep learning models (RNN and CNN) consistently outperform traditional machine learning methods across all 15 DOF. These findings highlight both the complexity of motor intent information encoded in nerve signals and the superior capability of deep neural networks in decoding such information. Among deep learning models, RNN achieves better performance than the CNN, further validating its suitability for time-series data. For most DOF with substantial movements (D5–D15), RNN achieves VAF scores of 0.7–0.9 (on a scale of 0 to 1), which corresponds to near-natural movements of individual fingers.

Figure 7(C) shows an example of 15-DOF predictions from all models mapped onto a virtual hand (MuJoCo). This visualization highlights the high performance standard required for AI neural decoders in neuroprosthetic applications. To generate correct hand gestures and lifelike movements, the decoder must consistently and accurately predict all DOF. Any decline in the accuracy of a single DOF could result in a suboptimal user experience. This requirement becomes even more critical when deploying the prototype neuroprosthetic hand, where the amputee uses the AI neural decoder to perform real-time control of the prosthetic hand during various daily living tasks.

C. AI Neural Decoder Enables Real-Time Control of Individual Prosthetic Fingers

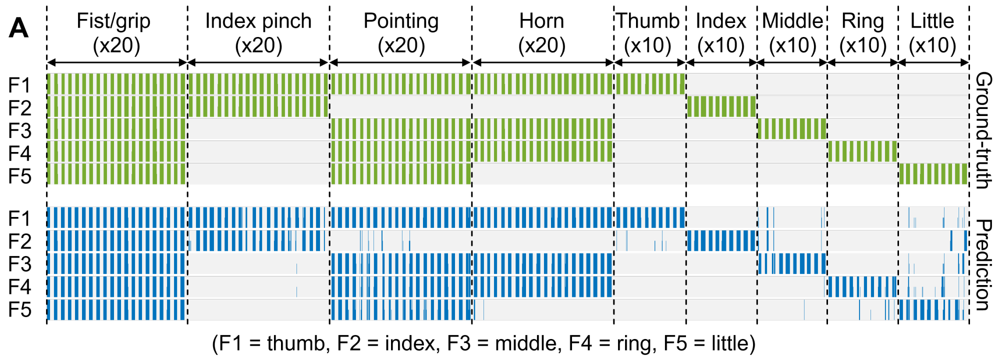
Figure 8(A, B) shows the prediction results and quantitative metrics of the online AI neural decoder on the validation dataset. The proposed AI neural decoder achieves an accuracy of 95–96% across five fingers. Feedback from the amputee during real-life use indicates that this level of accuracy is critical for achieving robust and reliable control of the prosthetic hand. While increasing the model size could potentially improve accuracy, it would also increase prediction time and latency when running on the Jetson Nano, leading to unresponsive performance of the prosthetic hand. At its current state, the decoder's performance appears to be limited by the hardware capabilities. The results also reveal that certain hand gestures are predicted with higher accuracy than others, which correlates directly with the SNR of the nerve signals during those gestures.

Figure 9 shows the patient testing the prototype neuroprosthetic hand in various real-life environments, including the lab, the office lobby, lounge, and at home. The system operates as a fully self-contained unit, with all data acquisition, processing, and decoding performed onboard the prosthetic hand. In the attached video, the amputee uses the able hand to show his movement intent to outside observers, which gives a sense of the system's accuracy and responsiveness. He also tests the prosthetic hand's robustness across various postures, including holding the arm straight out or up, which introduces considerable EMG noise. While the patient reports a slight change in responsiveness during these conditions, there is no significant degradation in motor decoding accuracy. The real-world settings introduce various potential noise sources, such as WiFi signals, cellphones, and electrical appliances, that could impact the neural recorder and overall system performance. However, during several hours of continuous operation, no significant performance issues or accuracy degradation are observed, demonstrating the system's robustness and reliability in diverse environments.

IV. Discussions & Future Works

A. Human-Machine Symbiosis

This study exemplifies a significant step toward achieving true human-machine symbiosis by seamlessly integrating neu-



B **Classification Results**

Finger	TPR (%)	TNR (%)	Acc. (%)
F1	95.24	96.21	95.87
F2	91.49	96.74	95.69
F3	95.42	96.80	96.43
F4	94.93	96.82	96.31
F5	95.47	96.61	96.41

Fig. 8. (A) Prediction results and (B) quantitative performance metrics of the online AI neural decoder on the validation dataset.

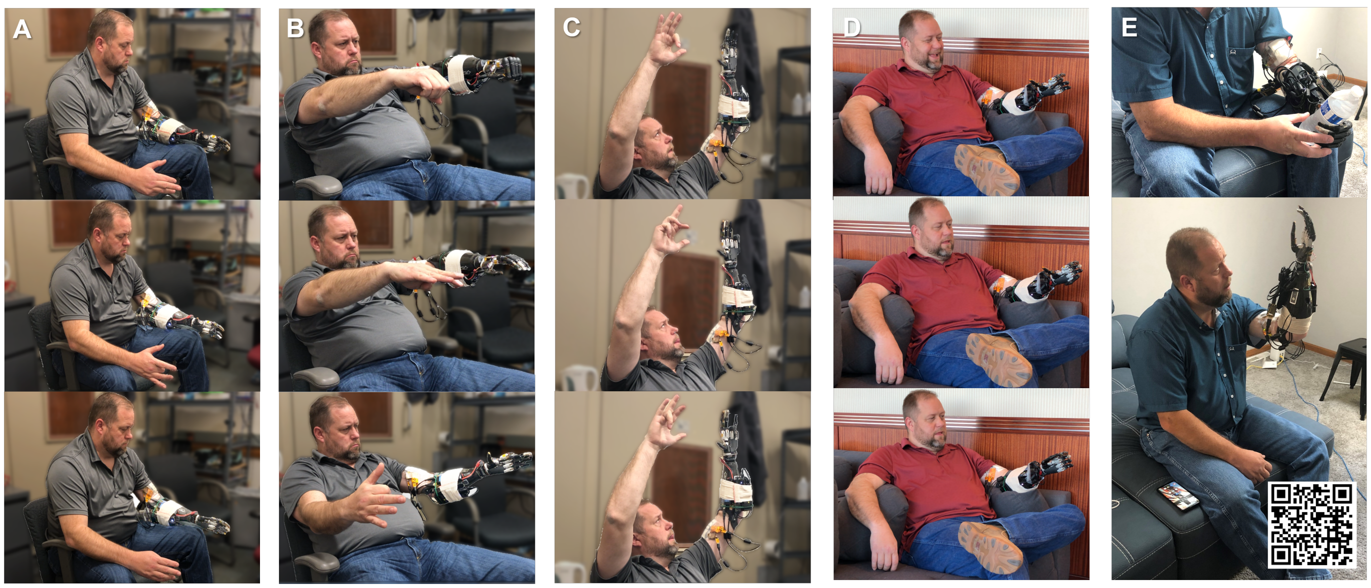


Fig. 9. (A–E) The amputee tests the prototype neuroprosthetic hand in various real-life environments. See video at https://www.youtube.com/watch?v=xxT2dT42cww or scan the QR code above.

ral interfaces with advanced AI for intuitive neuroprosthetic control. The ability to decode motor intent directly from peripheral nerve signals and provide real-time, lifelike control of a prosthetic hand represents a profound merging of human biology and machine intelligence. This work explores the potential of technology to extend human capabilities and restore lost functions in a way that feels natural and intuitive to the user. Such integration could pave the way for next-generation assistive devices that do not merely replace lost functionality but instead work harmoniously with the user, offering a new standard for prosthetic and rehabilitative technologies. These advancements highlight the transformative possibilities of combining bioelectronics, machine learning, and robotics to bridge the gap between human intent and machine execution, further blurring the line between human and machine.

B. Further Development

To advance this technology further, several critical areas require development. First, the neural interface should transition from an external setup to a fully implantable device, enhancing long-term usability and patient comfort. An implantable solution would minimize external components, reduce risks of infection, and provide a more seamless integration into the user's daily life. Second, the neuroprosthetic hand must be optimized for extended, full-day use, addressing durability, energy efficiency, and ergonomic design. This includes improving battery management systems to extend operational hours without compromising portability or functionality. Additionally, advancements in wireless data transmission and onboard data processing are essential to eliminate the need for tethered connections, reduce latency, and support real-time control in diverse environments. These improvements would significantly enhance the practicality and usability of the system. Larger-scale clinical trials are also necessary to rigorously evaluate the safety, reliability, and effectiveness of the system in real-life conditions. These trials would provide valuable insights into user experience and long-term performance, ensuring the technology meets the needs of patients across various scenarios.

V. Conclusion

In conclusion, this study represents a significant advancement in neuroprosthetic technology, achieving three key breakthroughs. First, we develop a neural interface capable of acquiring high-fidelity peripheral nerve signals and enabling access to rich neural information to pave the way for more intuitive prosthetic control. Second, we leverage deep learning AI to decode motor intent from peripheral nerve data. Our system achieves high accuracy in predicting multi-DOF movements, surpassing conventional machine learning methods. This demonstrates the transformative potential of AI in interpreting complex neural patterns for precise prosthetic control. Third, we demonstrate a portable, self-contained, AI-powered neuroprosthetic hand. Integrating all components - including neural signal acquisition, on-board AI decoding, and motor control - into a compact, standalone system highlights the feasibility of real-world deployment. The device enables intuitive, real-time control and provides a practical solution for amputees to perform daily tasks seamlessly. These breakthroughs collectively mark a critical step toward creating truly lifelike, intuitive prosthetic systems. By bridging human peripheral nerves with AI and robotics, this work lays the foundation for next-generation neuroprosthetics that restore functionality and improve quality of life for individuals with motor impairments.

Acknowledgment

The human experiment protocols are reviewed and approved by the Institutional Review Board (IRB) at the University of Minnesota (UMN) and the University of Texas Southwestern Medical Center (UTSW). The amputees voluntarily participate in our study and are informed of the methods, aims, benefits, and potential risks of the experiments before signing the Informed Consent. Patient safety and data privacy are overseen by the Data and Safety Monitoring Committee (DSMC) at UTSW. The subjects also complete the Publicity Agreements where they agree to be publicly identified, including showing their face.

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Zhi Yang is co-founder of, and holds equity in, Fasikl Incorporated, a sponsor of this project. This interest has been reviewed and managed by the University of Minnesota in accordance with its Conflict of Interest policy.

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