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Electromyography (EMG) Controlled Prosthetic Hand

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Authors
Ward, Nicholas
Vega, Alessandria Mira
Velasco, Antonio Samonte
et al.

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Electromyography (EMG) Controlled Prosthetic Hand

Nicholas Ward, Alessandria Mira Vega, Antonio Samonte Velasco, Vy Ngoc Huynh
Professor Hung Cao
University of California, Irvine

UCI Donald Bren School of Information & Computer Sciences
UCI Samueli School of Engineering
University of California, Irvine

Abstract

Traditional prosthetics are often prohibitively expensive ($5,000-$100,000+) and can require invasive medical procedures to function. To address this, we developed a low-cost, electromyography (EMG) controlled prosthetic hand that utilizes an embedded convolutional neural network (CNN) to translate muscle signals into mechanical motion. Using a non-invasive dry-electrode on the wrist, raw EMG data is processed and classified in under 40 milliseconds on average. The CNN accurately identifies three predefined hand gestures with >90% accuracy. By keeping total manufacturing costs, including electronics, mechanical hardware, and filament, to just $260, this project demonstrates the viability of highly accessible, neural-network-driven prosthetics.

Objectives

- Develop a multi-gesture EMG controlled prosthetic hand for a low cost (<$300).
- Utilize non-invasive and reusable EMG sensors.
- Ensure quick response time, from EMG input to servo motion, of <500 ms to mimic real-time locomotion.
- Achieve high-accuracy gesture recognition (>90%).
- Provide a user platform to interact with the device externally.

Implementation

The prosthetic integrates a single-channel electrode, a 100 MHz microcontroller (MCU), and five continuous rotation servos, all housed within a 3D-printed arm. To manage concurrent tasks and ensure strict timing requirements, the MCU runs a Real-Time Operating System (RTOS). A wrist-mounted electrode continuously gathers analog EMG data, which is digitized via an onboard ADC. The RTOS buffers this incoming data until a 64 ms chunk is acquired, triggering a Fast Fourier Transform (FFT) on a rolling window of the most recent 2,112 ms of data. The resulting spectrogram is passed to the embedded CNN for classification. This prediction is evaluated by the device's internal state machine to drive servo actuation and finger motion. Concurrently, the system streams telemetry over USB to a desktop application for data visualization and user interaction.

Diagrams/Figures/Experiments

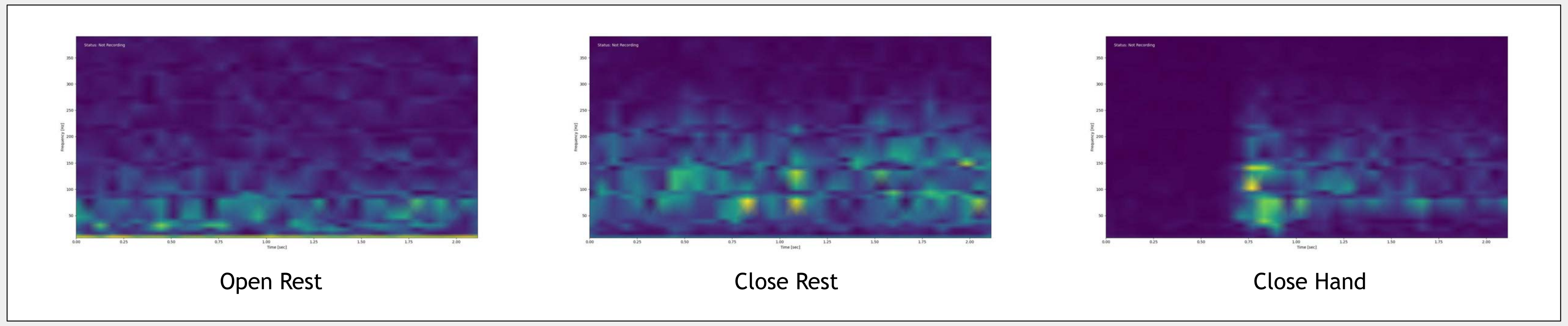

Figure 1: Spectrograms of the 3 predefined gestures the CNN is trained to classify

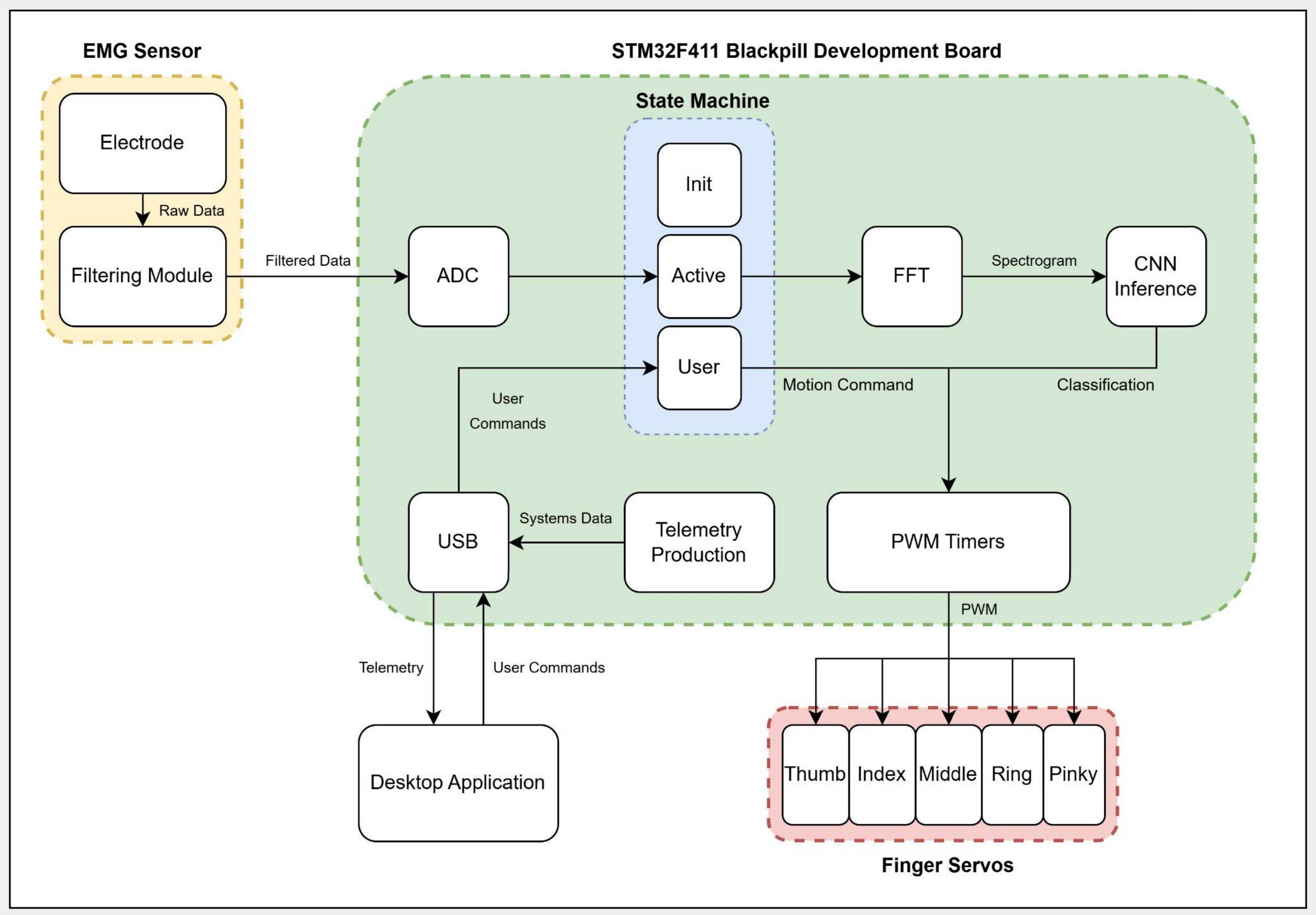

Figure 2: System architecture

Execution Unit	Time (ms)
Copy ADC Data	2
FFT	4
CNN Inference	33
Total	39

Figure 3: Average timing data in milliseconds for significant execution units

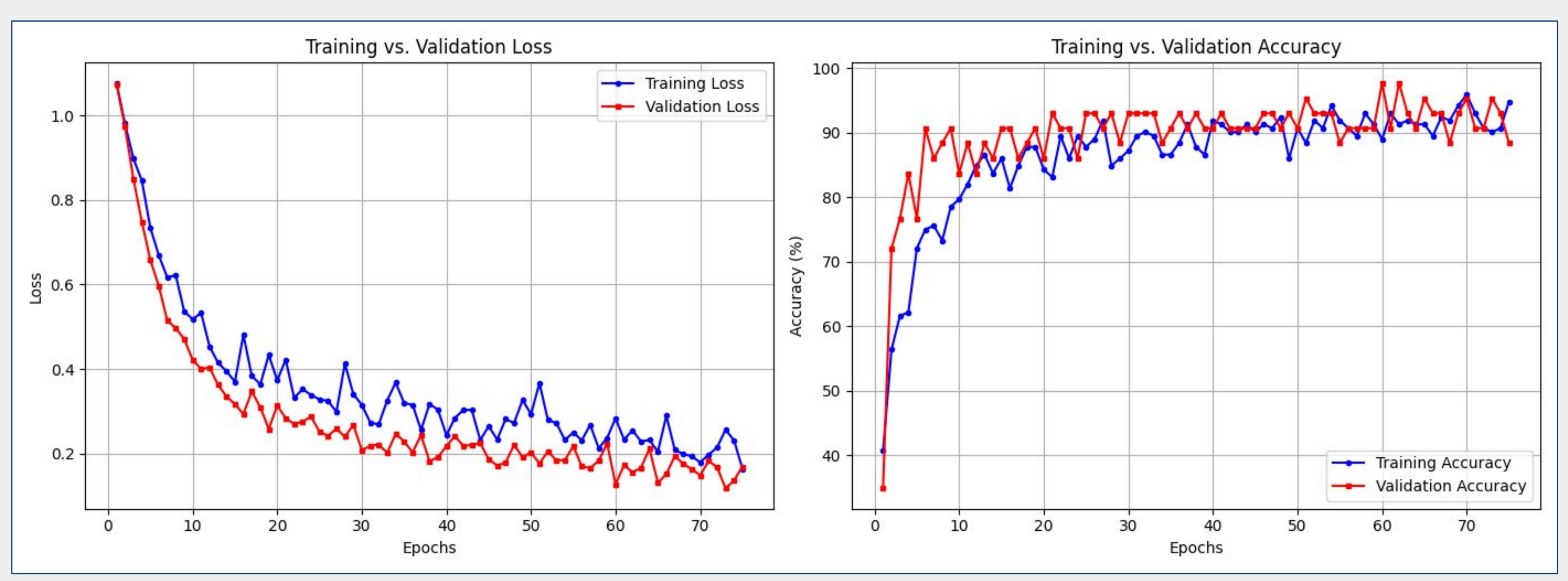

Figure 4: Training and validation loss and accuracy for spectrogram classification over 75 epochs. Both exhibit a healthy convergence, suggesting the network is robust, well-fitted, and accurate (>90% accuracy).

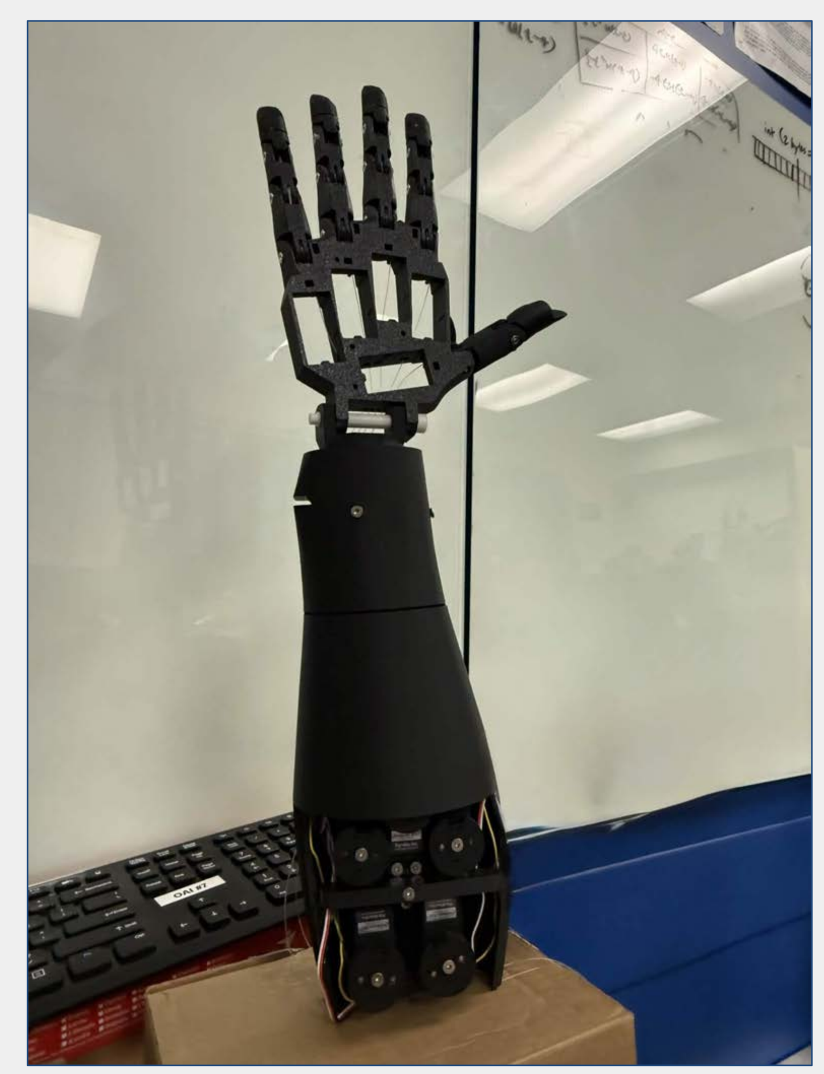

Figure 5: Hand in the open rest state

Results

- The complete device was **manufactured for <$260** utilizing accessible commercial 3D printers and off-the-shelf electronic and mechanical components.
- EMG signals are gathered using a **non-invasive dry-electrode.**
- The hand is capable of executing three predefined gestures, opened, closed, and active closing.
- The system achieved a **total average processing time of 39 ms per classification**. Converting raw EMG data to a spectrogram via **FFT averaged 6 ms**, while **CNN inference averaged 33 ms.** This latency satisfies the real-time requirements for fluid locomotion.
- The **embedded CNN achieved >90% accuracy** across the three gestures. During live operation, this accuracy is stabilized by the internal state machine, which filters out anomalous predictions.
- The desktop application can consistently read live telemetry over USB and send gesture commands to the prosthetic device without loss of packets.

Looking Forward

While the current prototype met its initial objectives, expanding the system is essential for broader viability. The main limitation of the current device is its small number of recognizable gestures. To address this, future iterations will utilize a multi-channel EMG sensor array to generate five spectrograms as input for the CNN. This will drastically increase the spatial resolution of the signals, enabling the classification of a wider variety of gestures. This also allows for electrode placement higher on the forearm, accommodating a larger demographic. We estimate such improvements will push the total cost to ~$400 when factoring in the increased compute requirements and sensors.

References

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[2] Raez, M. B., Hussain, M. S., & Mohd-Yasin, F. (2006). Techniques of EMG signal analysis: detection, processing, classification and applications. Biological procedures online, 8, 11-35. https://doi.org/10.1251/bpo115