Authors: Robert Youssef, Isaac Picov

Neurorehabilitation Device for Post-Stroke Recovery – Project Proposal

1. Problem Statement

Stroke is one of the leading causes of long-term disability in adults, resulting from vessel occlusion that disrupts blood flow to the brain and causes both motor and cognitive impairments[1]. This project focuses specifically on motor rehabilitation, a critical component of neurorehabilitation aimed at helping stroke patients regain lost motor function and improve quality of life. Among various motor deficits, impaired fine motor movement, specifically in the fingers, poses a significant barrier to regaining normal function.

Although progress has been made in terms of developing various approaches to rehabilitation, the recovery of motor movement in the upper limbs remains slow. Some of the main factors contributing to this issue include the limited availability of adaptable and personalized therapeutic methods that allow patients to take control of their own rehabilitation process. Most of the currently existing rehabilitation processes that offer personalized treatment options require the help of therapeutic professionals, with results often being dependent on therapist experience. Additionally, such therapeutic methods are expensive, making it more difficult for individuals with lower incomes to continue to fund the recovery process.

There is a critical need for intelligent rehabilitation systems that can detect and analyze motor intent using surface electromyography (sEMG) signals. By accurately monitoring sEMG activity in the upper limbs (more specifically the fingers), such systems can facilitate finger-specific rehabilitation, supporting targeted interventions. This project aims to address this gap by developing solutions that harness noninvasive methods of data collection to enable more adaptive stroke rehabilitation.

2. Methodology

Our collaborative project, spearheaded by NeurotechUofT and UTMIST, is dedicated to developing an innovative prosthetic device designed to restore fine motor function in patients suffering from impairment in their forearms and fingers. The core objective is to enable affected individuals to regain precise control over their hand movements through a progressive rehabilitation approach.

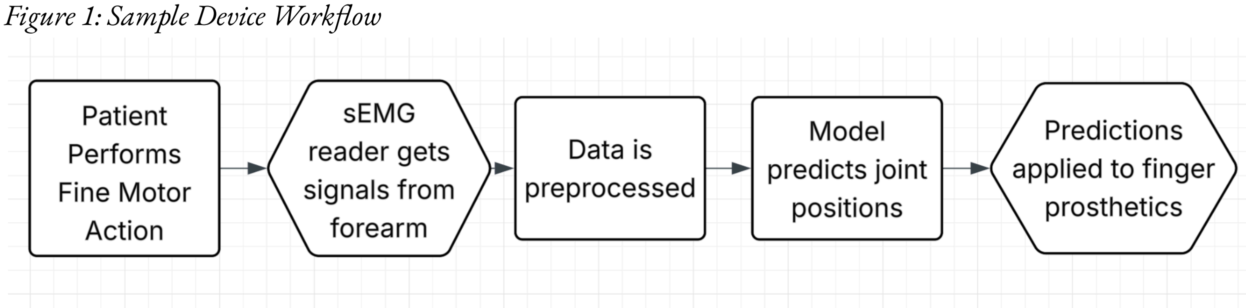
The prosthetic system is meticulously engineered to achieve this by integrating several key components:

- **sEMG Signal Acquisition:** The device will be equipped with sophisticated surface electromyography (sEMG) sensors strategically placed on the patient's forearm. These sensors will capture the electrical signals generated by muscle activity, providing real-time data on the patient's intent to move.

- **Machine Learning Interpretation:** The raw sEMG signals will be fed into a highly specialized and continuously trained machine learning (ML) model. This model will be developed to accurately interpret the complex patterns within the sEMG data, translating them into an understanding of the desired finger and hand movements. The training process will involve extensive data collection and refinement to ensure high precision and responsiveness.
- **Prosthetic Actuation and Feedback:** Based on the ML model's interpretation, the system will estimate the desired joint positions for the fingers. These estimated positions will then be translated into precise control signals for the prosthetics attached to the patient's hand. The prosthetics will be designed to mimic natural finger movements, allowing for a wide range of tasks from delicate manipulation to stronger grasping. Furthermore, the system will incorporate feedback mechanisms to allow for continuous refinement of the prosthetic's response and to aid in the patient's motor learning.

The overarching rehabilitation strategy focuses on progressive overloading of the involved nerves and muscles. This approach, akin to physical therapy principles, aims to gradually strengthen and re-educate the neural pathways and musculature responsible for fine motor control. By continuously challenging the patient with increasingly complex tasks and movements facilitated by the prosthetic, we anticipate a significant restoration of natural motor function over time. This project holds immense potential to dramatically improve the quality of life for individuals living with fine motor impairments. Shown below in figure 1 is a block diagram outlining the proposed workflow of the wearable.

Figure 1: Sample Device Workflow



As this project combines both Hardware and Neuroscience concepts (NeurotechUofT) with Machine Learning (UTMIST), we describe our proposed methods for both below.

2.1 Hardware

The hardware division involved in this project will direct their focus towards designing and iterating on different physical prototype designs to support fine motor movement rehabilitation targeting the upper limbs, more specifically the fingers.

In order to reach this goal, the team will investigate a wide range of existing methodologies and prototypes on the market that help support finger articulation, with the added objective of making the prototype adaptable to the user's needs by enabling the user to progress in their rehabilitation journey using input received from the machine learning model to actuate and effectively support finger movement.

Current prototypes on the market utilize both "contact" and "non-contact" methodologies[2]. Existing contact methods, such as gloves and exoskeletons, require consistent contact with the patient's limb during the rehabilitation period. These are usually more accurate due to the opportunity for implementing more precise motion tracking methods, but are also difficult to wear and often raise concerns regarding hygiene and sanitation. On the other hand, current non-contact methods typically involve the use of optical or depth sensors to monitor finger movement, eliminating the need for physical contact with the patient. These methods are not only easier to set up and use but are also more hygienic, making them better suited for home-based rehabilitation. However, their downside lies in generally lower accuracy compared to contact-based methods, with prototype performance being significantly affected by different environmental factors such as lighting conditions and device positioning, rather than actual patient progress.

For this project, our team will aim to iterate on currently existing methods in an effort to optimize key performance indicators such as range of motion, device responsiveness, comfort, hygiene, and ease of use – enabling the patient to independently progress in the rehabilitation process.

2.2 Machine Learning

Our initial approach involves a standard preprocessing pipeline, adhering to established best practices in signal processing, as detailed in various industry resources[3]. This foundational stage is crucial for cleaning and preparing the raw data, ensuring optimal conditions for subsequent analysis.

Following this robust preprocessing, we plan to explore and evaluate several advanced frameworks for signal interpretation. Our strategy encompasses a dual approach: incorporating established industry standards known for their reliability and performance, alongside novel methodologies that show promise in addressing specific challenges within our dataset. This comparative analysis will allow us to identify the most effective techniques for our project.

To gain deeper insights into the intricate relationships and interdependencies between different channels within our signal, we propose the integration of Graph Neural Networks (GNNs). GNNs are particularly adept at modelling complex relational structures, which we believe will significantly strengthen our ability to discern and analyze the connections between various signal components. This approach aims to move beyond individual channel analysis to understand the holistic signal behaviour.

Furthermore, we will extensively experiment with Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs). The nature of our signals, inherently time-series dependent, makes both CNNs and LSTMs highly suitable for capturing temporal patterns and dependencies. CNNs can effectively identify local patterns and features, while LSTMs are designed to handle sequential data and long-term dependencies, providing a comprehensive analysis of the signal's evolution over time.

Finally, a core innovative component of our methodology involves implementing a transfer learning system inspired by current research trends[4,5]. This system will leverage the strengths of pre-trained models by initially training on data sourced from healthy patients. This initial training will equip the model with a robust understanding of typical neural activity. Subsequently, we will fine-tune this model using data specifically collected from stroke patients.

2.3 Deliverables

The aim of this project is to develop a prototype that combines the benefits of both contact and non-contact rehabilitation methods, without the downsides. This project will deliver an intelligent wearable rehabilitation system designed to support finger-specific support, with the end goal of motor recovery in patients following hemiparesis. This will be done through a combination of wearable hardware and machine learning based methodologies. The prototype will be capable of acquiring sEMG signals from the patient's forearm, monitoring motor intent with the help of machine learning algorithms, and actuating a prosthetic to facilitate targeted finger rehabilitation in real time. The prototype will be developed iteratively and evaluated based on performance in clinical scenarios and user experience, with the objective of developing an affordable treatment device with a good level of scalability. A more detailed outline with deliverables for each aspect of the desired deliverables for this project are outlined below:

2.3.1 Hardware:

- A wearable rehabilitation device capable of actuated finger movement, designed with a focus on comfort, modularity, and adaptability
- A wearable prototype that iterates on both contact-based and non-contact-based designs, with the aim to have the benefits of each without the downsides
- Integration of actuators and sensors enabling real-time motion assistance and feedback

2.3.2 Machine Learning Pipeline:

- A robust preprocessing framework for handling sEMG signals
- A suite of trained models (e.g., CNN, LSTM, GNN - To Be Determined) capable of analyzing finger-specific motor intent from sEMG input signals
- Implementation of a transfer learning approach trained first on healthy subjects and fine-tuned for stroke-specific motor patterns

2.3.3 Documentation and Evaluation:

- Technical documentation covering design decisions, model architectures, and hardware schematics as well as CAD models

2.3.4 Published Literature:

- Publish a research paper as a general literature review of current methods used for stroke rehabilitation in the upper limbs, more specifically the fingers
- Publish a second paper specifically outlining the process used for our finalized prototype, with an outline of the results

3. Project Timeline

Table 1 below contains an outline of the aforementioned deliverables, including specific dates matching the corresponding milestones, with relevant details noted for each milestone.

Table 1: Proposed Project Timeline

Date	Milestone	Notes
Sept 20, 2025	Project Kickoff	Finalize team roles, research plan, goals
Oct 15, 2025	Initial Concept Review	Internal design review & risk assessment
Oct 31, 2025	Hardware Design Freeze	Present to UTMIST & NTUT engineering leadership for feedback
Nov 10, 2025	Paper 1 Literature Review Draft	Focus on prior post-rehab tech
Nov 15, 2025	Order Parts	Dependent on finalized hardware design and supplier lead times
Dec 5, 2025	Midpoint Progress Update	Internal milestone to track timeline risks
Jan 5, 2026	Assembly + Initial Testing Begins	Check mechanical and electrical interfaces
Dec 20, 2025	Paper 1 Finalized & Released	Submit to internal reviewers for approval
Jan 27-Feb 2, 2026	Devcon Conference (Checkpoint)	Present 1-2 physical components + team presentation
Feb 10, 2026	Mid-Testing Evaluation	Internal test feedback and log failures
Feb 28, 2026	Version 1 Prototype Complete	Internal deadline; Basic working system and key subsystems
Mar 1, 2026	Start Design Verification&Validation Phase	Start testing protocols, run tests, fix bugs
Mar 15-22, 2026	CUCAI Conference	Final presentation; fully functional prototype
Apr 5, 2026	Paper 2 Draft due	Internal and external reviewer comments
May 15, 2026	Paper 2 Finalized & Released	Include final data, design decisions, and conference outcomes

4. References

[1] Morone, G., & Pichiorri, F. (2023). Post-stroke rehabilitation: Challenges and new perspectives. Journal of clinical medicine. https://pmc.ncbi.nlm.nih.gov/articles/PMC9867345/

[2] Bo Sheng et al. (2023). Commercial device-based hand rehabilitation systems for stroke patients: State of the art and future prospects. Heliyon. https://www.sciencedirect.com/science/article/pii/S2405844023007958

[3] Aarotale, Parshuram N., Rattani, Ajita. (2024). Machine Learning-based sEMG Signal Classification for Hand Gesture Recognition. arXiv. https://arxiv.org/html/2411.15655v1#abstract

[4] Xu, F., Miao, Y., Sun, Y. et al. A transfer learning framework based on motor imagery rehabilitation for stroke. Sci Rep 11, 19783 (2021). https://doi.org/10.1038/s41598-021-99114-1

[5] Ma, J., Ma, W., Zhang, J. et al. Partial prior transfer learning based on self-attention CNN for EEG decoding in stroke patients. Sci Rep 14, 28170 (2024). https://doi.org/10.1038/s41598-024-79202-8

Signatures

Robert Youssef
Co-President of Engineering, NeurotechUofT

Isaac Picov
Research Director, UTMIST

Alvina Yang
VP Engineering, UTMIST

Ashmita Bhattacharyya
VP Engineering, UTMIST