From Thought to Movement

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Abstract[1]

Parkinson's disease impairs mobility due to the degeneration of dopamine-producing neurons in the substantia nigra, resulting in tremor, rigidity, and bradykinesia. This project introduces a non-invasive neurotechnology that predicts motor intentions using a multimodal Transformer model trained on EEG[2], EMG, and IMU data from both me and my father (diagnosed with Parkinson's). EEGs are collected from my homebuilt EEG-circuit and equipment donated by OpenBCI[3]. A homebuilt 6-axis robot arm from Arduino serves as proof of concept, controlled in real time by biosignal-driven predictions. Future iterations may bypass the damaged nervous system entirely using FUS and EMS to enable voluntary movement in Parkinson's patients once again.

Introduction

More than 10 million people worldwide are diagnosed with Parkinson's disease[4]. The symptoms result from the progressive death of dopamine-producing neurons in the substantia nigra, which impairs the brain's ability to initiate and control movement due to an imbalanced basal ganglia system.

My father was diagnosed with Parkinson's at 36 years old. His disease and daily struggles inspired me to develop a system that could assist not only him, but potentially many others. In December, a conversation with my best friend's father sparked the idea: "Why not combine artificial intelligence with Parkinson's disease?" which initiated the project. The aim is to detect movement intentions from brain signals using a wearable system. By training a Transformer-based AI model on EEG, EMG, and IMU data, the goal is to bypass impaired neural pathways and enable real-time control of movement. In the first generation of the project, I built a custom EEG circuit[5] with electrodes placed at motor cortex and developed a robotic arm prototype for real-time testing[6]. In the second generation, I integrated professional OpenBCI hardware, expanded electrode coverage to eight positions. This report presents the steps from signal

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[1] For references - see the appendix
[2] For abbreviations - see the appendix
[3] I was donated the following equipment: Cyton Biosensing Board (8-channels) and Ultracortex "Mark IV" EEG Headset
[4] (Parkinson.org, 2025), (Parkinson.dk, u.d.), (Paulson, 2024)
[5] See figure 5 and 6 in the appendix for the EEG-circuit, circuit diagram and OpenBCI equipment

acquisition to prediction and actuation and explores the potential of replacing robotic output with muscle stimulation through ultrasound and electrical impulses.

Problem statement

How can AI and the processing of EEG, EMG, and IMU data be applied to enhance mobility and improve the quality of life for individuals living with Parkinson's disease?

Literature review

The aim of this literature review is to explore current research within three key areas: (1) the use of EEG, EMG, and IMU signals for predicting movement intentions, (2) how Parkinson's disease alters brain structure and function, and (3) how this project compares to existing solutions. Together, these areas establish the scientific foundation of the proposed system.

Multimodal movement prediction in real time

Antony, et al., 2022 showed that an A-SVM with ORICA and CSP achieved 91% precision for EEG-based motor imagery prediction. Buerkle & et al., 2021 demonstrated real-time intention prediction using an LSTM-RNN with 84-92% accuracy. Zhang, et al., 2023 found that a predefined EMG threshold enabled 100% accurate movement detection when synchronised with EEG, while Aeles & et al., 2021 showed EMG signals are subject-specific, as a CNN-MLP achieved 99.3% precision in identifying individuals. Silva-Acosta & et al., 2021 demonstrated that combining EEG and EMG in an LSTM improved accuracy, especially when separated by subject and gender. Mahmoodi & et al., 2021 demonstrated that a TKEO-based threshold algorithm applied to a single EEG channel enabled real-time BP detection with 91.2% precision.

Neurophysiological changes in Parkinson's disease

Karimi & et al., 2021 found that patients with FOG showed reduced beta desynchronisation and increased theta activity at Cz prior to movement. Wang & et al., 1999 showed that Levodopa improved premotor EEG desynchronisation, correlating with faster movements across motor and prefrontal areas. Miladinovic & et al., 2021 reported that high delta and low alpha activity correlated with worse FOG, while high theta and low beta related to poorer UPDRS-III scores. Farashi & et al., 2023 predicted tremor onset using EEG and IMU data with 81.3% accuracy through KNN and feature extraction. Peláez Suárez & et al., 2021 found decreased alpha and delta connectivity in MCI patients, while Parkinson's patients showed randomised network topology with reduced segregation. Similarly, Conti & et al., 2022 reported reduced alpha/beta connectivity and increased gamma activity in de novo Parkinson's patients, possibly as a compensatory mechanism. Desai, 2023 used Random Forest and Extra Trees to distinguish Parkinson's patients from control patients with 97.5% precision via EEG processing. Zanini & et al., 2019 showed that MLP and LSTM models could predict EMG signals. Saikia & et al., 2019 achieved 98.8% accuracy using EEG and EMG in an ANN model, higher than models trained on either signal alone.

Similar solutions and existing approaches

Existing technologies relevant to this project include BCIs neuroprosthetics, and DBS. While they share thematic overlap, the FTtM system differs in its core approach and objective[7].

- **BCIs** use EEG or intracortical signals to control external devices such as robotic arms. Such system often relies on the user's conscious focus and require extensive training. Unlike FTtM, which aims to predict and re-enable natural muscle activation, BCIs typically bypass the body's physiological pathways entirely. FTtM could more accurately be described as a Brain-Physiological Interface (BPI), as it integrates biosignals to restore intrinsic motor functions rather than control machines.
- **Neuroprosthetics** involve external hardware that replaces, or augments lost neurological functions, usually through direct brain signal decoding or peripheral nerve stimulation. In contrast, FTtM does not replace movement but collaborates with the existing neuromuscular system to enhance or restore it, acting as an assistive rather than a substitutive technology.
- **DBS** modulates brain activity through surgically implanted electrodes targeting specific regions such as the STN or GPi. While it can alleviate symptoms like tremor or rigidity, it is invasive and not adaptive to real-time intention. FTtM, on the other hand, uses non-invasive surface signals to anticipate movement intention and could serve as a complementary or alternative pathway for motor recovery.

Conclusion on literature review

The literature informed critical design choices, including model architecture (Transformer), signal types (EEG, EMG, IMU), channel selection, classification strategies (e.g., CSP, TKEO, cross-validation) and EMG-electrode placements. The studies suggested that higher channel dimensionality yielded higher precision. These studies built the scientific foundation of the project and demonstrated the possibility of real time motor intention prediction using AI-models.

[7] See figure 12 in the appendix for a comparison between my project and similar solutions

FTtM stands out as a non-invasive, wearable, and adaptive neurotechnology that integrates the body's own biosignals. This approach requires minimal user training, supports real-time responsiveness, and offers scalable potential for clinical translation in neurodegenerative conditions.

Hypothesis

A Transformer-based model trained on EEG, EMG, and IMU data can predict intentional movements with greater than 95% accuracy, enabling actuator control based on decoded brain signals.

Research goals

The project follows these steps to test the hypothesis:

1. Train and compare several AI models (LSTM, CNN, A-SVM, Transformer) using EEG and EMG data from a public data set.
2. Build a test a real-time system in which IMU signals are used to control a robotic arm.
3. Develop and implement a Transformer-model trained on EEG, EMG, and IMU data collected during intentional movements from my father and I (and/or other subjects).
4. Demonstrate real-time classification and actuating by using the model's predictions to control a 6-axis robotic arm based on movement intentions.
5. Explore the future integration of EMS/FUS to replace the robotic actuator and directly stimulate muscle activation, thereby bypassing the damaged nervous system.

If successful, the project will demonstrate that AI can accurately decode movement intentions from brain signals and translate them into precise physical actions, potentially paving the way for a new class of neurotechnological interventions for patients with Parkinson's disease and motor impairments.

Methodology

The methodology is structured into three phases:

- **Choice of AI-model**: Seven AI models were trained on public EEG/EMG data (Kueper et al., 2024). Precision, AUC, and latency were used to compute an efficiency score. The transformer model achieved the best balance.
- **Robotic arm control using biosignals**: A 6-axis robotic arm was constructed. Three IMUs on the arm measured motion and controlled the servos in real time, validating biosignal-driven actuation.

- **Training and application of the Transformer-model on my own EEG/EMG/IMU-data**: EEG (collected using both the first-generation homebuilt EEG-circuit and the second-generation OpenBCI setup), EMG (BB) and IMU data were collected. Signals were pre-processed, normalized, and labelled. A Transformer model was trained and validated using 5-fold cross-validation and tested in real time.

Choice of AI-model

I trained and tested seven different AI-models (Antony, et al., 2022, Buerkle & et al., 2021, Zhang, et al., 2023, Aeles & et al., 2021, Silva-Acosta & et al., 2021) on EEG/EMG data from the article by Kueper, et al., 2024. In that study, subjects were instructed to perform right arm movements with an orthosis, which was used to label the data. All models were programmed to classify signal segments as either "movement" or "no movement" based on a predefined dynamic threshold: $\mathrm{Baseline} = 1.2\mu + 2\sigma$ (Zhang, et al., 2023). The goal was to identify the most suitable AI model for further development of the project. To prevent overfitting and ensure robust evaluation, 5-fold cross-validation was applied with an 80% training and 20% testing split. The models were evaluated using multiple metrics: inference time, training time, AUC score, precision, and a custom efficiency score defined as:

$$\mathrm{Efficiency} = \left(\alpha \cdot \frac{\mathrm{Precision}^2}{\mathrm{Precision}_{\max}^2} + \beta \cdot \mathrm{AUC}\right) \cdot \left(1 - \gamma \cdot \frac{\log(time)}{\log(time_{max})}\right)$$

This metric emphasizes high precision while penalizing long training times logarithmically, ensuring fair comparison across architectures. The coefficients values were, $\alpha = 0.8,\ \beta = 0.4,\ \gamma = 0.4$, to ensure the metric 'precision' was weighted most in calculation. All models had the same coding structure, differing only in architecture.

Based on the first results[8], I saw:

- **LSTM-RNN** and **LSTM-CNN** performed badly, due to their complexity and long training times.
- **SVM** had the lowest efficiency (58.44%) and was therefore not selected for further use.
- **CNN** and **DeepConvNet** were both fast and accurate but were not ideal for time-dependent signals like EEG/EMG and were thus excluded.
- **A-SVM** achieved a high efficiency but was not selected due to limited presence in the literature and because Transformer models are more advanced and promising in the AI field. Moreover, its precision was 13 percentage points lower than the Transformer model.

[8] See figure 1 and figure 2 in the appendix for the first results of the first generation of AI models

Initial results indicated possible overfitting, as evidenced by unusually high precision and AUC scores. To address this, a second iteration was conducted using GroupKFold-validation (same data split), F1-score, and inference time. All models were scaled to ~200,000 parameters for fair comparison. As anticipated, all models exhibited a drop in performance, with the Transformer ranking among the lowest: second to last in inference time and third to last in F1-score. Nevertheless, the Transformer was selected for further development due to its balanced precision, suitability for sequential signals, and strong future potential[9]. Its performance is also likely to improve with more training data and better hyperparameter tuning[10].

Robotic arm control using biosignals

To demonstrate biosignal-driven actuation, I built a 6-axis robotic arm on Teensy 4.1 platform with six active servos, each mapped to key physiological movements. I developed a prototype where three IMUs, mounted on my forearm, wrist, and upper arm, control a self-built robot arm in real-time. Each IMU tracks how the limb rotates and moves in space, translating this into motor commands for the robotic arm, enabling the robotic arm to mirror my arm's movement.

This prototype validates the core principle of the project: from biosignal to real-time actuation. The full source code is available at: https://github.com/TobiasBN1005/From-thought-to-movement-. In the generation, IMU control will be replaced by real-time predictions from a Transformer model trained on EEG signals, allowing the system to execute motor intentions directly from brain activity. Eventually, the robotic arm itself may be replaced by EMS/FUS-based actuators to restore movement without relying on the nervous system, offering a wearable assistive technology for individuals with Parkinson's disease and similar conditions.

Training and application of the Transformer-model on my own EEG/EMG/IMU-data

The Transformer model is trained on three biosignal modalities, EEG, EMG, and IMU, to capture the full motor process and enable the prediction of intentional movement - multimodal architecture also increases the precision of a model (Silva-Acosta & et al., 2021). EEG reflects cognitive intent (BP, ERD/ERS), EMG captures muscle activation, and IMUs detect movement onset and direction[11].

[9] See figure 3 and 4 in the appendix for the results of the second generation of AI models
[10] A preliminary judge for the Danish science competition *Unge Forskere,* also suggested for me to work with a transformer-model in my project.
[11] See figure 6 and 7 for the EEG-electrode placement, EMG setup and IMU setup

EEG data were collected in two generations**:**

1) In the **first generation**, I built a custom EEG circuit with electrodes placed at C3, C4 and Cz (motor cortex), following the international 10/20 system. Electrodes were secured using a swim cap, with the mastoid as reference and the nasion as ground. Conductive gel was applied to reduce impedance. These sites were chosen based on literature reporting disrupted beta desynchronization in Parkinson's patients at these locations (Karimi et al., 2021; Wang et al., 1999).
2) In the **second generation**, I integrated professional OpenBCI hardware, placing electrodes at Fp1, Fp2, C3, C4, P7, P8, O1, and O2 using a dedicated EEG headset. The channel count was expanded to increase spatial resolution, as higher dimensionality has been shown to improve classification accuracy.

Signals are bandpass-filtered (0.5 - 45 Hz) to capture relevant frequency bands reflecting voluntary movement.

EMG-signals are recorded from BB via surface electrodes. This signal indicates when and how muscles activate[12] and help define the EEG window for detecting premotor potentials. This was chosen, because it reflects the arm's movement (Kueper, et al., 2024). Skin is prepared to ensure low impedance.

IMUs are placed on the forearm, upper arm, and wrist. They detect angular velocity and acceleration to label movement onset, triggering the extraction of a 0.5 - 2 second EEG segment prior to motion. IMU data also enhances motion classification and supports BP isolation.

After data acquisition, all signals are filtered, normalized, and used for model training and testing. Feature extraction is adaptively refined to enhance learning. The Transformer model is trained offline and evaluated using 5-fold cross-validation, with metrics including precision, F1-score, AUC, inference time, and confusion matrix analysis. The system is subsequently tested in an online setting to ensure compliance with real-time performance requirements.

The model outputs 4-bit binary signals[13], each representing a specific movement. These signals are sent to the robotic arm, enabling real-time control based on thought-derived EEG signals. By integrating intention (EEG), muscle activation (EMG), and physical motion (IMU), the system models voluntary movement. This multimodal fusion enables

[12] (Johns Hopkins Medicine, u.d.), (wikipedia, 2025), (Cleveland Clinic, 2023)
[13] See figure 13 for the different arm movements and their binary values

robust, real-time decoding of motor intentions. In future generations, the robotic arm may be replaced with EMS and FUS, enabling direct muscle activation and bypassing the damaged nervous system in Parkinson's patients.

Results & evaluation

Although other models like CNN and A-SVM performed well in training, the Transformer model proved the most suitable overall for the goal of the project, achieving an F1-score of 83.03%, precision of 88.47% and inference time of 18 ms. This confirms the robustness of the model for EEG and EMG classification. Three IMUs mounted on the arm captured distinct angular velocity and acceleration differences during different movements, and the robotic arm mirrored these patterns in real time, validating the biosignal-to-action concept. EEG signals from first generation and second generation were clearly measurable using both my custom circuit and OpenBCI hardware, with the latter providing cleaner and more stable data. The Transformer for my biosignals will be trained using 5-fold cross-validation (80/20 split) on my EEG, EMG, and IMU data. The data acquisition was performed under varying physiological and environmental conditions (e.g., increased heart rate, external noise, closed/open eyes), to increase the generalizability and robustness of the model.

Limitations and uncertainties

Despite promising results, several limitations remain. EEG signals are inherently noisy and sensitive to electrode placement, impedance, and motion artifacts. My self-built EEG circuit introduced more signal variability compared to the OpenBCI hardware. The small dataset, based on one or two individuals, limits generalizability, and future work should expand the subject pool to assess long-term stability and inter-subject variation. Environmental noise and user fatigue may also affect signal clarity and introduce response delays. Currently, the system detects only coarse, high-intensity motions (e.g., lifting the arm). Future generations should focus on refining EEG resolution and Transformer sensitivity to capture more nuanced movement intentions.

Product concept & innovation

Current treatments method for Parkinson's disease includes medicine and surgeries to enable motor functions - but this project proposes a new method to completely bypass the damaged nervous system with the usage of EMS and FUS[14]. The functional and non-functional requirements were first defined to develop this solution[15]. This project

[14] See figure 15 and 16 in the appendix for a visualisation of the functionally behind the EMS/FUS system
[15] See figure 14 in the appendix for a table of the functional and non-functional requirements of the product

proposes an actuator system for bypassing the damaged nervous system in Parkinson's disease: a hybrid of FUS and EMS. Instead of controlling an external robotic arm, this method aims to directly stimulate the body's own muscles based on decoded movement intentions from brain signals. The user's EEG signals recorded from electrodes placed over the cortex cerebri, are processed by the Transformer model. The output is a binary code representing the intended movement, which is transmitted wirelessly to two subsystems:

- **FUS** primes the target muscle group using a 3D phased-array transducer, because FUS mechanosensitive ion channels like Piezo1 and TRPV4, increase the calcium permeability and make muscle cells more excitable when exposed to acoustics.
- **EMS** delivers a precisely tuned electrical current to the same muscle, triggering contraction.

This dual stimulation system (FUS preparing the membrane, EMS activating the contraction) enables muscle activation even in patients with impaired neural transmission, such as those with Parkinson's or spinal cord injuries. FUS increases the cell's response to stimulation by activating Piezo1, a stretch-sensitive calcium channel. When open, Piezo1 allows calcium influx, lowering the threshold for depolarization. This enhances EMS efficiency while reducing current intensity. The ultrasound focus can be controlled dynamically using 3D beamforming and phased-array technology. Ultrasound imaging (B-mode) may be used beforehand to map muscle locations. Following FUS priming, EMS is applied with low-frequency electrical pulses (typically 20 - 50 Hz) through surface electrodes placed over key muscles, such as the biceps or triceps. This stimulation is customized per movement type and user. Over time, the Transformer model can adapt the stimulation pattern based on prior performance and feedback.

The innovation lies in fully replacing the robotic arm with a wearable bio-stimulation system that non-invasively transforms neural intention into natural movement. Though much work remains, this EMS/FUS concept has the potential to restore autonomy to individuals with severe motor impairments.

Future perspectives

The next step is to train the Transformer model on larger and more diverse datasets to improve generalisability across age, gender, and disease stage. A key goal is to increase accuracy by filtering out tremor signals using adaptive noise reduction, inspired by DBS noise cancellation. This would allow the model to separate involuntary from intentional movement. The system may also be applied in neuroprosthetics or stroke rehabilitation and could be expanded to analyse speech-related brain activity. Future generations could decode mental intentions not only for movement but also for speech, enabling broader applications in motor and communication disorders. Ultimately, the robotic arm may be replaced with a wearable EMS/FUS system, completing the transition from thought to natural movement.

Ethical considerations

All EEG, EMG, and IMU data were anonymised and collected with informed consent. Before any testing on my father (a Parkinson's patient), I validated the system on myself and consulted my father's neurologist to ensure safety. As the system evolves towards clinical use, it must comply with ethical standards, medical research regulations, and GDPR. Future generations of the project will require more precise, medically certified equipment, but this prototype already demonstrates promising results under non-clinical conditions. The goal is to create a user-centred system that improves mobility while preserving autonomy and data privacy.

Conclusion

Parkinson's disease is progressively neurodegenerative, and the patient's mobility worsen as a biproduct of the damaged substantia nigra and brain structure. Existing solutions provide temporary help, but lasting assistance is still needed to enhance the patient's quality of life and voluntary mobility. This project demonstrates that it is possible to predict movement intentions using a Transformer model trained on EEG, EMG, and IMU signals. After testing seven AI architectures, the Transformer was selected for its superior performance on sequential biosignals. A complete signal pipeline was developed, from signal acquisition to real-time robotic control, and validated through 5-fold cross-validation, precision, F1-score, and inference latency.

Biosignals were collected from myself (and in the future from my father) across multiple sessions and varied conditions to simulate different physical and mental states. Data was originally collected by a homebuilt EEG circuit and later with donated equipment from OpenBCI, 3 IMUs placed on my arm, and EMG electrodes on arm muscles. This diverse dataset will in the future enable the development of a system capable of detecting motor intention and translating it into physical action. The robot arm served as a proof of concept for the fundamental idea behind the project: prediction of movement by AI modelling and biosignals. By combining cutting edge AI and neurotechnology, this project lays the groundwork for future assistive systems that restore mobility, preserve autonomy, and improve quality of life. The goal remains: to turn thought into movement, bringing it one step closer to reality!