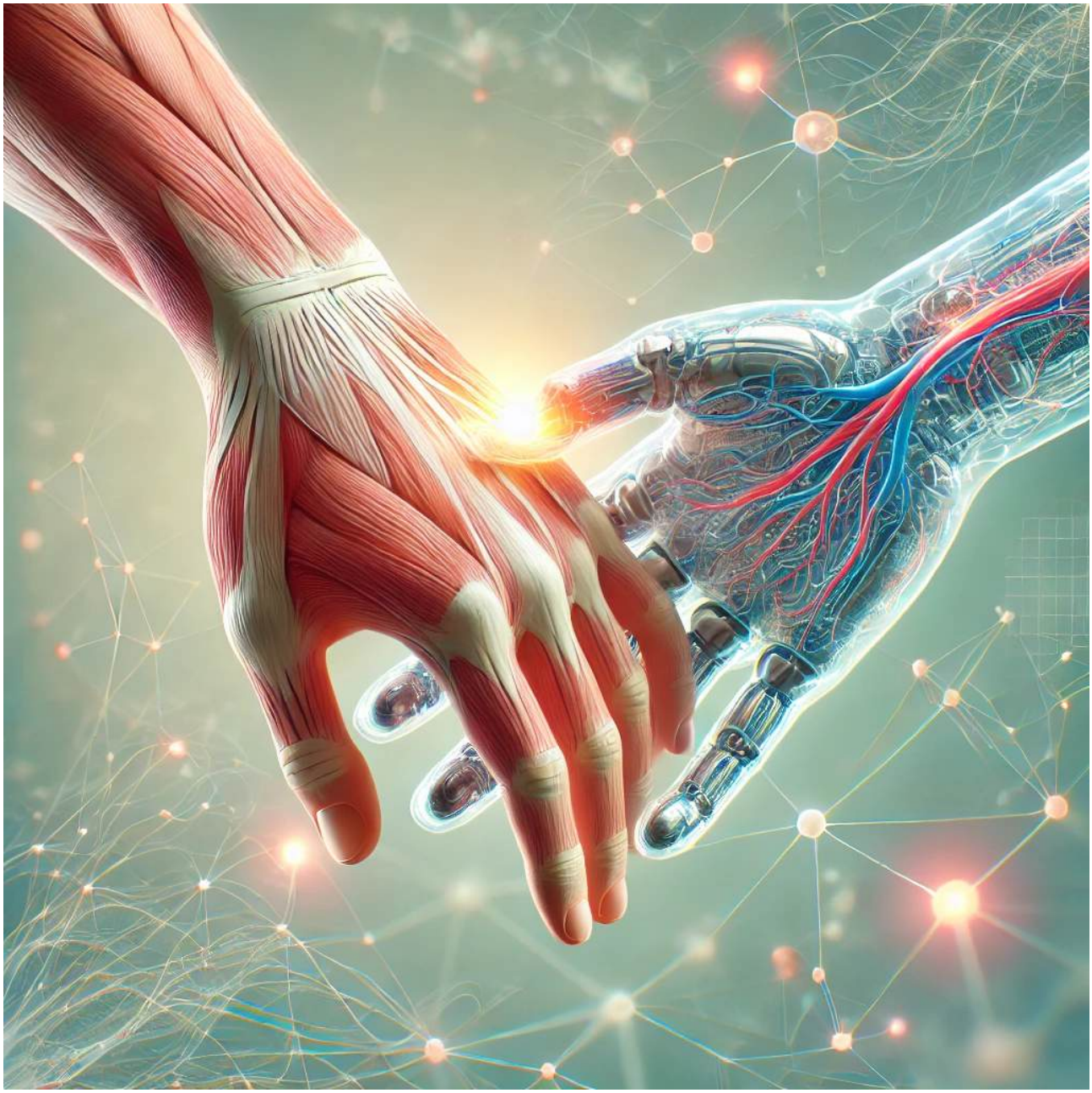
From thought to movement

Suppression of motor symptoms in Parkinson's disease via neural networks



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Introduction

More than 10 million people worldwide are living with Parkinson's disease, a neurodegenerative disorder characterized by motor symptoms such as tremor, rigidity, and reduced mobility. These symptoms result from the progressive loss of dopamine-producing neurons in the substantia nigra, impairing the brain's ability to control movement precisely[1].

My father was diagnosed with Parkinson's disease at the age of 36, which inspired me to develop a novel technology aimed at improving quality of life for him and others facing similar challenges. A conversation with my best friend's father in December sparked the idea: "Why not combine artificial intelligence with Parkinson's disease?" This marked the beginning of my project.

The goal of this project is to develop and test advanced AI models: Long-Short Term Memory (LSTM)[2] Convolutional Neural Network (CNN)[3], Transformer-models[4] and Adaptive-Support Vector Machine (A-SVM)[5], to recognize patterns in neural signals and predict intended movements in Parkinson's patients.

The AI models process signals from electroencephalography (EEG), electromyography (EMG) and inertial measurement units (IMU)[6]. To ensure high-quality data collection and precise signal processing, I built custom EEG instrumentation and adapted hardware for EMG and IMU acquisition on my own.

A comprehensive literature review was conducted to identify challenges and opportunities in signal processing, AI-modelling, and the neurophysiological differences between Parkinson's patients and healthy individuals. Ethical considerations were also addressed, including data privacy and the implications of technologies that directly influence motor function.

This report begins by defining the research problem and reviewing the relevant theory on Parkinson's disease and brain signals. It then presents a review of current research in EEG, EMG, movement intention detection, and AI-based approaches. Following this, the hypothesis is formulated, and the methodology is explained, including model selection, the data acquisition pipeline, and real-time robotic arm control driven by thought and AI-modelling alone. The ethical aspects and potential applications in everyday life, such as exoskeletons, gloves, or combined Focused Ultrasound and Electrical Muscle Stimulation (FUS/EMS), are discussed. The report concludes with a summary of current work and future development pathways.

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[1] (Parkinson.org, 2025), (Parkinson.dk, u.d.), (Paulson, 2024)
[2] LSTM is an AI-model, that remembers patterns over long time in data and is used to analyse sequences.
[3] CNN is an AI-model, which excels in pattern recognition of photos and signals, by filtering and highlight the most important details.
[4] Transformer-model is an advanced neural network, which uses self-attention to analyse and weigh different parts of the input, parallel to each other.
[5] A-SVM is an AI-model, that dynamically adjusts to changes in data, to better classify complex patterns in data.
[6] A measurement-instrument, which registers movement by using gyroscopes and accelerometers.

Formulation of problem

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?

Biosignals and Parkinson's disease

Parkinson's disease[7]

Parkinson's disease is a progressive neurodegenerative disorder that primarily affects dopamine-producing neurons in the substantia nigra, a structure within the basal ganglia[8]. Dopamine is a crucial neurotransmitter involved in the brain's regulation and coordination of movement. When dopamine production declines, as is the case in Parkinson's disease, a chemical imbalance arises in the basal ganglia, leading to motor impairments such as tremors, rigidity, bradykinesia (slowness of movement), and postural instability.

Current research on Parkinson's disease focuses on developing treatments aimed at halting disease progression and restoring dopamine production. Other active areas of investigation include advanced therapeutic approaches such as gene therapy, stem cell treatments, neurostimulation, and Deep Brain Stimulation (DBS)[9].

Electroencephalography (EEG)[10]

Electroencephalography (EEG) is a non-invasive technique used to measure the electrical activity generated by the synchronized communication of large groups of neurons in the brain. EEG signals primarily arise from the summation of postsynaptic potentials in the cerebral cortex and reflect the brain's electrical rhythms and functional states. The electrical impulses generated by the brain vary in frequency and are classified into specific frequency bands, each of which is associated with distinct brain functions and mental states. These different frequency bands are illustrated in Figure 1:

[7] The section is based on the sources: (Parkinson.dk, u.d.), (Paulson, 2024)
[8] A part of cerebrum, which plays a crucial role for movement and control. Explained further in appendix 5.
[9] DBS is further explained in the "Other solutions"
[10] The section is based on the sources: (Chaddad, Wu, Kateb, & Bouridane, 2023), (Wikipedia, 2024), (Regalado, 2014),

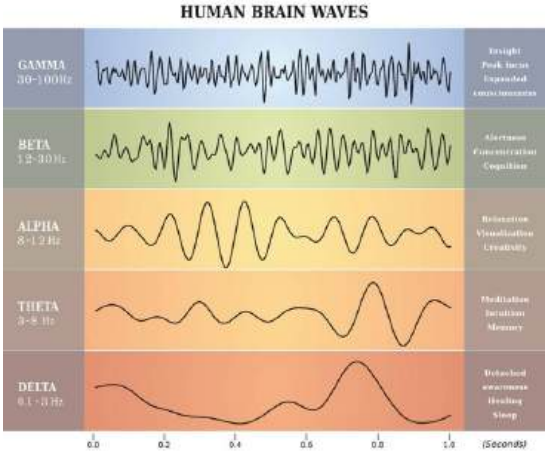

Figure 1: An overview of the different frequency bands[11]

Alphas waves (8 - 12 Hz) relate to relaxation and calm mental states, while beta waves (12 - 30 Hz) relate to focused activity and concentration. Gamma waves (30-100 Hz) are high frequency waves, which typically associate with information processing and conscious attention. Changes can in frequency bands can be observed in Parkinson's disease, e.g. reduced beta-desynchronisation and increased theta- and delta activity, which relate to motoric impairments such as bradykinesis and tremor[12]. Alpha waves over the motoric cortex are also known as Mu-waves.

EEG-signal is measured by placing electrodes on the head scalp in a system known as the international 10/20 system. The system can be seen on Figure 2

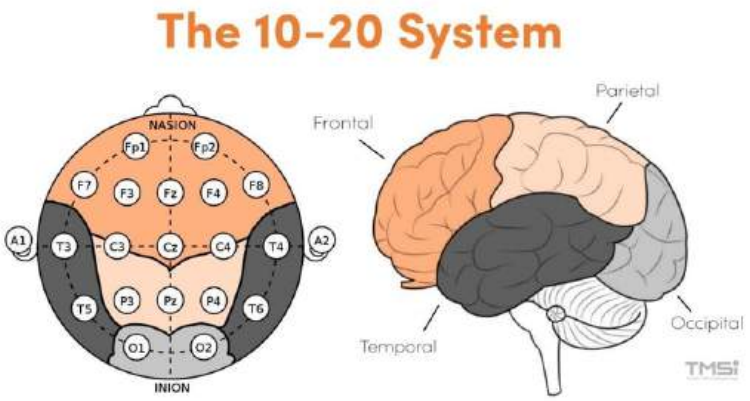

Figure 2: The international 10/20 system for the placement of EEG-electrodes[13]

The system was initially developed to ensure the electrodes were placed in a sustainable and logical way. The electrodes are placed on specific position on the head, which corresponds to certain anatomical reference points. This enables precise and comparable measurements of the brain's activity. The letters and numbers in the system are organized as follows:

[11] Loaned from https://coronatodays.com/5-types-of-brain-waves-and-their-link-to-different-states-of-consciousness/
[12] (Karimi & et al., 2021), (Miladinovic & et al., 2021)
[13] Loaned from https://info.tmsi.com/blog/the-10-20-system-for-eeg

- Even numbers are on the right hemisphere, uneven numbers on the left hemisphere
- Fp is for prefrontal lobe
- F is for frontal lobe
- P is for parietal lobe
- O is for occipital lobe
- T Is for temporal lobe
- C is for central (C3, C4 og Cz are on the primary motor cortex)
- A is the mastoid (the bone behind the ear)

When measuring EEG on the patient, must active electrodes be placed on the scalp, to measure the signals in specific regions in brain. But a reference electrode (typically on the mastoid, ie. A1 or A2), and a ground electrode (placed on Fz or nasion), too must be placed to measure the active signal relative to a defined reference.

EEG is capable of measuring brain activity in real-time, which is used to analyse different mental states of the user. An example would be using EEG to explore changes in the brain activity, when a person executes movement or in a resting state. These patterns may then be analysed (i.e. increased or decreased frequency band activity or a change in desynchronization power), to investigate how a disease, such as Parkinson's disease, may affect the brain's structure and functionality.

On Figure 3 and Figure 4 are shown examples of an electroencephalogram from this project and its corresponding spectrogram. The chosen channel is C3. The electroencephalogram has time one the x-axis, with the unit of seconds, and amplitude on the y-axis with the unit of μV. The x-axis on the spectrogram is frequency and the y-axis is the squared amplitude over the frequency, with the unit of $(\frac{\mu V^2}{Hz})$.

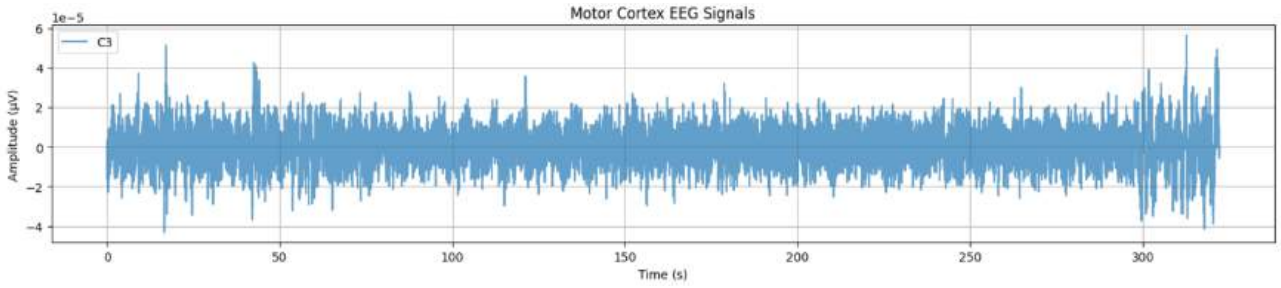

Figure 3: An example of an electroencephalogram based on the baseline data from the patient AQ59D analysed from the data of the article (Kueper, et al., 2024)[14]

[14] The photo is from a coded visualisation of the EEG data from (Kueper, et al., 2024)

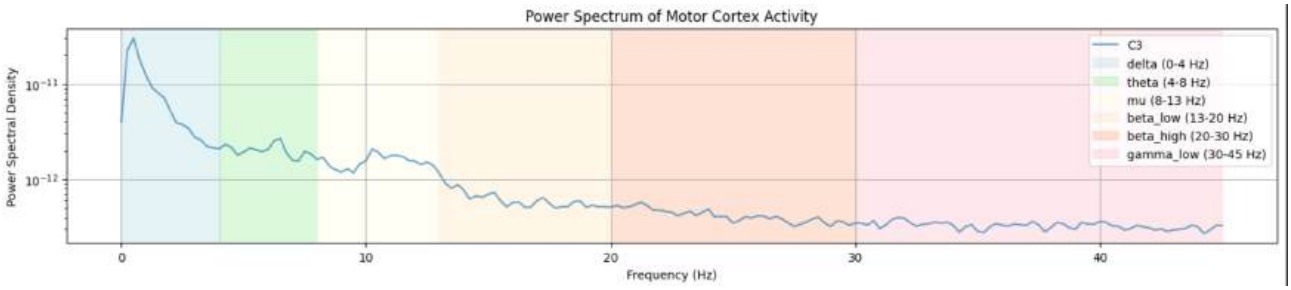

Figure 4: A spectrogram of the C4 electroencephalogram of the patient AQ59D, loaned from (Kueper, et al., 2024)[15]

Bereitschaftspotential (BP)[16]

The BP[17] is a slowly increasing negative voltage change in the brain's EEG signals, which occurs shortly before a voluntary intentional movement is made. BP represents the brain's motorically planning as is one of the earliest signals on a movement initialization - even before the person is concious about the intention. The two phases of BP are shown on Figure 5:

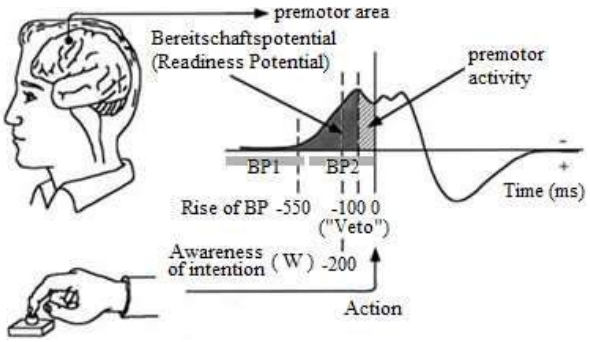

Figure 5: An example of BP[18]

The two phases of BP are as follows:

- **The early phase (BP1**): Can be measured approximately 1,5 to 0,5 seconds before the movement and is primary generated in supplementary motoric cortex (SMA). This phase reflects the general preparation of the movement.

- **The late phase (BP2**): Can be measured approximately 500 to 100 milliseconds before the movement, due to the increased activity in the primary motoric cortex. This phase reflects an initialisation of a concrete motoric activity.

In total, this means BP occurs before the conscious intention of a movement. This suggets that the brain begins to plan an action, even before the person experiences the wish of moving. It makes BP relevant for this project, because I aim to predict movement intentions from EEG-data measured in Parkinson's patients, which makes for another interesting case. A Parkinson's patient's EEG-signals are still intact, and the BP's can be measured and analysed, even though the signal may be reduced a bit.

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[15] Billedet kommer fra kodet spektrogram af EEG fra (Kueper, et al., 2024)
[16] Afsnittet er baseret på kilderne: (Wikipedia, 2024), (Georgiev, Lange, Seer, Kopp, & Johanshahi, 2016)
[17] Også kaldet præmotorisk potentiale eller parathedspotentiale
[18] Lånt af https://www.researchgate.net/figure/Bereitschaftspotential-and-the-Libets-experiment-At-550-ms-the-rise-of-BP-at-200-ms_fig14_268216375

If we instead of voluntary initiate a movement, react to an external stimulus, then a classical BP is not generated. This situation is denoted as a stimulus-responsive movement (SRM), where a sensory released response, called an event-related potential (ERP[19]) is generated in the sensory cortex. The signal is sent to the premotor cortex and afterwards to motoric cortex, where the motoric output is coordinated in close collaboration with the basal ganglia.

If we consider the human as a combined sensor and actuator, the difference between ERP and BP may be clearer. Assume I am standing in a completely dark room without any external stimuli, and voluntary decide to begin walking. This movement is self-initiated, and a BP may be measured. If I instead hear my phone ringing, and decide to walk towards it, then the situation is a SRM - and an ERP will dominate in my EEG-signals, while a BP may not be measured.

The difference between BP and SRM is crucial and relevant for this project. I've so far worked with BP signals and voluntary intention, but I wish to work explore stimulus-responsive mechanisms furthere in the future, and incorporate them to my Transformer-model, by including ERP measurements. I'll also immerse myself in the scientific literature on the interplay between sensor cortex, premotoric cortex and the basal ganglia.

Electromyography (EMG)[20]

EMG is a technique capable of measuring the electric signals generated when muscles contract. When a muscle is activated, electric impulses (axion potentials) are sent through the muscle celles, which creates a measurable voltage. The signals are either captured by surface elctrodes (placed on the skin) or needle electrodes (inserted directly into the muscle). A visualisation of EMG-measurements from thig project, is shown on Figure 6:

[19] (WIkipedia, 2025)
[20] The section is based on the following sources: (Johns Hopkins Medicine, u.d.), (wikipedia, 2025), (Cleveland Clinic, 2023)

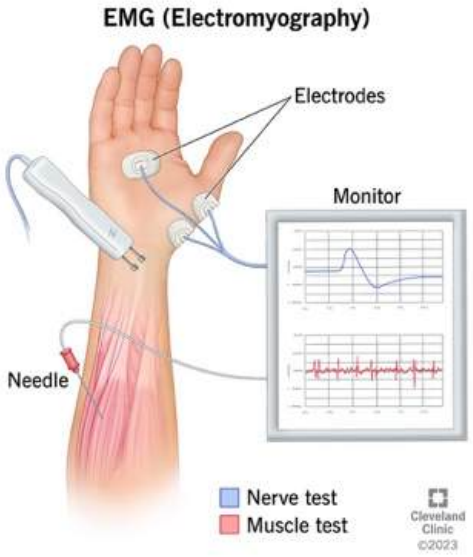

Figure 6: A typical EMG-measurement, with electrodes registering signals from underarm muscles during activation[21].

An EMG-signals reflects a muscle's activity and contains information on:

- The amplitude (the power of muscle activation)
- The timing of the muscle contraction
- Patterns in contraction and rest

An electromyogram is shown on Figure 7. The data is based on patient who flexes and extends his/her arm. The EMG-signal shows a clear cyclic activation and deactivation, which appears on the signal's characteristic wave shape. The x-axis is time and has the unit seconds, while the y-axis is the amplitude measured in milli voltage. The signal can be used to precisely estimate the movement's timing and intensity.

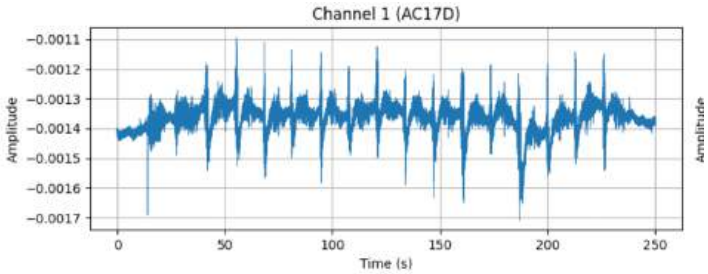

Figure 7: An example of an electromyogram from the project for the subject AC17D from (Kueper, et al., 2024)

EMG can be used to evaluate the changes in muscle activity in Parkinson's disease, because the disease often causes rigidity and bradykinesis, which is reflected in the EMG-patterns as slow or disturbed signals.

[21] Loaned from https://my.clevelandclinic.org/health/diagnostics/4825-emg-electromyography

Literature review

This review goes through the current research in EEG/EMG-signal processing, relevant AI-models and related technologies to this project such as Brain-Computer-Interface (BCI[22]), neuro prosthetics and DBS, which may contribute to the project. In addition to this, are changes in Parkinson's patients EEG/EMG highlighted.

The review is split into two parts: current research and already existing solutions related to the project.

Current research

The review starts on how EEG can be used for movement classification. Then it'll investigate EMG and EEG/EMG combined for movement classification using AI-models. Lastly will changes in EEG through Parkinson's disease be investigated, both motoric and cognitive symptoms are considered.

EEG-based movement classification

(Antony, et al., 2022) analysed EEG-based movement classification. Subjects were asked to imagine movements, which different AI-models[23] should classify the movements using different feature extraction-methods[24]. It was shown an Adaptive Support Vector Machine (A-SVM) with Online Recursive Independent Component Analysis (ORICA[25]) together with Common Spatial Patterns (CSP[26]), gave the highest precision (91%). The study shows advanced feature extraction can improve AI-models ability to recognise different intentional movements.

(Buerkle & et al., 2021) built upon this study, by using a LSTM-RNN model for real-time detection of movement intention. The model achieved a precision of 84-92% precision in an interactive environment, showing a LSTM-RNN can be used to fast and precise classification of movements in EEG-signals.

Partial conclusion on EEG-movement classification

With high precision can EEG-based models classify intentional movement, but they are dependent on feature extraction.

EMG-based movement detection and personalisation

(Zhang, et al., 2023) developed a method for automatic movement detection in EMG, by applying a threshold defined as ($T = \text{Baseline} + 1{,}2\mu + 2\sigma$). They evaluated five different AI models using this

[22] A BCI is a system that allows direct communication between the brain and an external device, by translating brain signals into digital commandos.
[23] A short description on AI-models can be found in appendix 3.
[24] Key information is extracted from the raw data to facilitate prediction—such as signal amplitude or dominant frequency components using methods like the Fast Fourier Transform (FFT) or bandpass filtering. This process transforms raw signals into meaningful input features for AI models.
[25] ORICA is a real-time adaptation of ICA used to separate independent signal sources from EEG data. Its adaptive nature makes it well-suited for dynamic EEG environments, particularly for real-time artifact removal.
[26] CSP is a feature extraction technique that enhances the discriminability between two signal states by maximizing the variance differences across spatial filters.

approach, with DeepConvNet (D-Conv) demonstrating superior performance for online detection (p = 0.001), achieving 100% precision in EMG detection.

(Aeles & et al., 2021) demonstrated that EMG signals are unique to everyone. They recorded EMG data from eight muscles in the right leg of 80 participants during walking and cycling. Using Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Multi-Layer Perceptrons (MLP[27])), they classified the EMG signals to identify individuals. Among these models, the SVM achieved the highest accuracy and fastest performance, with a precision of 99.3%. These findings suggest that personalized AI models may be necessary for my project.

Partial conclusion on EMG-based movement detection and personalisation.

EMG is effective for movement detection; however, personalized AI models may be necessary, as EMG signals are unique to everyone. AI models can accurately classify EMG signals across different individuals.

Combination of EEG/EMG and real-time aspects

(Silva-Acosta & et al., 2021) investigated how combining EEG and EMG signals affects the accuracy of movement classification. They employed a Long Short-Term Memory (LSTM) model to analyze data from both brain waves and muscle signals during arm movements and found that the LSTM model performed best when the data were stratified by gender. This suggests that personalized AI models can enhance movement classification.

(Mahmoodi & et al., 2021) developed a threshold-based algorithm for detecting the BP from single-channel EEG using the TKEO[28]. Their method achieved a precision of 91.2%, a sensitivity of 81.1%, and an average latency of -384.9 ms. These results demonstrate its potential for real-time applications, where BP detection could be combined with EMG signals.

Partial conclusion on combination of EEG/EMG and real-time aspect

The combination of EEG and EMG signals can improve classification accuracy, and threshold-based BP detection appears promising for real-time implementation. These methods have the potential to enhance motor control, which is particularly relevant for patients with Parkinson's disease.
The following section will examine how EEG and EMG are applied in clinical contexts.

EEG/EMG and Parkinson's-disease

This section is split into three parts:

- EEG and motoric symptoms (bradykinesis, tremor and of91 Freezing of gait (FOG[29]))

[27] MLP is a neural network, where neurons are organised in layers, and each layer relates to the next one via non-linear activation functions

[28] TKEO is a signal processing technique that estimates the instantaneous energy of a signal. This approach accentuates changes in both amplitude and frequency, making it particularly effective for detecting rapid variations in signals. Consequently, TKEO is well-suited for applications such as movement classification.

[29] FOG is a situation characterised with difficult initialisation of movement or to stand up. The person freezes in his/her movement.

- Functional connectivity[30] and network changes in Parkinson's disease
- EEG/EMG for stimulation and treatment

EEG and motoric symptoms (bradykinesis, tremor and FOG)

(Karimi & et al., 2021) analysed EEG- og EMG-patterns in Parkinson's patients with and without FOG. Patients with severe FOG had reduced beta desynchronisation and increased theta activity above the Cz electrode before movement. The study shows EEG-patterns are changed in Parkinson's patients.

(Wang & et al., 1999) found Levodopa[31] to better the premotor EEG-desynchronisation in Parkinson's patients, which corelates with reduced bradykinesis. This supports the theory on the basal ganglia releasing frontal areas from idling rhythms[32]. The increased desynchronisation corelated with fasten movement times above: sensory motoric cortex during simple movements, SMA during hand squeeze and prefrontal cortex during complex or sequential movements.

(Miladinovic & et al., 2021) analysed the interplay between EEG-activity and the Parkinson's patients' motor deficit scales. They found high delta- and low alpha-activity to corelate with worsen FOG, while high theta- and low beta-activity to relate to a worse UPDRS-III-score[33]. The results suggest EEG-slowing[34] to be a biomarker for motoric deterioration in Parkinson's disease.

(Farashi & et al., 2023) analysed if EEG-signals could be used to predict Parkinson's patients' resting tremor, before the tremor starts. By analysing data from IMU's, were tremor-onsets identified, and afterwards was the EEG-signals before and during the tremor analysed. Features like form coefficient[35] and entropy[36], especially in delta- and gamma-bands, were extracted. A K-nearest-neighbour-model (KNN[37]) achieved a predication precision of 73.7%, which increased to 81.3% after using feature-extraction.

[30] Functional connectivity refers to the temporal relationship between activities in different brain regions, specifically, whether they oscillate synchronously or exhibit statistical interdependence. Two regions are considered to have high functional connectivity if their EEG signals oscillate in synchrony.
[31] Levodopa is medicine, which converts is converted to dopamine in the brain. It is standard treatment against motoric symptoms in Parkinson's disease.
[32] Idling rhythms are the rhythms needed to be damped (desynchronised) to enable motoric activity. These brain signals dominate when the brain is in resting state (you make no movements)
[33] A scale to weigh the severity of Parkinson's disease, where the neurologists tick of boxes depending on the symptoms degree. UPDRS-III refers to the motoric test. Look up Se (S. & R., 1987) for the test.
[34] When high frequency waves (alpha, beta and gamma) decrease, while low frequency waves (delta and theta) increase
[35] A quantification for the complexity of a signal. High value → rough and complex, low value → smooth and regular
[36] A quantification of a signal's unpredictability or information content. High value → the signal is chaotic and rich on information, low value → the signal is predictable and structured.
[37] KNN is a model, that classifies new data points by looking at the k nearest neighbour in the training data. The nearest neighbours are decided by a distance function, such as Euclic distance.

Partial conclusion on EEG and motoric symptoms (bradykinesis, tremor and FOG)

Changes in the frequency bands exist in Parkinson's patients. EEG may reflect the motoric symptoms in Parkinson's disease. Desynchronisation in the alpha- beta band before movement, relates to the ability to initiate a movement - which is improved by Levodopa. EEG-slowing (increased delta and theta activity, reduced beta and alpha activity) corelates with worse degree of symptoms. Early changes in EEG may be used to predict resting tremor, which opens a door for real-time adaptive treatment. EEG-changes reflect the symptoms in Parkinson's patients.

Functional connectivity and network changes in Parkinson's disease

(Peláez Suárez & et al., 2021) analysed EEG-based functional connectivity in Parkinson's patients with and without mild cognitive impairment (MCI). The studied fount MCI-patients to have decreased connectivity in alpha- and delta band. Both Parkinson's patients had randomised network topology with lower segregation and increased integration[38]. The decreased integration in the beta band corelated with worse executive function and working memory in MCI-patients.

(Conti & et al., 2022) analysed functional EEG-connectivity in de novo Parkinson's patients[39]. The study showed a reduced functional connectivity in the alpha- and beta bands. Conversely, they found an increase in the gamma-band, which is interpreted as a possible compensatory mechanism in the early stages of the decease. Network measurements as assortativity[40] were also decreased in the Parkinson's patients.

Partial conclusion on functional connectivity and network changes in Parkinson's disease

The articles show Parkinson's disease to affect the brain's functional network already in the early stages. A general decrease in functional connectivity in alpha and beta band were observed, which corelated with a worsen motoric and cognitive functionality, while an increased gamma connectivity interprets a cortical compensatory mechanism.

EEG/EMG for stimulation and treatment

(Desai, 2023) analysed a Machine Learning (ML[41])-method to distinguish Parkinson's patients from healthy individuals by using EEG-signal processing and classification. The EEG-data from Parkinson's patients af 16 healthy subjects, were filtered, analysed where important features were extracted. Random forest[42] and Extra Trees[43], had a precision of 97.5%. The study showed that signal processing of EEG and ML, can distinguish Parkinson's patients from healthy individuals.

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[38] Network topology shows how the brain is connected; integration is cross-function cooperation, and segregation is division in specialised areas.
[39] Patients without prior medical treatment.
[40] A network's robustness
[41] ML is a sub-group of artificial intelligence where the computer learns patterns from the data and improves its performance without being explicitly programmed to do it.
[42] A collection of decision trees, which choose the best split for high precision. Is used in classification.
[43] Is like Random Forest, bust uses random split to increase the variation and decrease overfitting. Is used in classification.

(Zanini & et al., 2019) compared different AI-models (MLP, LSTM) capability to predict EMG-signals in Parkinson's patients, to improve the efficient in functional electric stimulation (FES[44]). The study showed that AI-models could precisely stimulate and predict EMG-patterns in Parkinson's patients, which enables more targeted and adaptive FES-treatment.

(Saikia & et al., 2019) analysed a classification-based method for EEG-EMG-corelations in Parkinson's patients in temporal periods compared to healthy subjects. They analysed EEG-signals above the frontal and temporal lobe and EMG from the wrist during flexion and extension. An ANN had a precision of 98.8% trained on EEG/EMG, which was higher than model soelely trained on either EEG or EMG.

Partial conclusion on EEG/EMG for stimulation and treatment

The three articles show how advanced signal processing and AI-model, can utilise EEG- and EMG-data to both identify Parkinson's disease and predict muscle activity, which enables a more precise and adaptive treatments methods. With a high precision, it is possible to distingiush Parkinson's patients from healthy individuals. EMG-signals in Parkinson's patients can be predicted and multimodal data integration gives a better classification precision.

Existing solutions related to the project

Other existing solutions related to this project include Brain-Computer Interfaces (BCIs), neuroprosthetics, and Deep Brain Stimulation (DBS). While these technologies share similarities with the project *From Thought to Movement* (FTtM), they also differ from it in fundamental ways.

Brain Computer Interface (BCI)[45]

A BCI is a technology that connects the brain's electrical activity to an external device, such as a computer, robotic arm, or exoskeleton. BCIs typically use EEG signals to translate the brain's electrical activity into commands that control external devices. A BCI generally consists of four components:

1) A sensor to record brain activity (often EEG)
2) A computer to process and analyse the signals
3) A device (actuator) to be controlled
4) A feedback system, that informs the user about the predicted or executed action

The architecture of a classical BCI system is illustrated in Figure 8:

[44] FES is a treatment method, that used electric impulses to activate axons from motor neurons the periphery nerves and stimulate muscles to induce movement.
[45] Sources used in this section: (University of Calgary, 2025), (Wikipedia, 2025)

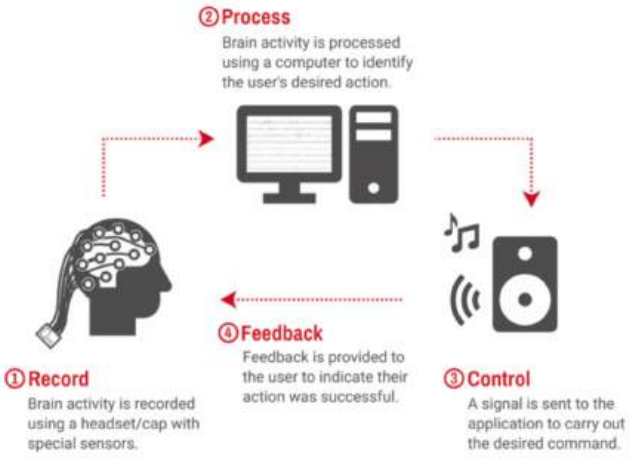

Figure 8: The functional principle of a classical BCI-system[46]

Active participation from the user is required in BCIs, as the system relies on the user consciously focusing on specific thoughts or intentions to initiate movements or actions. An example of such a BCI system is Elon Musk's Neuralink.

The main distinction between BCIs and the FTtM system lies in their objectives. FTtM aims to reconstruct the body's natural movements before they are executed, leading to the direct reactivation of the patient's own muscles, particularly in individuals with Parkinson's disease or other movement impairments. In contrast, BCIs are typically used to control external machines. FTtM, on the other hand, seeks to restore the body's intrinsic motor functions.

Because of this fundamental difference, an alternative term for FTtM could be *Brain-Physiological Interface* (**BPI**), as the brain signals in this system do not merely control an external device but reintegrate the body's own movements through its bio-signals.

Neuroprosthetics[47]

Neuroprosthetics is a field of medical technology that employs electronic devices, such as orthoses, prosthetics, or robotic limbs, to replace or restore neurological functions. This is achieved either by stimulating the nervous system (e.g., through electrical impulses) or by interpreting brain signals (commonly via EEG or intracortical measurements) to activate external actuators. Neuroprosthetic systems are typically utilized by individuals with paralysis, amputations, or neurological disorders where natural motor functions are partially or entirely lost.

In contrast, FTtM differs by not replacing bodily functions but by collaborating with the body's existing muscular and nervous systems to enhance or restore movement. FTtM interprets the user's intentions and assists muscle activation without assuming control, thus functioning as an assistive rather than a substitutive technology.

[46] Loaned from: https://cumming.ucalgary.ca/research/pediatric-bci/bci-program/what-bci
[47] Sources used in this section: (Gupta, Vardalakis, & Wagner, 2023), (Friedenberg, et al., 2017), (Wikipedia, 2024)

Deep Brain Stimulation (DBS)

DBS[48] is a compelling therapeutic approach, one that my father has personally undergone. It involves the surgical implantation of electrodes into specific brain regions to modulate neural activity through controlled electrical stimulation. While DBS does not cure the underlying disease, it adjusts the brain's electrical signals disrupted by conditions such as Parkinson's disease[49].

In the treatment of Parkinson's disease, the following brain regions are commonly targeted:

- Subthalamic Nucleus (STN)
- Globus Pallidus Internus (GPi)
- Ventral Intermediate Nucleus (VIM) of the thalamus

By delivering high-frequency stimulation, typically around 130 Hz, to these areas, DBS can significantly alleviate motor symptoms such as tremors, rigidity, and bradykinesia. This intervention is particularly beneficial for patients whose symptoms are not adequately managed with medication or who experience severe side effects from pharmacological treatments

DBS consists of three main components:
Electrodes, a pulse generator (IPG) and connecting wires

- Electrodes are implanted in specific regions of the brain
- The **IPG** delivers electric impulses to regulate the disrupted neural signals. It is implanted under the skin, typically in the chest or abdomen, and functions similarly to a pacemaker.
- **Wires** that run under the skin, connecting the IPG to the electrodes implanted in the brain.

An overview of DBS is illustrated in Figure 9. It shows how the neurostimulator (the IPG) is connected via wires to the brain electrodes. The IPG delivers the necessary electrical impulses to modulate the disturbed neural activity. DBS generally reduces beta-band synchronization in the basal ganglia, which facilitates the initiation of movement in Parkinson's patients.

[48] Sources used in this section: (Wikipedia, 2025), (Johns Hopkins Medicine, 2025), (Hospital, 2014), (Cleveland Clinic, 2022)
[49] A new iteration of DBS is adaptive deep brain stimulation (aDBS), which is a dynamic form of DBS that adjusts in real-time by measuring beta waves. It can stimulate based need, meaning aDBS only stimulates when it is needed. Source: (Oehrn & et al., 2024)

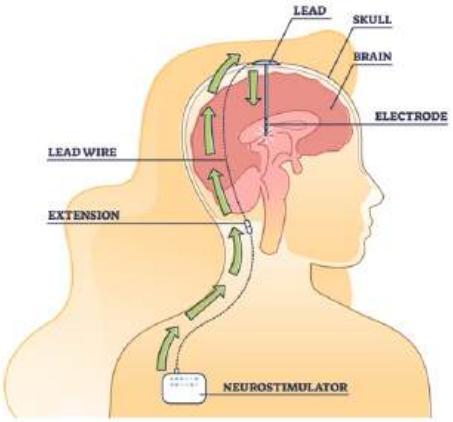

Figure 9: An overview of the DBS system pathway[50]

While DBS shares some parallels with this project, it remains fundamentally different.
DBS suppresses overactive neural activity using high-frequency electrical stimulation, whereas FTtM predicts movements based on intentional brain signals.

Figure 10 presents a table summarizing the differences between FTtB, neuroprosthetics, DBS, and BCI.

Kategori	Formål	Teknologi	Grad af invasiv	Patienten	AI-anvendelse	Træning
BCI	Kommunikation og styring vha. hjernesignaler	EEG eller implantater	Non-invasiv (EEG) eller invasiv (implantater	Neurologiske lidelser	Begrænset	Omfattende signaltræning
Neuroprost etik	Gendannelse af motoriske funktioner	EMG/EEG + aktuator	Ofte invasiv	Motorisk tab	Begrænset	Kalibrering på muskelaktivitet
DBS	Symptombehandling via hjernestimulation	Implementerede elektroder og pulsgenerator	Meget invasiv	Parkinsons-sygdom og tremor	Ingen	Ikke nødvendigt
FTtB	Forudsigelse og aktiv assistance af bevægelse via intention	Wearable EEG m. Transformer-model	Non-invasiv	Parkinsons, muligvis flere bevægelsesforstyrrelser	Transformer-model trænet på multimodal data	Træning med brugeres egen data

Figure 10: An overview of differences and similarities between my project and solutions akin to it.

FTtM distinguishes itself as a non-invasive, wearable system that integrates AI, EEG, EMG and IMU to predict and stabilize motor intentions. BCI, neuroprosthetics, and DBS, FTtM collaborates with the body's natural neuromuscular systems. It employs active AI algorithms and requires minimal patient training, rendering it both unique and potentially adaptable across various applications.

While this review emphasizes EEG and EMG as primary signals for movement prediction in Parkinson's disease patients, alternative technologies exist:

- **Magnetoencefalografi**[51] (**MEG**): A non-invasive technique that maps neural currents by measuring the magnetic fields generated by brain activity. MEG has demonstrated efficacy in characterizing Parkinson's disease by detecting abnormal phase-amplitude coupling in the brain.

[50] Loaned from https://www.ohsu.edu/sites/default/files/2022-05/GettyImages-1324195152-full-size-CROP.jpeg
[51] (Magnetoencephalography, 2024), (Cleveland Clinic, 2025)

- **Optically pumped magnetometers** (**OPM**[52]): An emerging technology that combines the precision of MEG with enhanced portability. OPMs operate at room temperature and can be placed closer to the scalp, providing high signal strength and improved spatial resolution

In this project, EEG was chosen due to its cost-effectiveness and feasibility for developing a real-time, neurostimulating wearable solution, making it more practical than MEG and OPM-based systems.

Overall conclusion of the literature review

This review demonstrates that combining EEG and EMG signals, analysed using modern AI models, offers a reliable and precise method for predicting movements based on neural intentions. EEG can detect premotor potentials such as the BP and Parkinson's disease-specific changes in frequency bands, including reduced beta desynchronisation and altered network connectivity. EMG captures movement patterns with high precision but is highly individualised, which is why I begin by training personalised AI models using data from a single subject.

Integrating EEG and EMG, particularly through real-time multimodal AI algorithms (e.g., LSTM, TKEO, and Transformer models), enhances both prediction accuracy and response speed. In Parkinson's disease, studies suggest that EEG deviations and changes in network topology can serve as biomarkers for diagnosis, symptom prediction (e.g., tremor and freezing of gait), and targeted treatments such as FES.

This review establishes the foundation for my project, which aims to develop a non-invasive, Transformer-based AI system capable of predicting movements in real time using EEG, EMG, and IMU data. Unlike existing technologies such as BCIs, DBS, and neuroprosthetics, FTtM leverages the body's own biosignals, requires minimal patient-specific training, and can be individually adapted. This makes the solution more flexible, wearable, and clinically transferable, particularly for patients with neurodegenerative diseases like Parkinson's disease.

Hypothesis

I hypothesize that a Transformer-based model trained on multimodal data—specifically EEG, EMG, and IMU signals—can predict intentional movements with a classification accuracy of at least 95%. This expectation is grounded in the Transformer architecture's robust capability to capture temporal dependencies and process complex, multimodal datasets effectively

In practical application, the model's output could be utilized to activate muscles or control mechanical devices, such as robotic arms or exoskeletons, thereby assisting Parkinson's patients in their movements. Alternatively, the output could be integrated into a hybrid FUS/EMG system, as elaborated in the section "Product, Future, and Ethics."

[52] (Tierney & et al., 2019), (Virginia Tech, 2021). The researcher Andreas Nørgaard Glud (Clinic lector in Institute for Clinical Medicine - Brain- og Back surgery in Aarhus University) suggested me this method.

To test this hypothesis, I will undertake the following steps:

1. Train and test various AI models to quantitatively and logically select the most suitable model for my project.
2. Collect EEG, EMG, and IMU data from intentional movements performed by my father and/or other test subjects.
3. Train and optimize the Transformer model by applying different feature extraction methods and tuning hyperparameters (e.g., batch size, learning rate).
4. Evaluate the Transformer model's ability to classify movements by comparing its predictions against actual movements from new datasets, both offline and in real time.
5. Build a test setup where I will perform measurements on myself using a custom-built EEG circuit. This system will measure the voltage difference between an active electrode and a reference electrode to record EEG signals. Additionally, I will construct a 6-axis robotic arm using Arduino, allowing me to demonstrate the system's ability to translate neural intentions into concrete, visible movements in real time.

If the hypothesis proves correct, it will demonstrate that artificial intelligence can effectively convert brain intentions into movements, for example, through electrical or acoustic stimulation, potentially opening new possibilities for neurotechnological applications aimed at helping Parkinson’s patients.

Design and methodology

Experiments have been conducted in this project, all of which contribute important partial results to the development of the complete system. The experiments build on one another and test the system's robustness and functionality—both through offline analyses and in real-time.

The project is divided into three phases:

1. **Training and test of AI-models on a public dataset**
   I have trained and tested seven different AI models on EEG/EMG data from the article by (Kueper, et al., 2024). The subjects were instructed to perform right arm movements using an orthosis while being monitored. The AI models were programmed to classify the signals as either "movement" or "no movement." The goal was to identify the most suitable AI model for further development in the project.

2. **Real-time control of a robot arm using IMU's**
   Next, I built an IMU-based system in which an IMU placed on my arm can control two of the robotic arm's servos in real time. The goal is to eventually control five servos using three IMUs placed on my forearm, wrist, and upper arm. The purpose is to demonstrate that motion signals from the body can be used directly to control an external device.

3. **Training and application of the Transformer-model og my own EEG/EMG/IMU-data**
   Finally, I will train a Transformer model on my own biosignals. I have programmed the Transformer model to predict intentional movements, identified through BP based on combined EEG, EMG, and IMU inputs. However, I have yet to test and train this model.
   I will use my own EEG hardware to record EEG signals and integrate them as input modalities for the Transformer model. The model's output will consist of binary values that will be translated into specific motor actions of the robotic arm (e.g., contraction or extension). The project will first be implemented offline and later transferred to a real-time setup. In the future, the next version will be applied to data measured from my father.

The most important methodological considerations are presented in the main body of the report, while technical details and experimental logs can be found in Appendices 2, 3, and 4. The following sections describe the choice of AI model, data collection, and measurement setup in more detail.

Methodical considerations

In this project, I will conduct three experiments to develop and test an AI model for predicting movement in Parkinson's patients. This will follow the three steps outlined in the previous section. It is a complex task that requires a series of sub-goals and intermediate processes. Figure 11 shows a flowchart illustrating how this process will unfold.

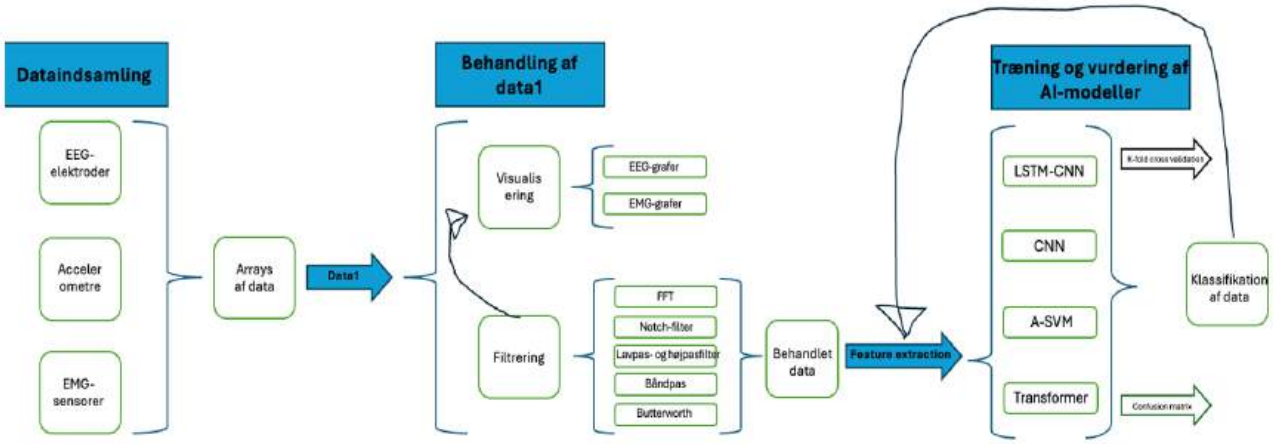

Figure 11: A flow diagram of the project[53]

Test of AI-models on public dataset

In this experiment, I tested seven different AI models—each selected based on findings from the literature review—to classify an output signal as either movement or no movement. The classification was based on the following predefined threshold value (chosen from (Zhang, et al., 2023))

$$T = \text{Baseline} + 1{,}2\mu + 2\sigma$$

Where: baseline is the average EMG-signal during rest, μ is the average EMG-signal during muscle active and σ is the standard deviation of the EMG-signal during muscle activity.

If the output exceeded this threshold, it was classified as 1 (movement); otherwise, 0 (no movement). The source code for these models is available at: https://github.com/TobiasBN1005/From-thought-to-movement-/tree/main/AI-models

The dataset used originates from (Kueper, et al., 2024) and contains EEG/EMG data from participants performing right-arm movements with an attached orthosis. The data was bandpass filtered between 0.5 Hz and 45 Hz, notch filtered at 50 Hz to remove noise and finally normalized. To mitigate overfitting, I used 5-fold k-cross-validation. Data from subject AA57D was excluded due to file corruption during upload.

[53] The author's own work

Only the time window from 30 to 230 seconds was analyzed, as the signals outside this range were too noisy. The evaluation metrics included precision, confusion matrix, ROC curve, and AUC. Additionally, I measured each model's training time and inference time to assess overall efficiency. Efficiency was defined to yield a value between 0 and 1 (with 1 being optimal), using the following formula:

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

Where[54]: $\alpha = 0{,}8,\ \beta = 0{,}5,\ \gamma = 0{,}7$, og
$\text{Præcision}_{\max}$ is the highest precision among all AI-models
$\text{tid}_{\max}$ is the longest training time among all models.

The following AI models were tested and trained using 5-fold cross-validation (80% training / 20% testing) to prevent overfitting:

1. LSTM-CNN
2. LSTM
3. CNN
4. Transformer
5. SVM
6. A-SVM
7. DeepConvNet

After training and testing, each model's training time, AUC score, precision, and inference time were recorded in an Excel spreadsheet. The efficiency score was automatically calculated using the formula above. The results are shown in Figure 12 and Figure 13. Green boxes indicate the top-performing model for a given metric. Red boxes indicate the lowest-performing model for a given metric.

AI-model	Præcision	Tid / s	AUC	Effektivitet
LSTM-CNN	99,92%	3655	100,00%	51,85%
LSTM-RNN	97,58%	14165,18	99,33%	37,75%
CNN	100,00%	1329	100,00%	61,53%
Transformer	98,50%	645	99,97%	67,15%
SVM	67,29%	8	69,48%	60,16%
A-SVM	85,67%	57	93,36%	74,19%
DeepConvNet	99,87%	1063	100,00%	63,55%

Figure 12: An overview of the AI-models classification's performance[55]

[54] The coefficients values are chosen to secure that a precise and fast AI-model is weighted most.
[55] The author's own work, made in Excel

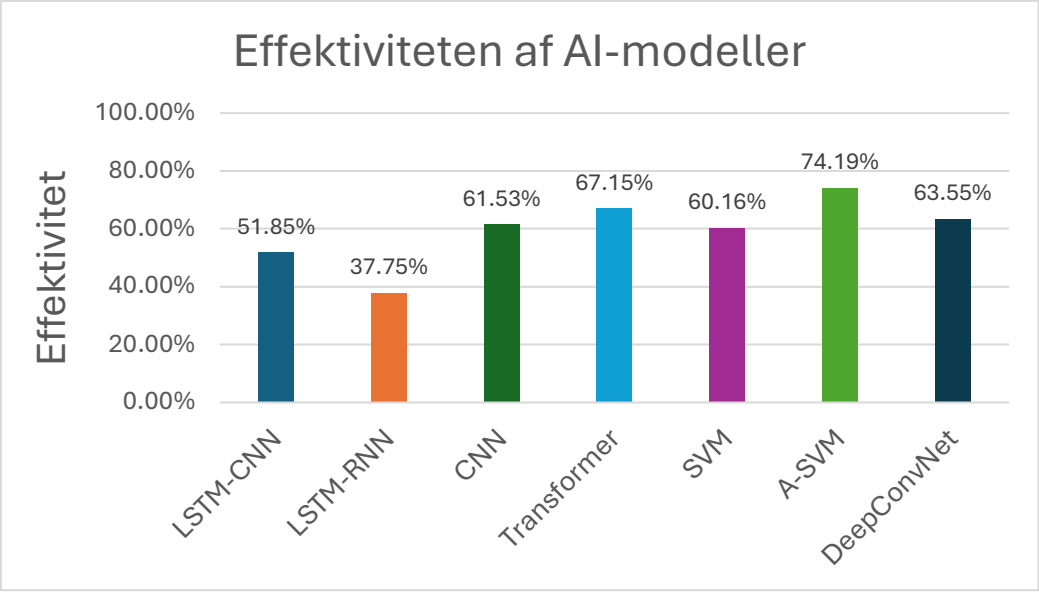

Figure 13: The efficiency of the different AI-models[56]

I can from the results conclude the following

- **LSTM-RNN** and **LSTM-CNN** performed worst, due to their complexity and long training times.
- **SVM** had the lowest precision (69.48%) and was therefore not selected for further use.
- **CNN** and **DeepConvNet** were both fast and accurate but are not ideal for time-dependent signals like EEG/EMG and thus were excluded.
- **A-SVM** achieved the highest precision 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's.

The Transformer model is therefore considered the most suitable for this project due to its balanced precision, strong performance on sequential data, and promising future potential. It will be used for further development in the next phase.[57].

[56] The author's own work, made in Excel

[57] A preliminary jury for the Danish science competition *Unge Forskere,* also suggested me to work with a Transformer-model in my project.

Real-time control of a robot arm by using IMU's

I constructed and built a robotic arm using an Arduino platform, consisting of six servos—five of which are active. Each servo controls a specific function of the arm and is numbered from one to six for easy reference. Servo 4 is not used, as it does not correspond to any meaningful physiological movement of the human arm[58]. On Figure 14 is the division and function of the servos shown.

Figure 14: How the servos were divided in the robot arm[59]

I have developed a prototype where each servo can be controlled in real time using data from three IMUs placed on my own arm. The IMUs measure angular velocity and acceleration, which are then translated into movements of the robotic arm. By measuring the angular displacement of each IMU along a selected axis relative to a reference point, it is possible to control the robot arm simply by moving my arm with the IMUs attached. This demonstrates the core concept of my project: translating biosignals into actuator-driven actions. The placement of the IMUs is shown in Figure 15:

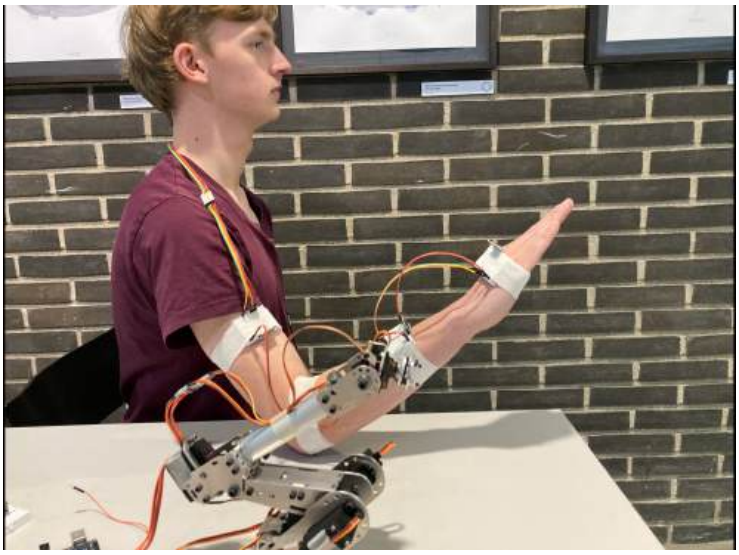

Figure 15: The placements of the IMU's on my arm[60]

[58] Look into Appendix 4 for the experiment's journal. The following link has all the code for the robot arm https://github.com/TobiasBN1005/From-thought-to-movement-/tree/main/Robotarm

[59] The author's own work

[60] The author's own work

The electrical circuit connecting the IMUs to the robotic arm is displayed in Figure 16:

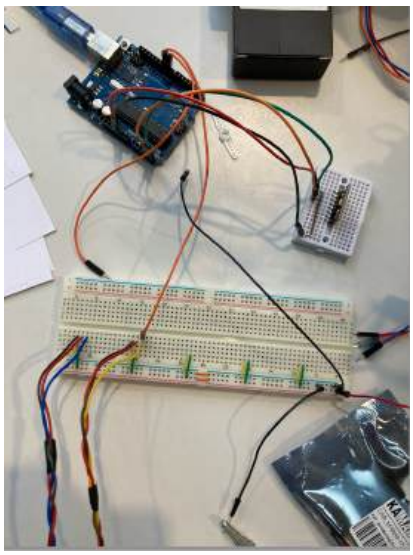

Figure 16: The circuit for the IMU and robot arm

Once the entire IMU-controlled robotic arm is fully functional, the next step will be to replace the IMUs with signals from my Transformer-based AI model, which processes EEG input directly. The goal is to control the robotic arm in real time based on the user's movement intentions as decoded from brain signals, thereby illustrating a central principle of the project: from intention → to action.

In the next phase of the project, the robotic arm will be replaced by an external actuator that directly stimulates the user's own muscles. For example, using FUS combined with EMS, it may be possible to restore movement without relying on the damaged nervous system[61]. The Transformer model, which initially controls the robotic arm, will eventually be used to activate the muscles directly, potentially restoring mobility in individuals with motor impairments due to neurological disorders, such as Parkinson's disease.[62].

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

The Transformer-model[63] will be trained and tested on three modalities: EEG, EMG, and IMU. Together, these represent the user's intentions (EEG), muscle activity (EMG), and arm movement (IMU)—providing a comprehensive view of how brain signals are translated into physical motion. A summary of the experimental setup[64] is presented in Figure 17.

[61] Look at the section" Product ideas" for more information on this
[62] Explained furthere in the section "Future perspectives"
[63] The code can be found on my Github: https://github.com/TobiasBN1005/From-thought-to-movement-/tree/main/Main_AI_model
[64] Look into Appendix 2 for a journal of this experiment.

Modalitet	Sensorer	Placeringssteder	Samplingrate	Funktion
EEG	Elektroder (C3, C4 & Cz)	Hovedbunden	256 Hz	Intention/tanke (BP)
EMG	Overfladeelektroder	BB, TB, TBLH & FDS	256 Hz	Muskelaktivering
IMU	IMU'er (accelerometer + gyroskop)	Overarm, underarm, håndled	256 Hz	Bevægelsesdetektion

Figure 17: Overview of the experimental design[65]

The first modality for the Transformer model is EEG signals recorded from the motor cortex. Electrodes are placed at C3, C4, and Cz, following the international 10-20 system. The mastoid serves as the reference electrode, and the nasion as ground. To reduce impedance, a conductive gel is applied to the electrodes, which are held in place using a swim cap to ensure they stay securely positioned on the scalp.

The most relevant EEG frequencies lie in the alpha/beta range and the 0–5 Hz band, as these are associated with voluntary movement and the Bereitschaftspotential (BP), respectively. To capture these, a bandpass filter from 0.5 Hz to 45 Hz is applied. The sampling rate is set to 256 Hz, based on recommendations from the literature[66]. Additionally, a notch filter is used to eliminate 50 Hz power line noise and the 10 Hz occipital alpha band.

The current EEG hardware and corresponding circuit diagrams are shown in Figure 18 and Figure 19 **respectively,** which will be updated as development progresses.[67]

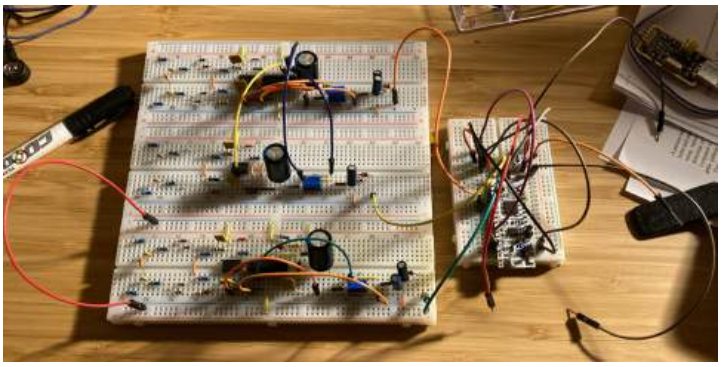

Figure 18: Current EEG-circuit[68]

[65] The author's own work
[66] The sampling rates ranged from 2000 Hz (Kueper, et al., 2024) to 128 Hz (Conti & et al., 2022), but many articles used a sampling rate of 256 Hz, which why I also use it.
[67] Look into Appendix 1 for a walkthrough of the electronics and code behind the EEG-measurements. The code is written in STM32CubeMX, where I used a NucleoF303K8 micro board.
[68] The author's own work

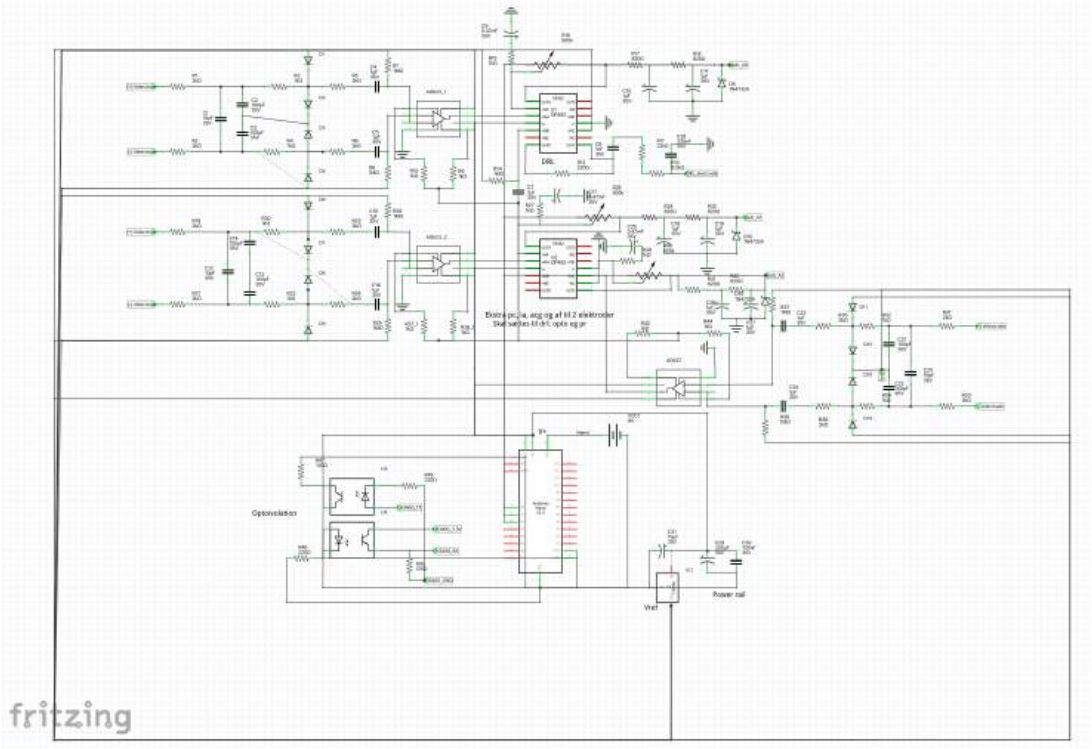

Figure 19: Current EEG-circuit diagram[69]

The circuit is composed of several sub-circuits to ensure a clean and robust EEG signal[70]. The raw EEG data undergoes filtering, amplification, and signal protection before being passed to the Teensy 4.1 microcontroller via its Zar ADC channel for digital processing. The digitized EEG data is then fed into the multimodal Transformer model for further analysis.

The second modality is EMG. I will measure EMG signals from four different muscles in my right arm:

- M. biceps brachii (BB)
- M. triceps brachii (TB)
- M. triceps brachii long head (TBLH)
- M. flexor digitorum superficialis (FDS)

Surface electrodes will be used for the measurements, with the ground electrode placed on the elbow and the reference electrode placed near the biceps. The EMG signals will be used to determine how and when muscles activate, and to define the start time for segmenting BP data.

To reduce impedance and ensure clean signal acquisition, I will take a shower and disinfect the arm to remove dead skin and bacteria before attaching the electrodes. The EMG setup and electrode placement are shown in Figure 20.

[69] The author's own work, made in Fritzing.

[70] Look into Appendix 1 for a further explanation of the circuit https://github.com/TobiasBN1005/From-thought-to-movement-/tree/main/EEG_code-kopi for the code

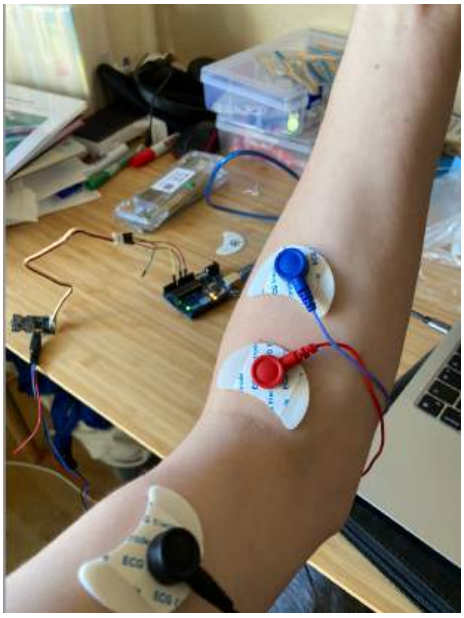

Figure 20: EMG-setup with electrode on the arm[71]

In the illustrations:

- The black electrode represents ground
- The red electrode is the active (signal) electrode
- The blue electrode is the reference electrode

The specific muscles where the active electrodes will be placed are shown in Figure 21.

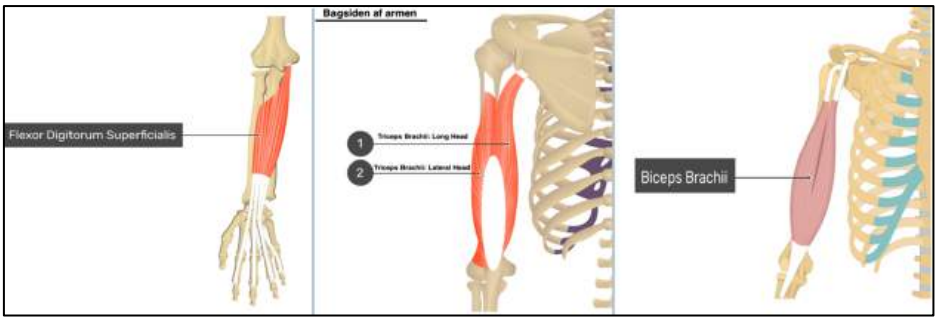

Figure 21: Target muscles for EMG electrode placement[72]

The third modality involves three IMUs, which will be placed on the forearm, upper arm, and wrist, all on the right arm, just as in the earlier experiment. The IMUs help identify the onset of movement, enabling analysis of the EEG signal before motion begins to identify the BP.

In addition to triggering BP analysis, the IMUs enhance the model's robustness and precision by providing real-time data on both movement angle and intensity. The IMU placements are shown again in Figure 15**.**

[71] The author's own work
[72] Loaned from https://www.getbodysmart.com/arm-muscles/

When a change is detected in the IMU data, a time window from 0.5 to 2 seconds before movement onset is extracted from the EEG signal to identify the BP. Simultaneously, EMG signal deviations are tracked to determine when muscle activation exceeds a predefined threshold. This dual tracking enables the identification of both the start of a movement and the preceding EEG patterns—effectively capturing the intention to move.

After data collection, all signals will be filtered to reduce noise and optimize quality for training and testing. I will apply a bandpass filter, notch filter, Butterworth filter, and normalize the data around zero to ensure comparability across channels.

During training and testing, I will continuously evaluate whether adjustments in feature extraction are necessary to ensure the model learns from the most robust and informative data structures. Based on this, I will select the most accurate and efficient Transformer model for the project's objectives.

After offline training, the model will be evaluated in real time to assess its ability to detect intentional movements before they occur. The output from the model will be a unique 4-bit binary code for each movement type, classified based on the EEG signal's BP segment. This allows the user's intention to be translated into a specific movement, which will then be executed by the robotic arm.

Figure 22 shows the seven primary arm movements used in the training data and experiments, along with their corresponding binary codes. These were selected because they represent the most fundamental arm functions.

Bevægelse	Ingen bevægelse (baseline)	Sammentrækning af underarm	Udstrækning af underarm	Hævning af arm	Sænkning af arm	Supination af håndled	Pronation af håndled
Billede af bevægelse							
Binærværdi	0000	0001	0010	0011	0100	0101	0110

Figure 22: A table with the different movement types

These binary values will be serially transmitted to the robotic arm, which will be programmed to interpret each binary sequence as a specific movement in real time.

By combining the three modalities, EEG, EMG, and IMU, the Transformer model will be trained and tested on multimodal data. This integrates intention, muscle activation, and physical movement into a unified architecture, enabling the prediction of movement based solely on the neural signals that reflect intent.

To quantify the model's accuracy, I will log every output generated by the Transformer model and compare it with the actual performed movement. In addition, true positives and false negatives will be recorded, allowing me to create a confusion matrix evaluating the model's classification performance.

As the Transformer model and data collection process are not yet fully completed, no results are available at this stage, but they will be ready for the final presentation!

Based on future results, it is expected that the Transformer model will demonstrate high precision and, importantly, prove that interpreting thought-based intentions is possible using relevant biosignals and a Transformer-based architecture. Figure 23 displays all the components used in the project to give the reader a sense of its complexity.

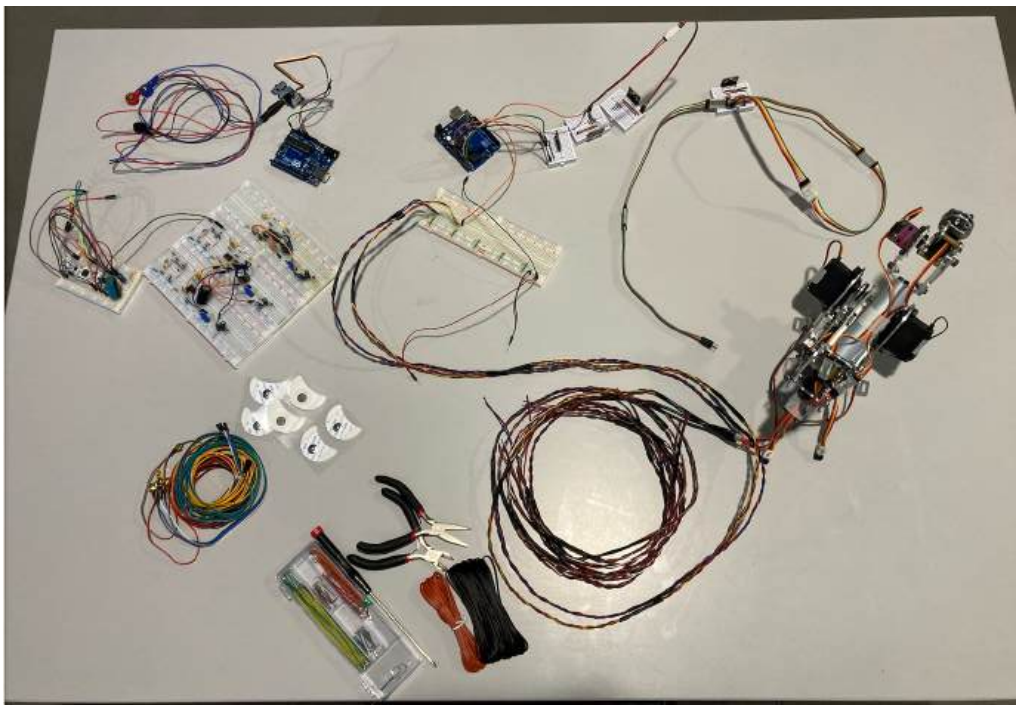

Figure 23: All components used in the project

Sources of error and uncertainties

This project involves the use of complex biosignals and AI, which naturally introduces potential sources of error and uncertainty. The most important sources of error are outlined below:

1. **Quality of EEG/EMG signals**
   EEG/EMG signals are highly susceptible to noise, especially from electrical sources, body movements, and poor skin contact. Incorrect electrode placement or high impedance can lead to poor measurements, which is why I use conductive gel and a swim cap to keep the electrodes securely in place.

2. **IMU-placement and sensor noise**

IMUs are sensitive to small placement variations and rotational noise. Even minor misplacements during monitoring can lead to incorrect angular calculations, resulting in inaccuracies in the real-time signal.

3. **Synchronisation of modalities**
   The EEG, EMG, and IMU signals must be recorded with precise time synchronization. This is crucial, as BP and muscle activation need to be correctly aligned with the movement onset for accurate timing matching.

4. **Overfitting and data leakage in the AI-model**
   The Transformer model may overfit if trained on small or biased datasets, which is why I employ k-fold cross-validation and ensure that the data split is free from overlap to minimize this risk. If signals from the same subject appear in both the training and testing sets, this can artificially inflate precision scores.

5. **Homebuilt EEG-hardware and circuit**
   The EEG circuit is homebuilt using basic components, which may result in lower signal-to-noise ratios compared to clinical-grade equipment. Potential errors in ADC conversion, filter design, or amplification could interfere with the signal quality.

These sources of error and uncertainty may affect the precision and robustness of the experiment, but they do not invalidate the core concept of the project. Most potential errors have been identified, and efforts have been made to minimize them. The experimental setup is designed to handle noise and variability to the best extent possible.

Product, future and ethics

Product

I am in the process of developing a Transformer model that can predict intended movements in real-time based on EEG signals recorded from electrodes placed on the scalp. The goal of this project is to eventually create a wearable, non-invasive device that can incorporate this model. Below are the functional and non-functional requirements[73] for this future product.

Functional requirements

Functional requirements define the system's concrete functions and capabilities, specifying what the system should do. The functional requirements for the product are presented in Figure 24:

[73] The source of the definition and difference between functional and non-functional requirements is: (Geeksforgeeks, 2025)

Nr.	Krav
F1	Systemet skal kunne opsamle EEG/EMG/IMU med høj signalkvalitet og filtrere støj
F2	Transformer-modellen skal kunne forudsige intentionelle muskelbevægelser, baseret alene på EEG-data i realtid.
F3	Elektroder og sensorer skal kunne monteres komfortabelt og sikkert på patientens hoved og arm, uden at forårsage irritation.
F4	Systemet skal kunne initiere og assistere bevægelser ud fra tankeaktivitet alene.
F5	Systemet skal virke i realtid: den binære klassifikations skal forløbe få millisekunder efter intention.
F6	Systemet skal være bærbart og kunne indeholde en kompakt Transformer-model med integreret batteri.
F7	Løsningen skal være medicinsk neutral, og ikke interferere med medicin som Levodopa
F8	Systemet skal kunne oversætte Transformer-model output til bevægelse ved at aktivere en aktuator.
F9	Systemet må ikke aktivere uønskede bevægelser. Derfor skal systemet have en stopknap, der med dette stopper hele systemet, som enten fysisk eller digitalt kan deaktiveres.
F10	Systemet skal kunne fungere kontinuerligt i minimum 16 timer, hvilket svarer til daglig brug, med opladning om natten.

Figure 24: The product's functional requirements[74]

Non-functional requirements

Non-functional requirements pertain to the quality aspects of the system, such as design, ease of use, and performance, essentially defining how the system should perform. The non-functional requirements for the product are listed in Figure 25:

Nr.	Krav
IF1	Systemet skal være økonomisk overkommeligt og bygges med lettilgængelige komponenter, især i prototypefasen
IF2	Løsningen skal være individuelt tilpasset (person-specifik træning), fordi der er variation i EEG-signaler og hjernestruktur
IF3	Systemet skal kunne opskaleres: fra personlige modeller til adaptive modeller, der kan generaliseres.
IF4	Brugerinterfacet skal være intuitivt og brugervenligt, så patienter og plejepersonale nemt kan tilgå systemet.
IF5	Systemet skal være robust overfor almindelig brug (bevægelse, regn, fugt og små stød).
IF6	Systemet skal kunne tilpasses forskellige former for motorisknedsættelse og forskellige kropstørrelser.
IF7	Transformer-modellen skal kunne forklare hvorfor den aktiverede en konkret bevægelse, f.eks. ved at gemme sine output i en database. På den måde kan fejl detekteres i systemet.
IF8	Patientens signaler og data skal behandles fortroligt og ikke sendes til lagring uden samtykke.

Figure 25: The product's non-functional requirements[75]

These requirements ensure that the product must be affordable, smart, and fast, all of which are crucial when implementing the Transformer model in a wearable solution. These different models are discussed in more detail in the next section.

Product ideas

I have three ideas to what a future product could look like. These are described in the following sections.

[74] The author's own work
[75] The author's own work

Glove with motors

A glove could be worn on the patient's hand/arm, where motors would assist and control movements predicted by the Transformer model in real-time. The movement predictions would be based on EEG signals, with electrodes measuring intentional movements in the brain.

Active exoskeleton

Another possibility is integrating the system into an active exoskeleton, where a mechanical system would support movements based on the predictions made by the Transformer model.

Focused Ultrasound and electric muscle (FUS/EMS)[76]

My third proposal is a new method for bypassing the motor nervous system and directly activating muscles based on mental intentions. This would be achieved through a hybrid model combining focused ultrasound stimulation (FUS) and electrical muscle stimulation (EMS). I would use ultrasound to prepare the muscle group, after which a concentrated electrical current would activate the muscles, allowing for precise movements. In this case, EMS and FUS would serve as the actuators, replacing the robot arm. The Transformer model would predict the movement based on EEG, with the output providing signals to the ultrasound generator and electrical current generator. A schematic overview of this idea is shown in Figure 26:

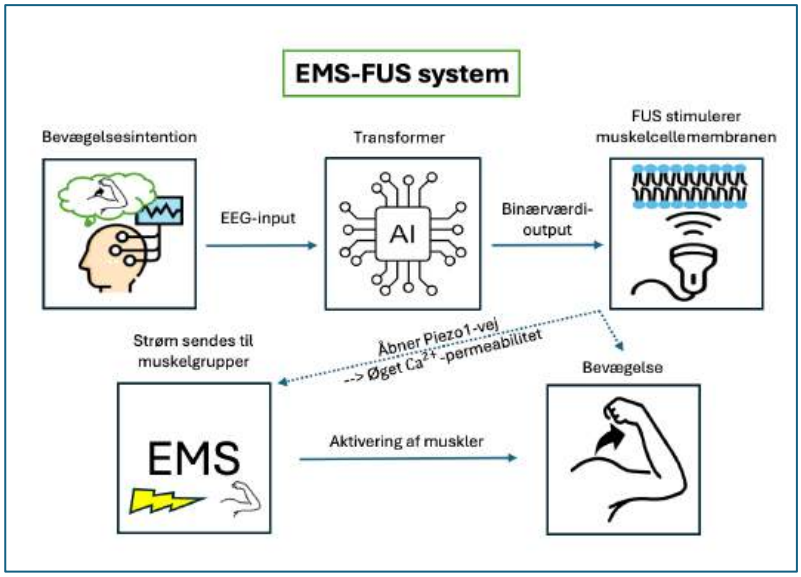

Figure 26: A schematic overview of the EMS-FUS[77]

EEG signals from the patient's movement intentions would be captured by electrodes placed over the motor cortex and processed by a Transformer model. The model classifies the signals into binary values, which are wirelessly transmitted (e.g., via Bluetooth) to two activation units:

[76] The section is based on the sources: (Evident, u.d.), (Wikipedia, 2024), (wikipedia, 2025), (Demi, 2018)
[77] The author's own work

1. A FUS with a 3D-phased array, which targets the signal to the relevant muscle group. Here the Piezo1 channels are stimulated, increasing calcium permeability and preparing the muscle cells for activation
2. An EMS, which sends electrical impulses directly to the muscles

The combination of increased calcium influx and electrical stimulation allows for precise muscle activation, even when the signal pathways in the nervous system are compromised, such as in the case of Parkinson's disease. Thus, my system bypasses the nervous system entirely.
In the following section, I explain more about FUS and EMS.

FUS for warmup of muscles

FUS will be used in the system to prime selected muscle groups, meaning it will increase their sensitivity to subsequent electrical stimulation. By focusing ultrasound waves precisely on the muscle, the permeability of the cell membrane can be increased. This happens through the activation of calcium ion channels, which lowers the threshold for electrical activation, making muscle contraction easier. The effect depends on the frequency, intensity, and pulse modulation of the ultrasound.

The underlying mechanism involves the mechanosensitive ion channel Piezo1, which opens in response to mechanical stimuli such as stretching, pressure, and vibrations[78]. Piezo1 is a non-selective cation channel, and when it opens, calcium ions flow into the cell. This alters the electrical potential across the cell membrane and makes the muscle cell more excitable to electrical stimuli, making it easier for the muscles to contract.

Figure 27 illustrates this mechanism:

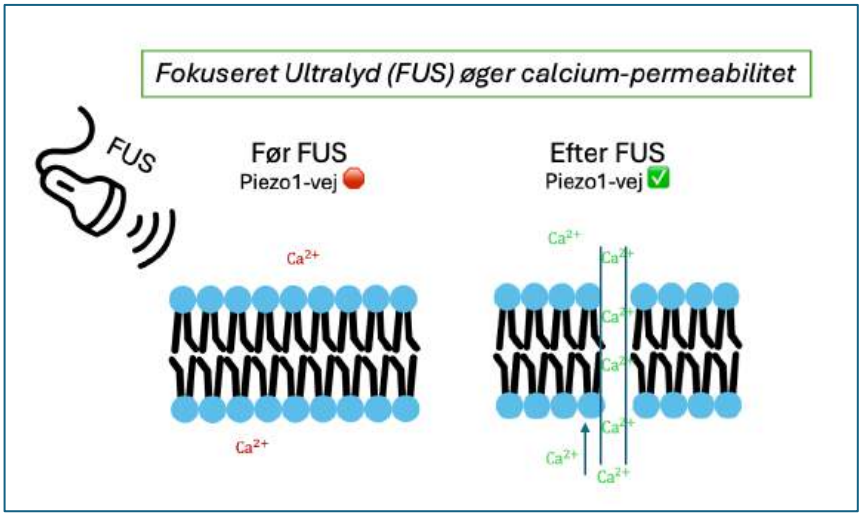

Figure 27: FUS can increase the calcium permeability, which makes it easier for current to activate muscles

In addition to mechanical activation through FUS, the Piezo1 channel can also be activated chemically:

[78] (wikipedia, 2025)

- **Yoda1** is an agonist that binds to Piezo1 and activates it directly without mechanical stimuli
- **Jedi1** and **Jedi2** are newer chemical agonists that offer faster at more reversible activation than Yoda[79].

On the other hand, Piezo1 can be inhibited by the antagonist Dooku1, which can, among other things, block the action of Yoda1. To ensure high precision in FUS, I will also employ:

- **3D-beamforming**: focusing the sound wave both in depth and direction[80]
- **Phased array-transducers**: allowing dynamic control of the focus point without physical movement.

The muscles' positions can be mapped using ultrasound scanning (B-mode). Once the muscle coordinates are known, each transducer can be directed at the relevant muscles. The input to the system comes from the Transformer model, which predicts the user's intended movement in real-time based on EEG. This prediction is then converted into signals that control both FUS priming and the subsequent electrical muscle stimulation, enabling the activation of the desired movements.

EMS for movement activation

After priming the muscles with FUS, I will use EMS with specific current intensities and frequencies, which will be optimized/selected through experimental work for each muscle and movement type. EMS will be delivered as low-frequency electrical stimulation, triggering muscle contraction. The transducers and electrodes must be strategically placed on the body so that all relevant muscles are within reach, for example, a transducer aimed at the biceps to activate the right arm.
It is important to note that much research is still needed in this field. Therefore, future work will focus on fundamental research into the possibility of accurately activating muscles with FUS/EMS, so that desired movements can be performed. There is still a lot to explore!

Future perspectives

The future development of the project will focus on making the Transformer model more generalizable. For example, training the Transformer model on larger datasets of EEG/EMG/IMU data from multiple patients to identify patterns across age, gender, and disease stages would be relevant. This would scale the project.

Another possibility could be noise reduction, inspired by noise-cancelling methods from DBS (Deep Brain Stimulation), to filter out tremor noise from EEG/EMG/IMU signals. If the Transformer model can separate intentional movements from tremor patterns, the accuracy of the predictions would also improve.

A third area for improvement could be integrating the system into neuroprosthetics or using it for the rehabilitation of patients with stroke or other motor disorders. The system could also be combined

[79] Yes! Scientists have named agonist based on Star Wars-characters
[80] By using an array of many small transducers, the direction of the three-dimensional wave can be controlled, allowing it to be directed toward specific muscles. By adjusting the phase differences between the signals sent to each transducer, the focal point can be dynamically shaped and steered, both in depth and laterally, without physically moving the transducer.

with speech recognition to analyse and improve Parkinson's patients' speech abilities. This would allow one to predict and even generate speech based on mental intentions.

The project is still in its early phase, and a fully developed product has not yet been realized. However, many ideas are in play, and my work continues with ongoing development and testing. It is a complex project, but I am highly motivated, curious, and open to new inputs that can take the project further.

Ethical considerations of the project

The question of whether AI should assist with motor functions is an important one. Parkinson's disease has significant consequences for patients' quality of life, and any technological solution should, in my opinion, be developed with a focus on the patient's health and needs.

Data collection in this project will take place outside of clinical settings, but with the utmost control and consideration for the patient's well-being. Before testing the Transformer model on my father, I will test the system on myself and consult with my father's neurologist to ensure the experiment does not pose any risks to him.

As the system is further developed for clinical use, it will be necessary to adhere to ethical guidelines for medical research, as well as applicable laws regarding data security and patient rights, including GDPR. The Transformer model must ensure the anonymization of patient data to protect their privacy. While the data collection in this project has not had access to clinical-standard measurement equipment, the results show that the system can function under suboptimal clinical conditions. However, future iterations of the AI will require more precise measurements, either via OpenBCI or other neurotechnology platforms, to ensure higher accuracy and reliability in predictions.

Conclusion

In this project, I have explored how a Transformer model can predict intentional movements based on EEG, EMG, and IMU data by collecting biosignals from my own body. The project started with a literature review of 16 scientific articles on EEG, EMG, and Parkinson's disease to identify relevant AI models and understand the neurological changes in Parkinson's patients. Based on the review, seven different AI models were chosen and tested to find the most suitable one. They were evaluated on their ability to classify EEG and EMG signals as either movement or non-movement. After testing, I concluded that a Transformer model is the best fit for this project.

Next, I built a 6-axis robot arm, which functions as a proof-of-concept and actuator for the Transformer model. I had it controlled by an IMU on my arm, and by the final stage, I aim to control it using the output from the Transformer model. I am currently developing my own EEG circuit to measure intentions through BP (brain potential) from C3, C4, and Cz. At the same time, I will collect EMG and IMU data, and the signals will be filtered before they are used for training and testing the Transformer model.

The Transformer model will be evaluated using 5-fold cross-validation, ROC curves, AUC, inference time, and F1-score. The output will be a binary value that corresponds to specific movements, which will be sent to the Arduino code, allowing the robot arm to imitate my arm movement in real-time—thus translating thoughts into action.

The Transformer model has not yet been trained or tested on my own biosignals, but I expect them to be ready for the final phase when I have further worked on the data collection and Transformer model.

However, I expect the results to show that the Transformer model is robust and accurate enough to be used in real-time. The project demonstrates that it is possible to translate intentions, measured as EEG signals, into movements through AI. This opens the door to new wearable systems for Parkinson's patients, which could help compensate for motor symptoms.

As a solution, I proposed three types of actuators: a glove with motors, an active exoskeleton, and a hybrid FUS-EMS system that bypasses the nervous system using focused ultrasound and electrical stimulation. I also discussed the ethical aspects and the future possibilities of the technology, including testing the architecture on data from Parkinson's patients, including my father.

The project shows that there are recognizable patterns in the brain's intentions that can be translated into movements—creating opportunities for new adaptive devices for Parkinson's patients. However, much work remains to be done, making the future even more exciting!

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Nanna Kalmar for always taking time out of her calendar to discuss my ideas and proofread my unfinished reports. Nerd

The biggest thanks of them all, goes to my own father, who both inspired me to do this project and in the future voluntary will provide his own body biosignals to data collection. He is the reason project was started and is still reason to why I am motivated and want to optimate project even futher in the future! So, from the bottom of my heat, thank you father. I really hope my work can help you and other people!

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