Automatic Search Algorithm using Signal Enhancement, Flex Sensors and exploration of Machine learning Features to improve Multiple Channel Neuromuscular Electrical Stimulation (NMES) systems

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Abstract

Neuromuscular Electrical Stimulation (NMES) is a method to stimulate the body's muscles using bursts of electricity on the skin that can strengthen the muscles, increase coordination, and simulate human muscle movement to prevent the formation of Deep Vein Thrombosis (DTV). Electrically sensitive skin areas, called Motor Points (MP), must be stimulated to achieve a robust muscular response and decrease perceived discomfort. Conventionally, locating MPs is done using a search pen, which is a slow and time-consuming process. This study investigates using a baseline automatic search algorithm to locate the motor points by utilizing flex sensors to measure plantar flexion (PF) response when electrically stimulating the muscles in the calf. Furthermore, signal processing is utilized to enhance accuracy and attempt to reduce search time. A total of 120 searches using the baseline algorithm and signal processing were conducted on three individuals to evaluate the accuracy of locating the MPs. This study demonstrates that performing a Fast Fourier Transform (FFT) on the sensor data enhances the detection of PF and, thus, the location of MP's at low current amplitude. Further research is warranted to enhance accuracy and search time by utilizing multi-electrode stimulation and machine learning in decision-making.

Preface

I, Elliot Berthold, am a student of Biomedical Engineering at Lunds Tekniska Högskola. This paper represents my master's thesis, conducted during the spring of 2024 together with Matrix Muscle Support AB [1] at Karolinska Institutet in Stockholm.

I am grateful for the prototype provided by MMS, which enabled testing during the study. Moreover, I would like to thank the entire research team at MMS, especially Robin Juthberg and Paul Ackermann, for everything they have done to help me along the way.

Finally, I would like to give a special thanks to my academic supervisor Nebojsa Malesevic for his excellent guidance and feedback during the entire master's thesis.

Abbreviations

- MMS - Matrix Muscle Support AB
- DTV - Deep Vein Thrombosis
- NMES - Neuromuscular Electrical Stimulation
- MP - Motor Point
- PF - Plantar Flexion
- FT - Fourier Transform
- DFT - Discreate Fourier Transform
- FFT - Fast Fourier Transform
- BLE - Bluetooth Low Energy

Contents

1 Introduction

Neuromuscular Electrical Stimulation (NMES) has shown evidence-based effects on several medical disorders such as reducing the risk of deep vein thrombosis. By simulating muscular movement in the extremities, more specific the calf, blood flow can be increased. Increasing blood flow has a direct decrease in blood clot formation. [2, 3]

However, compliance with treatment is a significant issue due to discomfort, pain, and problems with using NMES for a prolonged time. It is established that placing electrodes on individual, specific locations on the skin, so-called muscle motor points, overlaying a muscle, reduces discomfort [4, 5]. If the electrodes are placed on the "motor points", the stimulation intensity needed for muscle contraction can be significantly lowered and thus increase comfort [5]. Hand-held search pens have been used to identify "motor points"; however, this is time-consuming and impossible in everyday use.

1.1 Project aims and objectives

The aim of the project is to investigate approaches to search for motor points using an automatic algorithm and by attempting to improve signal to noise ratio, increase the searching speed and to verify the search accuracy.

1.2 Work process

The project consisted of two phases, the first phase included the development of an application for mobile devices that could communicate with the Bluetooth Low Energy control unit in order to send stimulation commands and read the feedback from the flex-sensors. The second part included the creation, testing and evaluation of different search algorithms. The results from each search algorithm should be evaluated against each other and to a ground truth based on observing the muscle contraction when the stimulation is active.

2 Background

2.1 Circulatory system

The circulatory system is highly complex and integrated, involving several organs. It provides the body's cells with essential nutrients and removes waste produced from the cells. It consists of two parts, namely the pulmonary and systemic circulation. Figure 1 shows how these two parts work. The pulmonary circulation transports deoxygenated blood through the capillaries in the lungs, where the blood is oxygenated. Then, it is transported throughout the body via the systemic circulation [6].

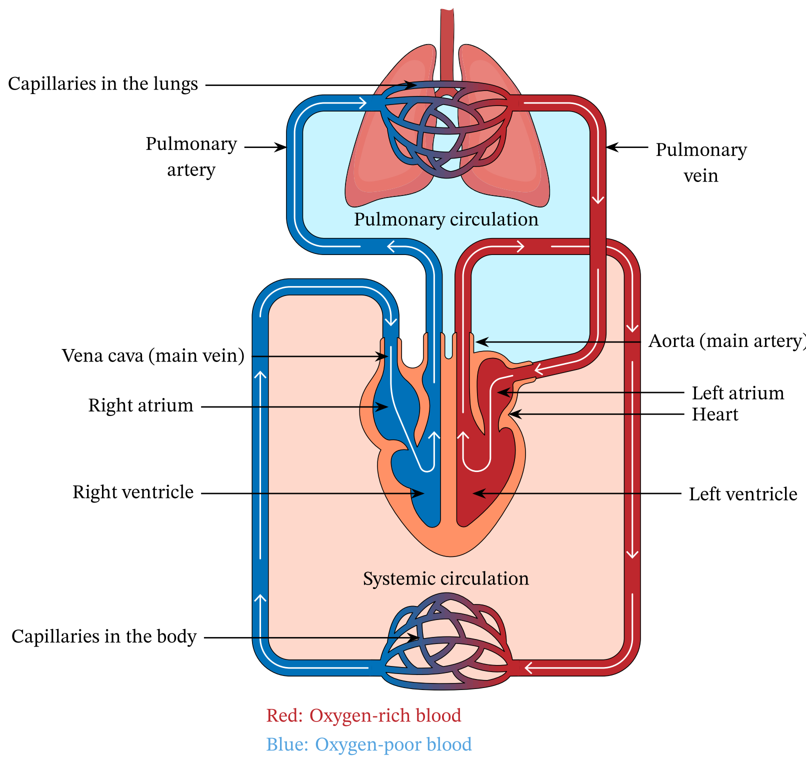


Figure 1: The circulatory system with the pulmonary circulation and the systemic circulation separated [7]

2.1.1 Pulmonary circulation

The pulmonary circulatory system is a small system that transports the blood from the heart to the lungs and back. The blood starts in the right atrium, where deoxygenated blood enters the heart. It flows into the right ventricle, which pumps the blood into the pulmonary artery. The pulmonary artery splits into smaller blood vessels in the lungs called capillaries [8]. Capillaries are small vessels with single cell walls that exchange nutrients, oxygen, and waste between the blood and cells [9]. Through these capillaries, oxygen enters the blood, and carbon dioxide is released into the lungs from the blood. The blood then enters the heart's left atrium and is transported throughout the body via the systemic circulatory system [8].

2.1.2 Systemic circulation

The systemic circulation begins at the heart, where oxygenated blood enters the left atrium, flows into the left ventricle, and is pumped to the body's arteries through the aorta. The aorta is the main branch of a complex network of arteries consisting of smaller arteries and capillaries throughout the body [8]. In the capillaries, the nutrients and waste are exchanged; after the exchange, the blood must be transported back to the heart to enter the pulmonary system and become oxygenated again. The blood is transported back to the heart through small veins in the body that combine into larger ones until they reach the heart [8]. Unlike arteries, veins also rely on the muscles surrounding them to create blood flow back to the heart, as the venous pressure is insufficient. Veins have one-way valves that prevent blood from flowing backward, as shown in Figure 2. When muscles contract, they deform the veins and push the blood through the one-way valves in stages [9]. Therefore, staying active and moving around is crucial to ensuring good blood flow.

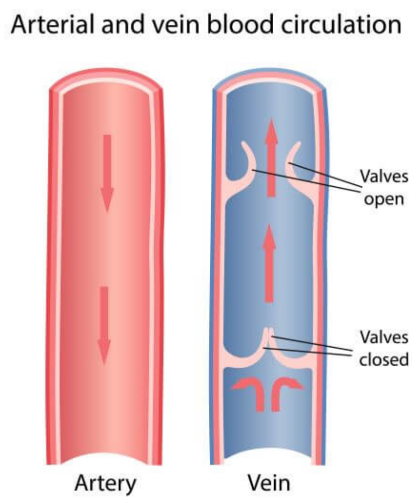


Figure 2: The structural difference between veins and arteries [10].

2.2 Deep Vein Thrombosis

When blood is not moving, physical processes start to coagulate the blood; the coagulation thickens the blood and makes it clot. Blood coagulation is essential to minimize blood loss and initialize self-repair when blood vessels are damaged and blood leaks. However, this causes severe problems if the coagulation process of blood is started within the blood vessels. If this happens, blood clots are formed that could potentially block small arteries, reducing blood flow causing cells to be starved of nutrients [11]. These clots are called thrombosis as they are stationary inside the blood vessels. Deep vein thrombosis (DTV) consists of clots originating from deep veins inside the distal parts of the body. This is often caused by the blood being stationary for too long, and the coagulation process starts [12]. The deep vein clots can dislodge and travel to the areas where they can have fatal consequences. The blood clots that break loose and travel throughout the circulatory system are referred to as embolisms. Embolisms in sensitive areas such as the brain, lungs, or heart could have fatal consequences.

The coagulation of the blood inside the deep veins is often due to a lack of movement in the muscles around the veins. The muscles play a large part in the circulatory system, squeezing the veins to push the blood back towards the heart. Figure 3 illustrates how blood clots can start forming around the valves when there is a lack of muscle movement to induce blood flow. The lack of muscle movement is for example often due to sitting down for a significant time or immobilization after, e.g., a surgical procedure.

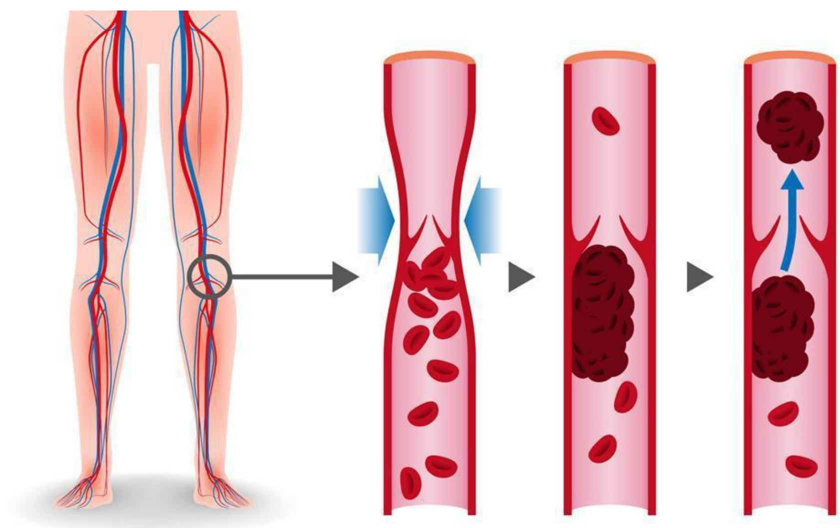


Figure 3: Illustration of how blood clots can be formed inside the veins when there is a lack of muscle movement [13].

2.2.1 Preventative methods

Clots can often form in the legs, specifically the calves, as they are located far away from the heart, and thus, the venous blood pressure is shallow. Therefore, activating the muscles in the calves is crucial to ensure that the blood is transported back to the heart and does not remain stationary. When the calf is active, the muscle movement results in a peek of 200% increase in blood flow. This increase in blood flow is only induced when the calf activation results in plantar flexion (PF) [2]. A plantar flexion is the downward flexion of the foot when the calf is activated, a part of the walking movement. Therefore, standing up and walking around is an excellent preventative method to reduce the risk of blood clot formation. However, there are situations where walking is impossible; these cases require external aid to induce blood flow from the calf. One mechanical aid used to induce blood flow for immobile patients is intermittent pneumatic compression devices (IPC). IPCs are cuffs placed around, e.g., the calf, inflated with air to squeeze the calf and force blood flow [14]. Even though the IPC devices reduce the risk of DTV, medical compliance is low. Patients do not follow the prescribed treatment [15]. Another method that shows promising results in reducing DTV is Neuromuscular Electrical Stimulation (NMES) [2].

2.3 Neuromuscular Electrical Stimulation

Neuromuscular Electrical Stimulation is a method to stimulate the body's muscles by inducing a low current to prompt human muscle movement. As early as the 1790s, Luigi Galvani showed that electrical stimulation could create movement in the muscles of frog legs [16]. This created a foundation for electrical muscle stimulation and prompted further research and implementation with the human body.

The intended purpose of inducing muscular movement could vary, according to Nussbaum, E. L et al. NMES can be used to treat muscle-impaired patients [17]. Electrical stimulation can improve muscle movement by strengthening the muscles and creating stronger coordination between the muscles and the patient. As muscles have a significant role in the systemic circulatory system, another application of using NMES is for preventative measures, specifically reducing the risk of blood clots. NMES can be used as a substitute for mimicking muscle movement when a potential patient is movement impaired or cannot exercise the muscles due to other disorders [2, 3].

2.3.1 Stimulation comfort

One drawback of using NMES is that it can be perceived as uncomfortable when the electrical pulses are applied to the skin [5]. Lack of comfort can limit medical compliance when using NMES, where the patient does not use the treatment according to the prescription. This is problematic for clinical treatments as the prescribed treatment plan must often be followed to ensure improvement. It has been shown that stimulation parameters have a substantial effect on comfort. Using a frequency above 25 Hz has shown an increase in comfort, the frequency describes how many times a second the current is applied in quick bursts. However, muscle fatigue increases with higher frequencies, meaning that the stimulation is not as effective over time [18]. Another relevant area relating to comfort is the size of the electrodes. Some studies show that the electrode size could vary the perceived comfort when using NMES. A larger electrode gives less discomfort compared to smaller ones [19].

2.4 Motor points

The electrodes' placement significantly impacts the current needed to enforce muscle contraction and, thus, comfort. When electricity is applied to the skin, the pulse must trigger the motor nerve that enters the muscle to get the muscle contraction. If the current is applied far away from this nerve, then the tissue will disperse the current, and thus, a greater amplitude is needed for it to reach the motor nerve. If the electrodes are placed on the area where the motor nerve is located and enters the muscle, then the current needed to stimulate a contraction is significantly reduced; these areas are called motor points (MP) [5]. The location of these motor points varies from individual to individual; locating these before stimulation could reduce the current used and thus increase comfort. Figure 4 shows the most common locations of motor points on the calf based on a study by Schriwer E. et al [4]. The red areas correspond to locations where the probability of MP location is significantly higher. There also exist orders of motor points, ones that create good muscle contraction but at increasing current amplitude

2.5 Finding motor points

Finding the motor points on the skin is, as mentioned earlier, traditionally done with a search pen. This search pen is dragged across the skin with a current applied. The physician applies a low current and scans the whole surface of the targeted area. If no muscle contraction is seen, the current is increased, and the scan begins again; this is repeated until one area induces a visible contraction. That area is then labeled as the motor point, most perceptible to electrical stimulation of the muscle. Another viable method of finding the motor points is to stimulate the muscle between different areas of the muscle and measure the resulting movement. This would allow for a feedback loop where an algorithm could automatically find the motor points based on sensor output. These systems allow for feedback on the stimuli and facilitate changes in how to stimulate to enhance the response

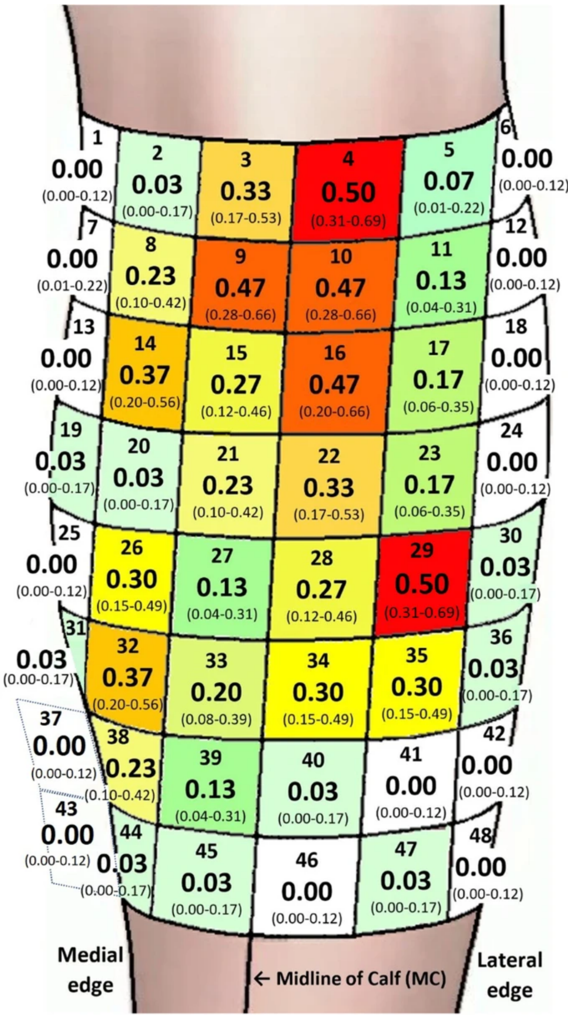


Figure 4: Shows a heat map of the probability of a motor point being located in the highlighted area [4].

2.6 Muscle movement measurements

Measure the movement of muscles is essential when automating the search for muscular motor points. There are different viable approaches to measure muscle activation, including the utilization of flex sensors [20] and inertial measurement unit (IMU) [21] to detect the change in angle in joints connected to the examined muscle.

2.7 Digital signal processing

When working with digital signals, it is common to process them to highlight, remove, or analyze different parts of the signal [22]. One common approach for dissecting and analyzing the signal is a Fourier Transform (FT). FT is a method to transform signals from the time domain to the frequency domain. This means that the signal is represented based on its raw frequencies instead of amplitude over time. The mathematical formula for FT can be seen in equation 1, where it should be applied to a continuous signal. However, this is not viable when analyzing signals gathered using, e.g., sensors, as these are not continuous; signals from sensors are discrete. Discrete means they are sampled at different time stamps based on the system's Sampling Frequency. The sampling frequency limits the number of data points, and thus, equation 1 will not work as it should be calculated on a signal with data on all time stamps.

$$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-i\omega t}dt \tag{1}$$

where ω is the frequency and t is the time

To preform a time to frequency domain transform on a discrete signal the Discrete Fourier Transform (DFT) has to be used, it differs from the original FT in the way that it summarizes the discrete data points instead of calculating the integral of the continuous data with infinitely small time steps, seen in equation 2

$$F(\omega) = \sum_{n=0}^{N-1} f(n)e^{-i2\pi kn/N} \tag{2}$$

where ω is the frequency, n is the sample, n is the total number of samples
and k is the index of the frequency

One problem with the DFT calculation is that it is computationally expensive, making it inefficient on larger datasets and when analyzing the signal in real time. Thus, the Fast Fourier Transform (FFT) can be used instead as it optimizes the DFT calculations and allows the DFT to be applied on larger datasets and in real time [23].

2.7.1 Filtering

Another important part of signal processing is the use of filters. Filters are applied to the signals to alter the content of the signal. These filters could be used to e.g. remove all the lower frequencies from the signal, high-pass filter, remove all the higher frequencies, low-pass filter, or even alter isolated frequencies, notch filter [24].

3 Method

The main objective of this project was to find a viable approach for locating muscular motor points. This was done using the provided prototype from Matrix Muscle Support AB, located at Karolinska Institutet in Stockholm (MMS) [1], whom the study was preformed with. It contained the outline for stimulating electrodes attached to the calf. The study also included integrating the prototype with an application to enable data communication, both sending commands to stimulate the electrodes and reading the data from the sensors. Furthermore, two automatic search algorithms were explored based on MMS's requirements and internal testing.

3.1 Provided material

The following sections lists the resources provided from MMS show in figure 5.

3.1.1 Control unit

The control unit integrated the electrodes and sensors with the BLE connection. It was capable of bipolar stimulation, meaning stimulation between two different electrodes. The available amplitude range was 1-200 mA and the frequency used was 35 Hz, these where pre-set. The control unit had a sampling frequency of 50 Hz.

3.1.2 Electrode patch

The electrode patch used to stimulate the muscles was a silicone pad containing seven electrodes and two flex sensors. Figure 5 shows the layout of the components. Each electrode and sensor connects to the control unit.

3.1.3 Electrodes

The electrodes are hexagonal in shape with sides of 2.5 cm. They are made from chopped carbon and silicon. Water was added to the electrodes to enhance the transfer of electricity to the skin. Different kinds of gel were also tried, but water gave the best comfort and was thus used throughout.

3.1.4 Flex sensors

Muscle movement was measured using two flex sensor, model 2.2" made by Sparkfun [25]. In the control unit, the range of data was between 0-4096 unit steps. The idle response from the flex sensors was between 2038-2054 unit steps and flexing the sensor resulted in increasing or decreasing output based on the direction of deformation.

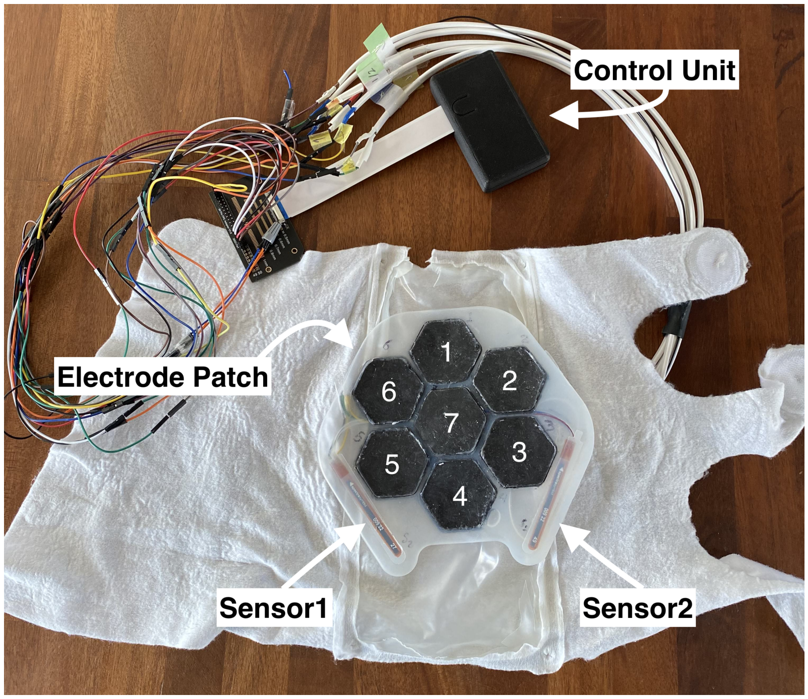
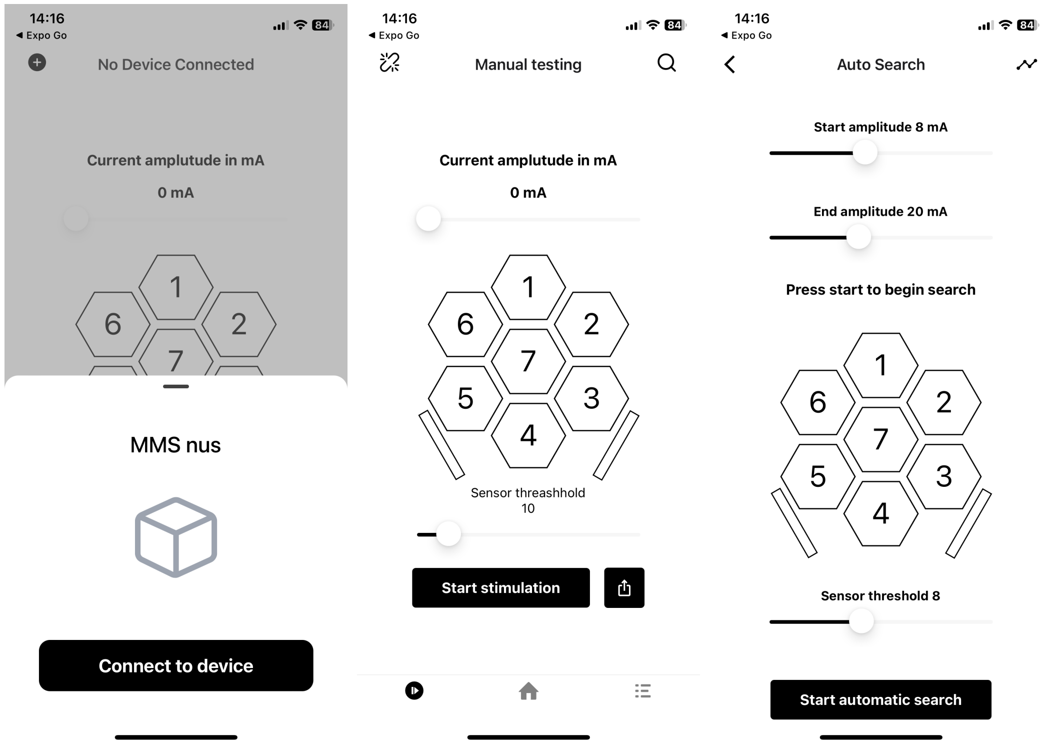


Figure 5: Prototype provided by MMS. The different components are highlighted and explained in the figure.

3.2 Application

An application needed to be developed to facilitate sending and receiving data to and from the control unit. This application is connected to the Bluetooth Low Energy (BLE) module of the control unit and communicates with the appropriate message interface. The diagram, Figure 7, provides an overview of the application's structure and communication flow.



(a) Starting the applicatioon (b) Manual testing (c) Automatic search

Figure 6: The three figures shows the user interface for the created application.

The application establishes a separate BLE connection system to connect with the control unit. Users can input commands using the application's user interface, which can initiate or terminate the search for motor points. To enable communication between the search algorithm and the control unit, the message handler converts the commands and responses to the correct format for the control unit. The application was created with Expo [26] and React Native [27] and the user interface is visualized in figure 6. When the application starts the user connects to the BLE device as seen in 6a, this later allows the user to start stimulation and searches. To retrieve data from bipolar electrode stimulation without searching through each electrode pair, "manual testing" was added as shown in 6b. Note that the numbered hexagons corresponded to the electrodes placed on the skin and the rectagles on the lower part corresponed to the sensors. Finally, the different search procedures had their own interface, shown in Figure 6c, where the user could change the starting amplitude and end amplitude. Note that the end amplitude was created as a safe limit if the algorithm did not find a good electrode pair and terminated the search automatically. The "sensor threshold" was used to determine when the sensors should activate and show as filled on the screen, this value was also used in the first version of the search algorithm but in the second one there where more calculations to determine whether there was a muscle contraction or not.

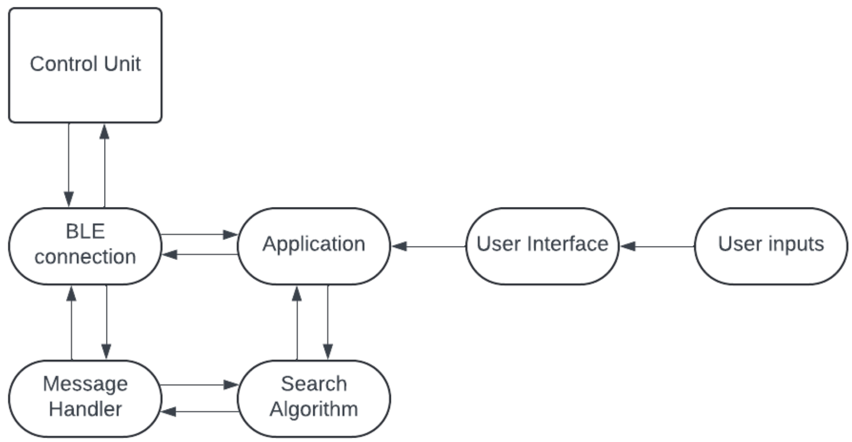


Figure 7: The diagram visualizes how the application communicates. The application is started on a local device and connects to the control unit via a stable BLE connection. Commands are sent and received using the message handler to ensure that the correct protocol is followed.

3.2.1 Message Handler

Bluetooth Low Energy (BLE) devices operate on a specific communication protocol with a range of commands that can be transmitted to the device. To ensure accurate transmission and receipt of these commands and responses, a message handler was developed. For reference, the communication protocol is presented in appendix A, where the commands are categorized into three types:

- those that elicit an acknowledgment response from the BLE unit.
- those that do not produce a response.
- those that result in the transmission of a data stream.

3.3 Understanding the signal

With the application created in the initial phase of this project, the first step of creating a search algorithm was to analyze the sensor data when electrically stimulating the calf to determine the characteristics of the respons. This was done by manually locating two electrodes, one that induced plantar flexion and one that did nothing, and stimulate them both with the same current. The current used was 16 mA as it resulted in a PF in one combination, the stimulation program was stimulation for 500ms and then nothing for 1000ms. The on/off time was pre-set from MMS and was only used when doing manual tests. The signal response from the sensors where then stored and analyzed using MatLab 2023b [28] to retrieve the average idle value from the sensors, determine the change in sensor value when muscle movement was induced and the signal-to-noise ratio for each sensor data. This gave essential insight to the idle response of the sensors, how much noise is present and the fluctuations in sensor value when there is PF.

3.4 Search algorithms

The search for motor points was iterative, with a small current applied between two electrodes and measuring the response from the flex sensors. The search always starts with electrodes one and two and then cycles through all the unique pairs. This was repeated for each unique electrode pair, and when each pair was tested, the applied current was increased by 1 mA, and the same pair combination was used. This was repeated until the deciding algorithm found a suitable pair based on the response from the flex sensors, a higher flex response correlated to a better MP. The algorithms started at a low current with increasing amplitude to find the MP while subjecting the user to as little current as possible due to comfort being a large factor in this study.

3.4.1 Base line

The base line algorithm, a crucial starting point in the search procedure, was designed to evaluate the responses from the flex sensors and determine the most suitable pair for stimulation, i.e. motor points. This algorithm stimulates each pair for 700ms, continuously gathering the flex sensor data and evaluating the result based on a threshold. The evaluation of the flex sensor data involves calculating the squared difference from the idle value, as shown in equation 3.

$$\begin{aligned} y_{\text{sum}} &= \sum_{n=1}^{N} (s(n) - s_{\text{idle}})^2 \\ y_{\text{avg}} &= \frac{y_{\text{sum}}}{n} \end{aligned} \tag{3}$$

where N is the number of data points and n is the sample.

The evaluation of each sensor is calculated and their average is referred to as the "effectiveness". If the effectiveness exceeds a pre-set threshold, the response is considered relevant. The threshold can be adjusted based on the patient's needs. The threshold was empirically set to $8^2 = 64$ based on the output from the flex sensors during a muscle contraction induced by electrical stimulation. To determine the best pair, the algorithm first calculates which pair has the highest effectiveness for each amplitude. If a pair has a higher effectiveness than the average at that amplitude, it is marked as a potential candidate for the best pair. The best pair is selected if one pair has the highest effectiveness value on two consecutive current amplitudes. At higher currents, the muscle may contract even if it is not stimulated on the motor points, and it is susceptible to noise that can be misinterpreted as muscle contractions, this was especially prevalent at lower amplitudes. Therefore, a second algorithm was created to attempt to handle these factors.

3.4.2 Processed signal

The flex sensor signal was stored and evaluated separately using MatLab to learn more about the characteristics of the signal. A Fast Fourier Transform (FFT) was done to extract all the frequencies that the signal is composed of. Based on the frequencies inside the sensor signal, a definable peak at lower frequencies existed when a muscle contraction was induced. Therefore, the second approach to improve the search algorithm was to filter the signal with a low pass filter; this removed a significant amount of noise in the signal, and muscle movements could be identified more easily. However, determining the best electrode pair was still binary in its decision-making; another approach was therefore created utilizing a confidence metric-based decision. The confidence metric was based on several factors: signal-to-noise ratio (SNR), effectiveness, and activation rate. SNR was calculated according to equation 4.

$$SNR = 10\log_{10}(\frac{P_{signal}}{P_{noise}}) \tag{4}$$

where P_{signal} is the signal power and P_{noise} is the noise power

The signal power refers to the amount of low-frequency, periodic signals within the raw data. It is calculated by applying a low-pass filter at 5 Hz on the signal to isolate the low-frequency components in the signal. The filter used is an 8th-order Butterworth low-pass IIR filter. The filter is applied in both the forward and reverse directions using the filtfilt function in MatLab to achieve zero-phase filtering. The low-pass filter was created based on the FFT spectrum when analyzing the signal when there movement was induced and when it was not. The noise part is then calculated by subtracting the periodic signal power from the total signal, leaving the residual noise within the signal. It is also important to center the signals around 0 before calculating to remove any offsets that might affect the analysis.

The SNR was then averaged based on the number of muscle activations for each electrode pair. Finally, the value was normalized with the average SNR for all the other electrode pairs. The activation rate was simply a stimulation ratio for each electrode pair, resulting in muscle contractions. Lastly, the effectiveness metric was calculated by normalizing the resulting effectiveness from the stimulation with the global average for all the electrode pairs. Additional factors weighted the response to value the simulations that resulted in muscle activation. When muscle activation was detected, the confidence metric was weighted based on the number of contractions in a row and the total number for that electrode pair compared to the global average activation rate. The final equation for calculating the confidence metric was as shown in equation 5.

$$\text{confidence metric} = 0.2 * \text{SNR} + 0.6 * \text{effectiveness} + 0.2 * \text{activation rate} \tag{5}$$

Each component was weighted to highlight the factors with the most impact and relevance. The weights where tuned during testing. The algorithm marks an electrode pair as the motor points if the confidence metric is above 60% and all electrode pairs have been tested once.

3.4.3 Server

Since the required calculations where quite advanced and resource heavy for the mobile application, thus a separate server was created and hosted to which the application sent the sensor data and the server returned the result from the calculations. The server was written in Python and hosted locally on a computer. To start the communication with the server the application used API endpoints. To ensure that the server was running and stable one endpoint was created to check the health of the server (/health). This endpoint only returned ok, thus if the server is running then the returned data can be read. Otherwise, if nothing is returned then it means that the application can not communicate with the server and the search can not be preformed. When the server is running, the python code that handled the calculations was created under another API endpoint (/analyze). When this API route was called it performed each calculation on the new sensor data together with data that the server has stored from previous electrode pairs.

3.5 Evaluating search algorithms

The two search algorithms were tested on three people. Both algorithms where tested on the test person numerous times, 20 unique searches for each algorithm per person. All in all 120 searches where done. The resulting best pair from the different search algorithm was noted and if the stimulation induced a muscle contraction it was also noted by the researcher. The muscle contraction observed from the researcher was used as ground truth as where the motor points are located. The test person was then asked to evaluate which of the pair they felt a muscle contraction, if there existed one. This gave a good understanding to how accurate the different search algorithms where and to evaluate if they could find points where muscle movement was prompted at low current, i.e. the motor points. The starting amplitude for the search was set to 10 mA and the end was set to 25 mA as a hard limit to not exceed if the algorithm did not find a good pair before then. Then the starting amplitude was increased to 15 mA with the same end amplitude. This was done to get a more nuanced result showing if the algorithm preformed as intended from both low and high amplitudes.

4 Result

Figure 8 shows one sample from several conducted test stimulations from which the raw sensor data is plotted for each sensor. 8a shows the noise from the sensors when they were in an idle state when no muscle movement was induced; the mean signal value was ~ 2040 units for the idle signal. The Signal To Noise Ratio for each sensor was

$$SNR_{sensor1} = -1.3674 \text{ dB}, \; SNR_{sensor2} = -0.23648 \text{ dB}$$

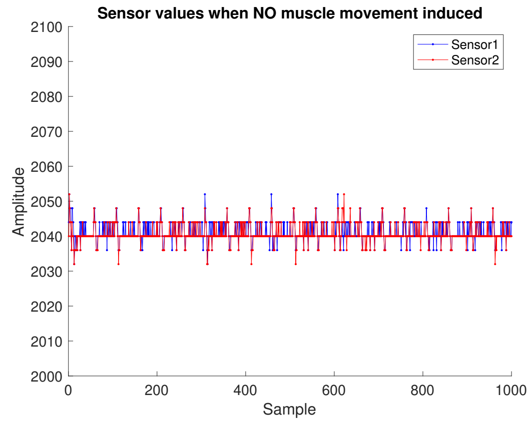
$$\text{when there was no muscle movement}$$

Both SNR calculations are negative and it indicates that the noise component from the signal is greater than a periodic signal corresponding to muscle movement. Figure 8b shows the response when the electrodes are placed at a location manually located to induce muscle movement. The second stimulation results in a consistent and periodic signal response where the muscle movement is defined; it was, however, only registered by the sensor 1. There was a notable increase in SNR for the sensor one signal, showing that the periodic muscle movement is present. The SNR for each sensor was

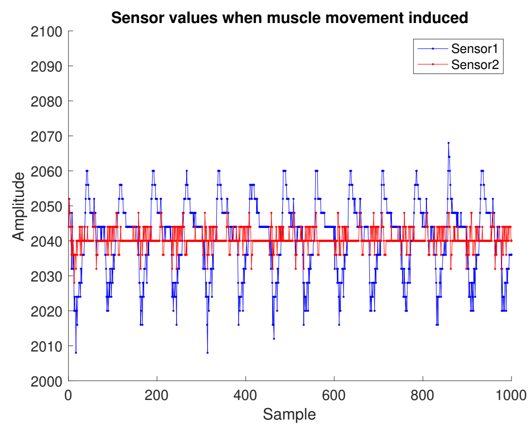
$$SNR_{sensor1} = 12.3039 \text{ dB}, \; SNR_{sensor2} = -0.96971 \text{ dB}$$

$$\text{when there was muscle movement}$$

Note that these results were gathered in a controlled test environment. The current was periodically applied to one constant electrode pair, and no "searching" was conducted.



(a) No muscle movement



(b) Muscle movement

Figure 8: The two figures visualize the signal from both sensors when muscle movement is induced and when it is not. The signal was gathered during a test in which the current was periodically applied to a single electrode pair. The x-axis shows the gathered samples over a set time during the stimulation.

4.1 Baseline search algorithm

Based on the observed results from the test stimulation, the threshold for the first search algorithm was set to 8 units and thus $8^2 = 64$ when calculating the squared difference from the idle value. The results from 20 unique searches on person A are shown in table 1 where data from starting amplitude 10-25 mA and 15-25 mA are listed. The motor points for test person A is 2-4 based on it being the electrode pair that induced a PF at the lowest amplitude.

Start amplitude: 10 mA, End amplitude: 25 mA				
Test	Best pair found	Amplitude	PF observed	Found MP?
1	5-6	12 mA	None	NO
2	2-3	12 mA	None	NO
3	2-3	11 mA	None	NO
4	5-6	12 mA	None	NO
5	2-3	16 mA	2-4 from 15 mA	NO
6	1-2	11 mA	None	NO
7	2-3	17 mA	2-4 and 3-4 from 15 mA	NO
8	1-2	13 mA	None	NO
9	1-3	11 mA	None	NO
10	2-3	14 mA	None	NO
Start amplitude: 15 mA, End amplitude: 25 mA				
Test	Best pair found	Amplitude	PF observed	Found MP?
1	2-4	18 mA	2-4 from 16 mA	YES
2	5-6	17 mA	2-4 from 16 mA	NO
3	2-4	19 mA	2-4 from 16 mA	YES
4	1-2	16 mA	None	NO
5	6-7	18 mA	2-4 from 17 mA	NO
6	1-7	16 mA	None	NO
7	2-7	17 mA	2-4 from 16 mA	NO
8	1-7	17 mA	2-4 from 16 mA	NO
9	1-3	20 mA	2-4 from 17 mA	NO
10	2-3	17 mA	3-4 from 16 mA	NO

Table 1: Summary of tests from person A using the baseline algorithm.

If the algorithm found a good electrode pair representing the muscle MP, then the search was terminated and noted. The current amplitude at which the algorithm found the MP was also noted. During the search, it was marked if one electrode pair resulted in plantar flexion. The MP's were successfully found if the algorithm found an electrode pair that resulted in plantar flexion. As shown in table 1, the baseline algorithm found no motor points when the search started at the lower current amplitude. However, the MP's were found twice when the starting current was increased. For test person B, the results were different, partly when starting from 10 mA but substantially from 15 mA, as shown in table 2. The motor points for test person B are 3-4 based on it being the electrode pair that induced a PR at the lowest amplitude. Based on all searches from test person B, the baseline algorithm successfully found the motor points 2/10 when the starting amplitude was 10 mA and 7/10 from 15 mA, table 2.

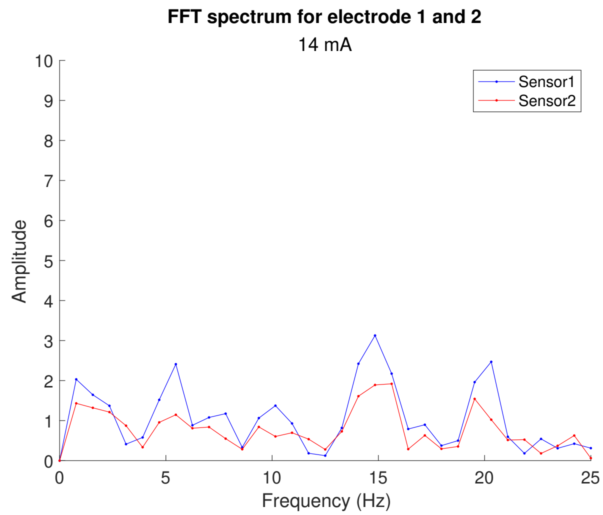
Start amplitude: 10 mA, End amplitude: 25 mA				
Test	Best pair found	Amplitude	PF observed	Found MP?
1	2-7	11 mA	None	NO
2	1-4	19 mA	3-4	NO
3	2-7	11 mA	None	NO
4	1-3	13 mA	None	NO
5	2-3	15 mA	3-4 from 13 mA	NO
6	1-4	15 mA	3-4 from 13 mA	NO
7	1-3	13 mA	None	NO
8	1-6	15 mA	3-4 from 13 mA	NO
9	3-4	12 mA	None	YES?
10	3-4	14 mA	3-4 from 13 mA	YES
Start amplitude: 15 mA, End amplitude: 25 mA				
Test	Best pair found	Amplitude	PF observed	Found MP?
1	1-2	17 mA	3-4 from 15 mA	NO
2	3-4	16 mA	3-4 from 15 mA	YES
3	3-4	17 mA	3-4 from 15 mA	YES
4	3-4	17 mA	3-4 from 15 mA	YES
5	1-2	18 mA	3-4 from 15 mA	NO
6	3-4	17 mA	3-4 from 15 mA	YES
7	1-2	16 mA	None	NO
8	3-4	16 mA	3-4 from 16 mA	YES
9	3-4	16 mA	3-4 from 16 mA	YES
10	3-4	17 mA	3-4 from 16 mA	YES

Table 2: Summary of tests from person B using the baseline algorithm.

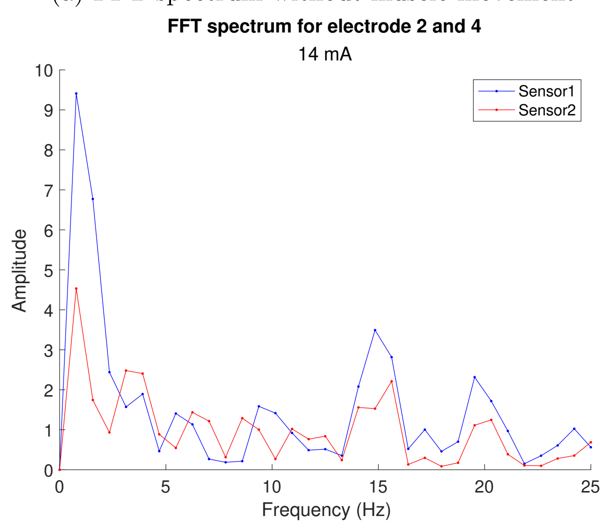
The number of correctly found MPs from the searches done with test person C using the baseline algorithm was 3/10 when starting from 10 mA and 10/10 from 15 mA. The summarized results from all the searches using the baseline algorithm were 24/60 times it found the correct MPs.

4.2 Signal analysis

The sensor data from different searches using the baseline algorithm were stored, and a frequency analysis was done to retrieve more information on the frequency composition. In figure 9, the sensor data from two different stimulation at 14 mA are plotted; the stimulation was between electrodes 1-2 (sub-figure 9a) and 2-4 (sub-figure 9b). No muscle contraction was observed when the current was applied between electrodes 1 and 2. However, when the current was applied between electrodes 2 and 4, the muscle had an observable twitch. The resulting FFT diagram from the sensors showed a peak at ~ 1 Hz when there was a resulting muscle contraction from the stimuli. This peek seemed consistent at around 1 Hz when further stimulation was done and evaluated, and it created a foundation for the logic in the second search algorithm.



(a) FFT spectrum without muscle movement



(b) FFT spectrum with muscle movement

Figure 9: FFT spectrum from two stimulation, one that induced muscle movement and one that does not.

4.3 Search algorithm with signal processing

Table 3 shows 20 unique searches from one test person. The results were gathered using the second search algorithm, which utilizes signal processing in its decision-making process. Its decisions were based on the FFT diagram and the total power of the low frequencies below 5 Hz. The exact start and end current amplitudes were used for the tests using the baseline algorithm, 10-25 mA and 15-25 mA.

Start amplitude: 10 mA, End amplitude: 25 mA				
Test	Best pair found	Amplitude	PF observed	Found MP?
1	2-4	15 mA	2-4 from 15 mA	YES
2	2-4	16 mA	2-4 from 15 mA	YES
3	2-4	16 mA	2-4 from 15 mA	YES
4	2-4	16 mA	2-4 and 4-6 from 15 mA	YES
5	2-4	16 mA	2-4 and 4-6 from 15 mA	YES
6	1-2	11 mA	None	NO
7	2-4	11 mA	None	NO
8	2-4	18 mA	2-4 and 4-6 from 15 mA	YES
9	1-2	17 mA	2-4 and 4-6 from 16 mA	NO
10	1-2	17 mA	2-4 and 4-6 from 16 mA	NO
Start amplitude: 15 mA, End amplitude: 25 mA				
Test	Best pair found	Amplitude	PF observed	Found MP?
1	2-4	17 mA	2-4 from 16 mA	YES
2	2-4	17 mA	2-4 from 16 mA	YES
3	2-4	18 mA	2-4 from 16 mA	YES
4	2-4	17 mA	2-4 from 16 mA	YES
5	2-4	16 mA	2-4 from 15 mA	YES
6	2-4	16 mA	2-4 from 15 mA	YES
7	2-4	19 mA	2-4 from 15 mA	YES
8	2-4	17 mA	2-4 from 15 mA	YES
9	2-4	17 mA	2-4 from 16 mA	YES
10	2-6	16 mA	2-4 from 15 mA	NO

Table 3: Summary of tests from person A using the algorithm with signal processing.

The results from the second search algorithm were significantly improved. The algorithm found the motor points 6/10 when starting from 10 mA and 9/10 from 15 mA for test person A. The algorithm made fewer wrong decisions at low currents than the baseline algorithm. When the starting amplitude was increased to 15 mA, the algorithm improved even further as data from the correct motor points masked the noise and random peaks. The same is true for test person B as shown in table 4 where the results are similar.

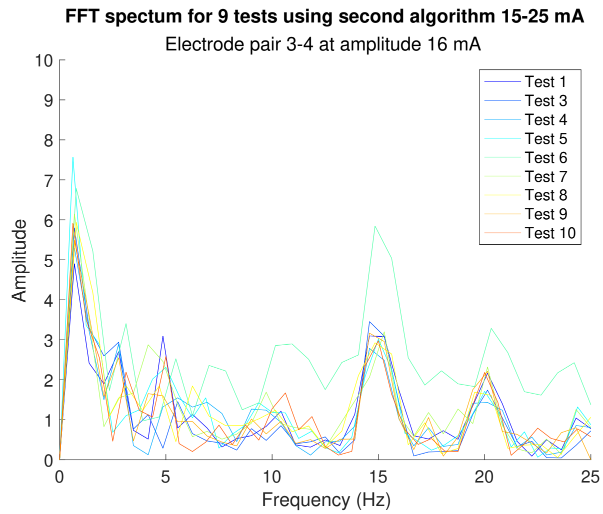
Start amplitude: 10 mA, End amplitude: 25 mA				
Test	Best pair found	Amplitude	PF observed	Found MP?
1	3-4	14 mA	3-4 from 13 mA	YES
2	3-5	15 mA	3-4 from 14 mA	NO
3	3-4	13 mA	3-4 from 13 mA	YES
4	3-4	14 mA	3-4 from 14 mA	YES
5	1-6	14 mA	3-4 from 13 mA	NO
6	3-4	15 mA	3-4 from 14 mA	YES
7	1-2	12 mA	None	NO
8	1-2	13 mA	None	NO
9	1-2	13 mA	None	NO
10	3-4	18 mA	3-4 from 15 mA	YES
Start amplitude: 15 mA, End amplitude: 25 mA				
Test	Best pair found	Amplitude	PF observed	Found MP?
1	3-4	16 mA	3-4 from 15 mA	YES
2	3-4	16 mA	3-4 from 15 mA	YES
3	3-4	16 mA	3-4 from 15 mA	YES
4	3-4	16 mA	3-4 from 15 mA	YES
5	3-4	16 mA	3-4 from 15 mA	YES
6	3-4	16 mA	3-4 from 15 mA	YES
7	3-4	16 mA	3-4 from 15 mA	YES
8	3-5	16 mA	3-4 and 3-5 from 16 mA	NO?
9	3-4	16 mA	3-4 from 15 mA	YES
10	3-4	16 mA	3-4 from 15 mA	YES

Table 4: Summary of tests from person B using the algorithm with signal processing.

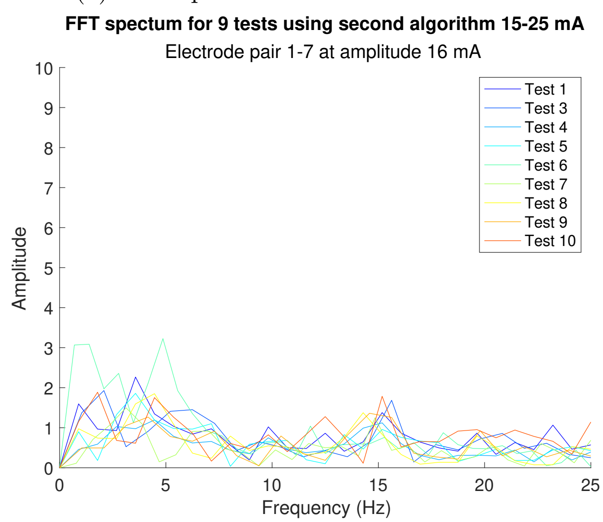
The number of correctly found MPs from the searches done with test person C using the second algorithm was 6/10 when starting from 10 mA and 0/10 from 15 mA. It could not find any MPs when starting at 15 mA as several combinations of electrodes gave PF, and the algorithm could not determine the first and best. The summarized results from all the searches that utilize signal processing were 35/60 times it found the correct MPs.

4.3.1 Further analysis from search

A sample from test person B using the algorithm with signal processing can be seen in figure 10. The sample corresponds to 9 searches where the current was 15-25 mA; (the second search got destroyed when transferred from the application to the computer, and thus, only nine were available). The FFT spectrum 10a, from the sensors when stimulating electrode pair 3-4, motivates the decision-making in the algorithm. The low-frequency peak is present when the stimuli result in a muscle contraction. Even though the test person might move or random noise increases the sensor output, the characteristic low-frequency peek is only present from an electrically induced muscle contraction. When stimulation between two electrodes that neither are placed at a motor point, the FFT spectrum is similar to the sample 10b. There are a lot of frequencies present, but mostly noise. Some random peeks at different frequencies occur occasionally, but these are false inputs that should be disregarded, which the second algorithm does successfully.



(a) FFT spectrum when PF was induced



(b) FFT spectrum when no PF was induced

Figure 10: FFT spectrum from test person B consisting of 9 different searches

5 Discussion

The two search algorithms differed in the number of correct motor points found based on the visual confirmation of plantar flexion. The baseline algorithm had difficulties finding the motor points, especially at lower frequencies, as noise and random signal inputs due to, e.g., unintended movement made the algorithm finish the search prematurely and suggest motor points not based on actual muscle movement induced from the stimulation. When utilizing signal processing, the results dramatically improved. The decision-making in the algorithm became more robust and less sensitive to random signal changes and noise, especially at lower currents. However, some results show existing problems and limitations with the second algorithm. Although it is more sensitive and less susceptible to noise at low currents, the signal processing algorithm has difficulties deciding when many electrode pairs induce a strong PF, i.e., the starting current is above the current needed to stimulate the MPs. This happened with test person C when starting from 15 mA. Almost every combination of electrodes gave a good PF at 15 mA. Thus, the algorithm could not determine the first electrode pair that induces a PF at the lowest current. Comparing the results to the baseline algorithm, it found the MPs 10 times when starting from 15 mA.

The seemingly contradictory results could be attributed to the test person's high sensitivity to NMES. This implies that the motor nerve and, thus, muscle require a very low current to be stimulated. In situations with numerous PFs, the search algorithms face difficulties as they are designed to find the first electrode pair that induces a PF. However, if the starting current is below the limit for an individual's PF, then the second algorithm shows promising performance, marking an improvement from the baseline algorithm. This suggests that the second algorithm could outperform the baseline algorithm under specific conditions, sparking curiosity about its further potential.

5.1 Flex sensors

The integrated flex sensors in the patch were designed to measure significant movement. However, as a muscle twitch results in minuscule movement, these tiny twitches were challenging to separate from the sensor signal noise. The idle value varied between 2038-2054 unit steps, and the muscle movement changed the value with only $\sim 10 - 20$ units. Therefore, having flex sensors with higher resolution at lower movement levels could significantly improve the quality of the resulting signal, i.e., higher output from less movement. This would limit the range the sensor could measure, but the limited range would suffice as muscle movements often nudged the flex sensors. Testing other sensors in this project was not possible due to the existing flex sensors already being molded within the silicone patch, and there were no resources available to create a new patch. However, it is believed that better sensors can potentially improve future versions of search algorithms.

5.2 Problems with the tests

The tests contained many altering variables that had to be controlled as much as possible. Two prevalent problems that had a large impact on the results were patch placement and loss of conductivity due to the patch drying. As the test program took between 2 and 3 hours, it required the test person to take breaks and move around during the test. When re-applying the patch to the calf, it was important that it was located in the same place as previously to have a consistent result.

5.2.1 Patch placement

The placement of the electrode patch was essential to ensure good stimulation and responses from the flex sensors. When performing the tests, there were times when the placement of the patch resulted in no plantar flexion when stimulating. There were also times when the flex sensors did not pick up anything from any movement. Thus, placing the patch and testing the responses by manually flexing the calf had to be done to ensure that the sensors were located in the correct place. Figure 4 states that the MPs are found closer to the knee crease and thus the patch was placed on the upper part of the calf.

5.2.2 Reapplying water to the patch

The first searches in a test program often resulted in excellent and definable plantar flexion when the stimulation was on motor points. However, it was observed that the current needed to stimulate the muscle gradually increased due to the worsening conductivity. This was also confirmed when asking the test persons if the stimulation felt as strong as before; the response was often that it had a downward trend. An attempt to counteract this was to reapply water between the patch and the skin to ensure good conductivity. This resulted in notable improvements as the required current remained relatively consistent. Thus, ten consecutive searches were done before reapplying water to the patch and skin during the tests. However, muscle fatigue is another factor that could explain the slight drift that the conductivity did not solve.

5.2.3 Muscle fatigue

Another factor that seemed to affect the test results was muscle fatigue. It was noted that even though water was reapplied between the patch and the skin, there was still a trend of increasing current needed to induce plantar flexion on the motor points. When muscles are stimulated over a more extended period, they become fatigued; the stimulation is less effective. During testing, the effects of muscle fatigue were prevalent, and the tests had to extend in time to ensure that the test person had time to recover muscle strength during the tests. This was a factor that was initially unknown.

5.3 Base line algorithm

As the noise contaminated the signal from the muscle movement, the first baseline algorithm had problems finding the motor points, as the results show. The algorithm was susceptible to noise, which tricked the algorithm into marking everything as muscle movements even though there were none. This resulted in potential pairs being marked falsely. When there was a lot of movement and noise from the sensors, the algorithm started marking almost every pair as the best. This made it hard to find one pair that had the highest effectiveness throughout two consecutive amplitudes. Thus, the algorithm did not find a final electrode pair based on the conditions set to determine the best one. This resulted in higher and higher current being applied, and the discomfort often resulted in the search ending prematurely by the test person. In other cases the algorithm made quick decisions to mark the motor points based on simply noise and other unwanted signal, resulting in a rather random behaviour. This was most relevant at lower currents when the stimulation's did not induce a PF.

5.4 Filtering the signal

A lot of different solutions where investigated to improve the signal quality. However, the fundamentals of the signal resulted in further problems. One of the main goals with the search algorithm is that it should be quick, this means short bursts of current but also substantially small amount of data from the sensors. The time stimulated was set to 700 ms, mentioned in the method section, resulting in around 14.7 s search time through all unique electrode pairs for each amplitude.

$$0.7 * 21 = 14.7s$$

The signal obtained from this 700 ms is only around 40-70 data points, depending on the latency of BLE communication. That low amount of data points is difficult to work with when creating a more advanced filtering process, as more statistical information about the signal is required. One approach to solve this problem would be accumulating all the signal data for each electrode pair over all amplitudes. Thus increasing the data points and analyzing the whole data sequence. As the sampling frequency of the control unit is said to be 50 Hz, the theoretical number of data points should be 35 samples. However, the amount of samples gathered varies due to potential clock drift, BLE latency, and the logic of sending the data back to the device.

5.5 Accuracy and time

One major objective of the project was to limit the time searching for motor points. This process would be as quick as possible and therefore the time spent stimulation and number of pairs per iteration had to be limited. As mentioned, the stimulation time was set to only 700 ms, the lowest time that could give sufficient data to analyze. However, the number of electrode pairs tested per iteration was constant at 21 unique combinations. The number of pairs had the greatest impact on the time as the algorithm needs to test them all. There were discussions with MMS to enhance the method by clustering electrodes together and stimulate them all at the same time. This would enable the algorithm to decrease the number of unique pairs and be a broader first search, locating areas that are of interest. Then, if one cluster gives plantar flexion then each electrode would be tested and analyzed individually. This multi-electrode stimulation was however not possible with the current setup provided from MMS. It shows great potential to improve the search speed but would require additional future testing to validate the theory.

5.6 Adaptive filters

There exist more advanced filters that are able to adapt to the signal over time. These filters utilizes the statistics within the signal to process it and even predict the future data points. There are many applications for these types of filter as they can adapt to different environments rather easily with the correct setup. One such application is noise cancellation, to remove noise from a signal. This is done by having a reference signal of pure noise and the actual signal that contains the desired part and noise. An adaptive filter could then adapt to the change in the noise and remove it from the signal [29]. During this study a noise canceling approach was explored due to being able to adapt to different environments such as different test people. However, there did not exist a good reference signal that only contained noise. One could explore the possibility of using one of the two sensors as the reference signal, but this created new problems as the movement picked up from the sensors varied. There were times when only one sensor picked up the movement from the calf and the other simply noise, there was however other times when both registered the muscle movement and there was no consistency throughout the tests. The problem with finding a reliable reference signal together with the inadequate dataset size to retrieve statistical properties resulted in this approach being abandoned.

5.7 Machine learning

Another exciting area briefly explored was utilizing machine learning within the algorithm to enhance decision-making and search speed. Machine learning is a field that involves the use of Neural Networks to create models that make decisions based on the statistical content of the input. These Neural Networks can be large, complex systems containing many parameters that all affect the decision-making process. A model must be trained to identify the desired outcome by tuning its parameters. Training a Neural Network requires a significant amount of training data containing the input and labels corresponding to the desired output for the data. There are many different approaches to training these networks, but the common denominator is that they require a large training dataset, which was unavailable during this study. By storing and labeling data when performing search tests, future research could explore further the implementation and testing of machine learning in decision-making when a significant amount of test data is acquired.

6 Conclusion

This study demonstrates that a specific type of signal processing, such as FFT, can enhance accuracy when automatically searching for motor points on the calf. By isolating the characteristic signal from a plantar flexion, it reduces the effect of noise that negatively impacts the measured sensor data. This leads to a higher accuracy in finding the correct motor points at low currents, which is desirable as it minimizes the discomfort the user experiences. However, further research is needed to improve the performance across a broader range of current and to enhance the accuracy even more. Gathering a large dataset could open the door to exploring the integration of machine learning to enhance accuracy. Using multi-electrode stimulation could also reduce the search time required, thereby increasing the user's medical compliance.

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Appendices

A Communication protocol

A.1 Commands with Response

`t`	Test communications
`a`	Set current amplitude [mA] 1 mA - 32 mA or higher (pp. 31, Chap 3)
`A`	Set current amplitude alternative [mA] 1 mA - 32 mA or higher (pp. 31, Chap 3)
`f`	Set frequency [Hz] 15 - 50 (pp. 32, Chap 3)
`d`	Set phase duration [us/50] (200us - 400us $\rightarrow$ 4 - 8) (pp. 83, Chap 6)
`k`	Symmetric = 1, asymmetric = phase_negative / phase_duration = [2,4,8]
`o`	Set ON time [s] 2s-4s (pp. 86, Chap 6) ON/OFF $\approx$ 4:12, 1:3
`O`	Set OFF time [s] ON/OFF 1/3 to 1/5 over 10-15 contractions
`c`	Set number of contractions
`r`	Set ramp-up time [ds] depends on the muscle and exercise, typically below 2s (pp. 89, Chap 6)
`R`	Set ramp_down time [ds]
`s`	Save program configuration in EEPROM
`l`	Load program configuration from EEPROM
`n`	Start stimulation program
`N`	Stop stimulation program
`M`	set multiplexer channel 1
`m`	set multiplexer channel 2
`Q`	set multiplexer channel 3
`q`	set multiplexer channel 4
`W`	Initialize IMU (NY MED SVEKON)

A.2 Commands without Response

`e` binary program channel1,2 and start/stop

`I` Stop measure IMU

`B` deactivate sensors

A.3 Commands with Callback Function

`b` activate sensors

`p` Read current program configuration

`i` Start measure IMU

`g` Start contact scan