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Design of an improved EMG measuring system

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Prothese Academie

Bioinspired MEMS and Biomedical Devices

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Contents

Abstract

Proper control is a key element in the use of myoelectric prosthetics. Factors such as weak muscles, noisy signals or muscle crosstalk can contribute to a reduction in signal detection, reducing the accuracy and quality of prosthetic control. This makes it more difficult to use a prosthesis, leading to users rejecting their usage and losing the benefit these tools should provide. The main goal of this research was to create a new EMG signal processing algorithm for muscle onset detection, removing the influences of noise and muscle crosstalk, allowing for better prosthetic control. Two processing techniques were combined and used to process the EMG signals of both the biceps and triceps muscles of a prosthetic user, to attempt and improve the obtained activation sequence. The obtained signals were preprocessed using the highly modifiable Extended Generalized Teager-Kaiser Energy (EGTKE) operator. The EGTKE has previously been used in the detection of weaker signals and shows promise in the field of prosthetic control. The EGTKE response was processed using an morphological close operator (MCO), followed by a morphological open operator (MOO) to filter out any remaining onset artifacts. The implemented algorithm shows promise in regards to noise filtering, obtaining a clear activation response that remains largely unaffected by noise. Future research should focus on further improvements of the algorithm by performing an optimization study and comparison tests with different methods.

Preface

The Prothese Academie (Prosthesis Academy) is an independent organization that was created with the aim to combine the knowledge about arm and leg prosthetics in one central location, prevent multiple groups from working independently on the same issues and instead work collaboratively to improve research quality. It consists of multiple groups across the Netherlands including hospitals, universities and companies involved with the creation of prosthetics. By connecting researchers and students with healthcare providers and prosthetics developers, a broader range of knowledge becomes available. It is possible for prosthetic users, doctors and other individuals to submit questions or issues to the Prothese Academie. These questions are redefined into concrete problems which can then be investigated by students or other researchers. Due to the direct questions and answers format it is possible for the person that submitted the question to give feedback and further information to provide researchers a better understanding of the problem and allow them to find a better solution. The work conducted in this research project was based on a problem submitted by a prosthetic user to the Prothese Academie.

1 Introduction

There is a large population of people worldwide living with an amputation. A 2020 study reported as many as 20 million people worldwide have undergone amputation of the upper limbs[1]. Other studies report lower values, such as 3 million worldwide in 2009, or report numbers for specific countries such as 41,000 in the United States[2, 3]. Finding an exact value is difficult due to the differences in scope, location, and inclusion criteria that different studies use. Some studies only include severe amputations above a certain level, whereas other studies include every level of amputation up to and including the loss of a single digit. This makes it difficult to obtain an exact value of the amount of upper limb amputees worldwide. Having undergone an amputation of the wrist level or above results in a significant loss of motion due to a total loss of hand function, reducing quality of life. Arm prosthetics are an important tool for rehabilitation, increasing mobility and range of motion, and improving quality of life.

The control of prosthetic arms can be divided into two main categories: (1) direct control (DC), in which the user muscle signals directly correspond with movement of the prosthetic, allowing each muscle pair to control one degree of freedom, and (2) pattern recognition (PR), in which features are extracted after measuring the muscle signals. The characteristics of the extracted features determine the specific prosthetic movement that will be performed[4]. This allows the mapping of different movements to one muscle pair[2, 5]. The accuracy of PR control systems to correctly identify the correct patterns for specific movements is called the Classification Accuracy (CA). This accuracy depends on multiple factors such as the types of sensor used, the muscle strength of the prosthetic user and the amount of patterns that need to be discerned. The most common type of prosthesis is the myoelectric prosthesis, which uses EMG sensors to measure the electrical activity of the muscles. In addition to myoelectric prosthesis other types of signal acquisition exist. Most of these have been developed as an alternative to solve the issues that are common for myoelectric control systems.

1.1 Issues with prosthetic control

While prosthetics are a valuable aid in rehabilitation post amputation, not all upper-limb amputees continue using their prosthesis long term. Prosthetic rejection is common, with rates between 9% and 81% found in literature, depending on the nature of the amputation. Rejection rates are higher for amputations of the dominant hand, or for amputations of a transhumeral or higher level[6, 7, 8]. Proper prosthetic control is a key factor for long term prosthetic use. Issues with control due to a slow or inaccurate response can lead to frustration and non-use of the prosthesis. There are multiple factors that contribute to issues with the control of prosthetics. A common problem is unintended alteration of the EMG signal. This can happen due to movement artifacts, shifting of the electrodes, sweating or changes in skin impedance[9]. Repeated donning and doffing of a prosthetic sleeve can also result in misalignment of the electrodes[10]. These changes cause a degradation of the EMG signal, with the impact depending on factors such as the type of sensors used or the direction and severity of the electrode movement[11]. Larger electrodes are less affected by a shift, but have a lower overall accuracy as the larger surface area results in more interference. A perpendicular shift can lead to the measurement of a different set of muscle fibers, greatly hindering the accuracy of PR based control systems[12]. As well as causing a reduction in signal quality due to changes in skin impedance, sweating can also cause skin irritation and reduce the comfort experienced by the prosthetic user[13, 14]. The effects of these problems are only exacerbated in cases where the starting EMG signal was weak to begin with. Conventional EMG measuring relies on obtaining an adequate signal quality from the muscles. A weaker signal is more susceptible to background noise and other interference.

Muscles are often damaged due to the traumatic nature of an amputation, having a lower firing rate and amplitude resulting in a signal with a worse SNR. This makes standard processing methods unreliable, as the lower signal quality reduces the accuracy and can cause detection issues. Proper control in cases of a weak muscle signal requires either a specialized method for signal detection and processing, or the choice for a more robust and simpler system that foregoes abilities such as PR based control[15, 16, 17]. Multiple studies have been conducted into changing the hardware and software of prosthetic limbs to alleviate issues with weight, comfort or control. This has led to a wide variety of prosthetic arm designs, using different sensors, control systems or signal processing methods. But in spite of these recent advances, issues still persist. Current literature has no decisive solution, with solutions either being untested in real settings, or having downsides that make it not widely applicable. Control problems are often worse for amputees with weak muscle signals or a higher level of amputation. Improving the control of prosthetics by increasing the signal quality and solving common problems that cause prosthetic control will allow more people to make proper use of their prosthesis. This can lead to a higher quality of living by allowing a wider range of motion, potentially reducing the rate of prosthetic rejection.

The overall aim of this study is to create a new and improved EMG measuring system that allows for better prosthetic control. This goal is based on a user submitted question to the Prothese Academie and focuses on two primary subjects. The first objective is to get an overview of the different approaches that currently exist in literature that have tried to solve the mentioned issues. The second objective is to use the information obtained from this literature investigation together with the outcomes of a user interview to create a new EMG measuring system that improves the control of myoelectric prosthetics in cases of weak and noisy muscle signals.

2 User interview

An interview was conducted with the involved prosthetic user and his rehabilitation doctor to gain a better understanding of the problems the new EMG measuring system has to address. This interview served to identify the main problems the user is experiencing and get more background information about his situation and what has been tried before. The prosthetic user has undergone an osseointegration, as well as TMR surgery to re-innervate new muscle sites. Three main problems were identified during the interview. The first problem is a weak muscle signal from the triceps, creating a noisy and weak EMG signal. It was indicated that the strength of the triceps signal was only around 30%, making it difficult to obtain a good signal with standard myoelectric signal processing. The second problem was the interference between the biceps and triceps due to crosstalk between these muscle groups, further complicating prosthetic control. The final problem was the loss of contact of electrodes with the skin, preventing the electrodes from picking up the signal at all. The prosthetic user expressed an additional wish for the new system to be compatible with pattern recognition based control.

3 Literature Investigation

A literature investigation was performed to find current methods that exist in literature to solve prosthetic control problems. The scope and boundaries were set by the problems the prosthetic user experiences. The main requirements of the new system are: 1) the ability to properly detect muscle activation in weak signals with a low SNR, 2) have the ability to filter out crosstalk influence from other muscle groups, 3) have a fast response time with a maximum delay of no more than 175 ms[18], 4) be non-invasive in nature, and 5) to allow for the possibility to be integrated for pattern recognition control in the future. These requirements formed the leading question for the literature investigation: to find different non-invasive methods that have been tried to improve the control of upper arm prosthetics in case of weak and noisy muscle signals. The literature investigation was divided into a hardware component and a software component. The hardware component investigated alternatives to EMG sensors as well as possible adaptations to EMG sensors. The software research investigated the different processing algorithms that can be used to obtain a higher quality EMG signal.

3.1 EMG sensor alternatives

Many alternatives to EMG sensors have been proposed to remove issues that are commonly found in conventional prosthetics. EEG and ENG are alternatives that use implanted sensors, obtaining signals directly from the central nervous system, bypassing the problems that occur when the muscle signals itself are weak[19]. This allows for easier pattern recognition control, but does mean an invasive procedure is required to obtain the nerve signals[20]. Other alternatives make use of the signals of the muscles at the site of amputation. Sonomyography (SMG) uses ultrasound imaging to detect changes in the muscle structure. Ultrasound has the advantage of being able to detect both superficial and deep muscle activities, allowing for greater prosthetic control[21, 22]. Force myography (FMG) mechanically measures muscle contraction, and is therefore insensitive to electrical interference[23]. The simplistic nature makes it less reliant on precision when placing the sensors, reducing the negative effects of electrode shift[24]. Another alternative sensor type is magnetic-based Hall myography (HMG), a technique that measures muscular contraction using a magnetic coupler. Compared to EMG this method is not hindered by electrical interference or sweating, but the linear output of the sensor removes the ability for it to be used for pattern recognition control[25].

In addition to changing the type of sensor used, other approaches have been done involving the combination of EMG sensors with a secondary sensor[26]. Mechanomyography (MMG) measures the low frequency vibrations that are produced by contraction of the muscles and can be used to increase the classification accuracy when used for pattern recognition.[27, 28]. Another possible combination to increase the classification accuracy is the addition of near-infrared spectroscopy (NIRS) sensors[29, 30]. As NIRS sensors are larger than conventional electrodes this can make physical problems such as sweating or electrode shift worse. Another method is to change the EMG sensors itself. Tattoo electrodes can be used to remove factors such as sweating or electrode shift while maintaining signal quality and still allow for EMG based control algorithms to be applied[31].

3.2 Alternatives in signal processing

An alternative approach to improve the obtained signal quality is by using a more sophisticated method to process the signal. More advanced algorithms can result in a better processed signal, yielding more accurate results in cases where conventional methods fail. However, the use of a more complex algorithm can also have the downside of increasing the response time of the system due to complex calculations or the requirements of a large window size to process the signal[32, 33, 34]. For this literature investigation a qualitative comparison was made between the different processing techniques that have been developed in recent years, with a focus on the processing of weak and noisy muscle signals.

In general, processing algorithms can be divided into three categories: 1) preprocessing methods, which alter the signal before detection occurs, 2) onset detection methods, which determine how the periods of muscle activity are detected, and 3) postprocessing methods, which alter the sequence obtained from onset detection. Onset detection and postprocessing methods are sometimes combined into one method, but can also be done in separate steps. The most simplistic and often standard method for EMG activation detection is by using a single threshold (ST) to detect muscle activity, without any additional processing. However, this technique often has issues when identifying activity under suboptimal conditions. If the SNR is low due to low muscle activity or noise false positives may get detected, or periods of signal activity might be missed[32, 33].

Two of the most common alternatives in detection are by either using a double threshold (DT), or an adaptive threshold (AT). The DT method uses a secondary threshold to condition the final activation response. Often this threshold is a window threshold, only counting activation if the amplitude has been above a certain value for a certain amount of time during this window. This can remove false positives due to noise spikes, making it more accurate in signals with a low SNR. This method is often used in combination with additional preprocessing techniques[32], and can result in a large increase of the response time due to the relatively large window sizes used[33]. An adaptive threshold changes the required amplitude for activation based on other signal characteristics such as the SNR[35]. The AT method can be used to avoid the need of manual calibration that is required for other threshold detection systems. The increase in computational complexity by using an automated threshold can result in larger processing times, creating a response delay of 500 ms[36]. And therefore this method is not feasible for real-time prosthetic control. Instead of threshold detection, statistical methods can be used to detect muscle activity but these often have issues detecting all periods of muscle activity if the signal is weak[37]. Postprocessing techniques can also be applied on the different threshold detection techniques to further improve the signal. By filtering out the remaining false positives an increase in quality can be obtained. One study investigated the effects of applying two morphological operations after using a single threshold detection system. The addition of these operations resulted in removal of background noise, and created a signal response that could be detected clearly[16]. This postprocessing method has been tested against other methods and resulted in a large accuracy increase when applied to weak or noisy signals.

Another approach to improve the quality of the detected signal is by conditioning the obtained EMG signal using a preprocessing technique. These techniques alter the signal, allowing for a higher accuracy when combined with threshold detection or statistical methods. One method to process the signal is to use the continuous wavelet transform (CWT). This is a time-frequency domain technique that can obtain a clear signal in cases of low activation amplitudes[15]. A later study improved the CWT method by implementing the use of an adaptive threshold, removing the need for precise threshold selection and resulting in a higher accuracy. The overall delay of this system was found to be 200 ms[38], which is potentially feasible for real-time applications. Other more complex methods exist that can obtain information using only one measuring electrode per muscle group. Methods such as the detrended fluctuation analysis (DFA), can be used to identify low level muscle activity[34]. While the complex nature of these methods gives rise in classification accuracy, the systems are often not applicable for real-time control due to the large processing times required.

A faster preprocessing method is the Teager-Kaiser Energy (TKE) operator. The basic TKE operator was originally developed for speech detection in 1990, but has since been used in the field of EMG measuring[39]. The TKE operator highlights the amplitude variation of a signal by localizing the immediate amplitude spike that happens during muscle activation[15]. This performs an amplification of the muscle activation signal without amplifying the background noise, resulting in a high quality signal independent of the SNR[16, 39, 40, 41]. The simplistic calculation behind the TKE operator means the increase in delay is negligible, making it an ideal choice for real-time control. As the TKE operator is a preprocessing method, it can be combined with different onset detection techniques or postprocessing methods. Multiple studies have been conducted that analyze the influence of preconditioning the EMG signal with this technique for different detection methods. Integration of the TKE operator improves detection accuracy for standard thresholding methods and frequency techniques such as the wavelet transform (WLT)[42, 43]. It has also been used to improve methods that conventionally have issues with low SNR signals such as AGLR[44]. Expansions of the TKE have been proposed that further increase the accuracy and allow for more precise signal modifications[41, 43]. The newly included parameters of this expansion do increase the delay of the overall system by increasing the window size required to perform the calculation. This delay is dependent on the values of these new parameters as well as the sampling rate of the EMG measurement system and can thus be bound to keep the overall response time low.

4 Methodology

The information obtained from the literature investigation was used as groundwork for the solution proposed in this paper. The different methods were compared to find the best method applicable to address the control problems. A new software algorithm was created as a combination of different techniques found in literature, as an attempt to create a further rise in quality of the final detected signal. The new algorithm combined the Extended Generalized Teager-Kaiser Energy (EGTKE) operator with a postprocessing technique. This choice was made due to multiple reasons: 1) the EGTKE operator has a fast response time due to the simpler nature of the performed calculation, making it ideal for real-time prosthetic control, 2) the inclusion of three modifiable parameters allow for further optimization to obtain a better signal, and 3) the EGTKE operator can be combined with multiple detection techniques, allowing for easy comparisons to be made between different detection methods. For this study the choice was made to use a single threshold detection followed by a two-step post-processing procedure. The procedure used has been tested in combination with the TKE before, and is applied to remove any background noise that still remains after the application of the EGTKE[16]. Originally the goal was to combine this new algorithm with the use of EMG tattoo sensors, but due to external factors this was not realized, placing the focus solely on the new signal processing algorithm.

4.1 Materials

4.1.1 Data acquisition

EMG measurements were performed using an OpenBCI Cyton board. This device can acquire real-time signals from multiple channels simultaneously and operates by a wireless connection using an OpenBCI USB dongle. The device operates at a relatively low sampling rate of 250 Hz. Commercial gel electrodes were used for all EMG measurements. Two sessions of EMG measurements were conducted. Initial testing consisted of placing two electrodes on the biceps brachii, and a ground electrode placed on the elbow. These tests were performed to set up the mechanics of the signal processing algorithm and determine whether it was working correctly. These tests consisted of simple isometric contractions of the biceps, with equal periods of rest each contraction. Following the initialization tests a second round of testing was performed involving the prosthetic user. For this test two sets of muscles were measured: the biceps brachii and the triceps brachii. Two electrodes were placed per muscle group, interspaced approximately 3 cm from each other, with exact placement being done by the acting physician. A reference ground electrode was placed on the shoulder blade. An exact overview of the electrode placement can be seen in Figure 1. The raw EMG data obtained from the Cyton dongle was read using serial communication with the PC. For all tests EMG data was collected for both muscle groups. A total of eight different tests were performed. For each test the movement was repeated three times with equal periods of rest in between. Two basic muscle contraction tests were performed in which the participant was instructed to perform a constant isometric contraction of either the biceps or triceps muscles. These measurements served to provide a groundwork to which the parameters of the processing algorithm were optimized. Four tests consisted of different limb phantom movements: elbow flexion, elbow extension, wrist pronation and wrist supination. Following the basic movement measurements a test was conducted in which the participant was instructed to pick up an empty cup. For this test use was made of the users non myoelectric prosthesis to aid in this movement. The final measurement conducted consisted of alternating muscle activation. For this measurement the participant was asked to alternate between isometric contraction of the biceps and triceps, with each muscle group being contracted three times with equal periods of rest in between each movement.

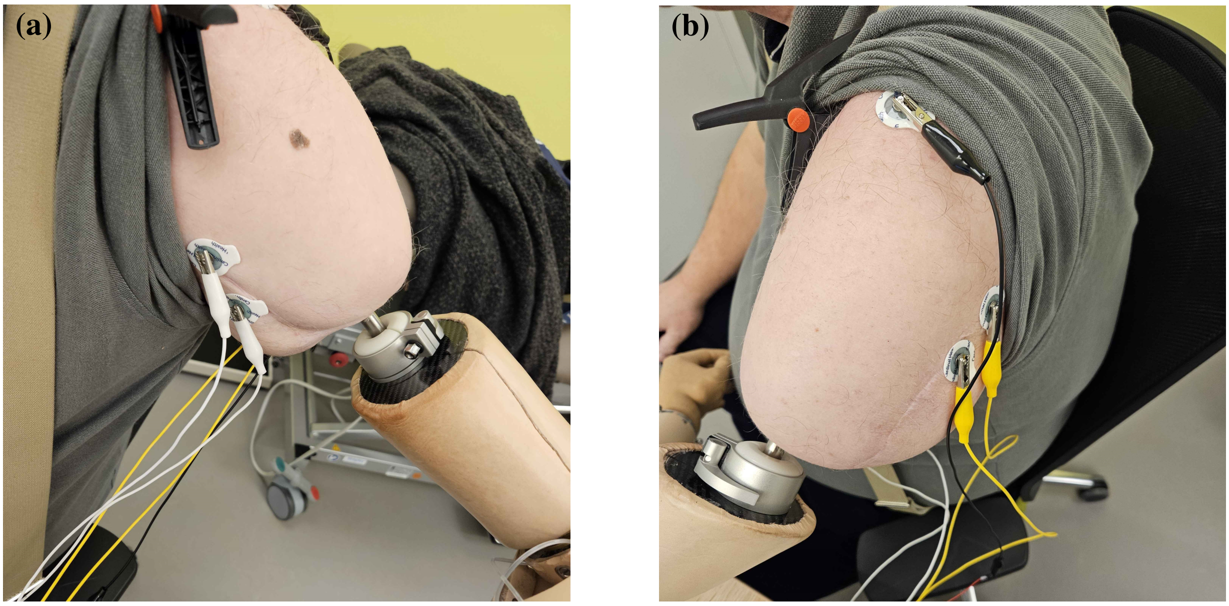

Figure 1: Electrode placement on (a) the biceps and (b) the triceps.

4.2 EMG signal processing

The obtained raw signal was processed and analysed in python using the open-source scientific Spyder environment. Two different approaches were used: a direct real-time version of the algorithm to test its usability in a practical setting, and a postprocessing version. The postprocessing version was used to optimize the different parameters by applying the algorithm to the collected EMG measurement files. The methodology of each processing step is described more in-depth below. An explanation on the code of the python files is given in the appendix. The raw EMG signal obtained from the Cyton board was first filtered with two standard filters: a 50 Hz Notch filter to remove the power line noise followed by a 20 Hz 3rd order high-pass Butterworth filter to remove the low frequency movement artifacts. As the Cyton only has a sampling rate of 250 Hz no low-pass filter was required. The signal is scaled using the scale factor obtained from the OpenBCI repository to get the amplitude in microvolt. The high-pass filtered EMG signal was then filtered using the processing algorithm proposed in this study consisting of a preprocessing procedure and a two part postprocessing operation.

4.2.1 The Extended Generalized Teager-Kaiser Operator

To preprocess the signal the choice was made to use an extension on the Teager-Kaiser Energy operator. The discrete form of the TKE operator ψ is given in (1) where $x(n)$ is the EMG value at sample number n. The default form of the TKE operator uses a symmetric window of three samples and provides a localized description of the signal amplitude[43]. The TKE operator can be rewritten as the determinant of a (2 x 2) matrix as can be seen in (2).

$$\psi[n] = x^2[n] - x[n-1] \cdot x[n+1] \tag{1}$$

$$\psi[n] = \det\left(\begin{bmatrix} x[n] & x[n+1] \\ x[n-1] & x[n] \end{bmatrix}\right) \tag{2}$$

An extension can be made to the TKE by the introduction of two lag parameters m and s that allow for asymmetric modification of the window size. A secondary extension is to introduce a parameter d that alters the matrix size of the calculation. By implementing these extensions an upgrade can be made to the Extended Generalized TKE (EGTKE). The inclusion of these parameters allows for a better localization of amplitude spikes, and results in a higher accuracy for the detection of EMG activity[41, 43]. Each column in this new matrix can be seen as a vector of length d. Combining the vectors obtained from (3) in (4) results in a new square matrix $\mathbf{X}_n$. The EGTKE value of each point can then be calculated by taking the determinant of this resultant square matrix. When choosing a parameter set of (2,1,1), that is; a matrix size of 2, a lag parameter m of 1, and a lag parameter s of 1, the EGTKE reduced back to TKE. For this reason, those values were chosen as the "default" parameters.

$$\mathbf{x}_n = \Big[x[n], \quad x[n-m], \quad x[n-2m], \quad \ldots, \quad x[n-(d-1)m]\Big]^T \tag{3}$$

$$\mathbf{X}_n = \Big[\mathbf{x}_n, \quad \mathbf{x}_{n+s}, \quad \ldots, \quad \mathbf{x}_{n+(d-1)s}\Big] \tag{4}$$

$$\psi[n] = \det\left(\begin{bmatrix} x[n] & x[n+s] & \ldots & x[n+(d-1)s] \\ x[n-m] & x[n-m+s] & \ldots & x[n-m+(d-1)s] \\ \vdots & \vdots & \ddots & \vdots \\ x[n-(d-1)m] & x[n-(d-1)m+s] & \ldots & x[n-(d-1)m+(d-1)s] \end{bmatrix}\right) \tag{5}$$

The introduction of these new parameters changes the window size to $[n-(d-1)m, n+(d-1)s]$. In practice this means that the real-time delay of the EGTKE signal is equal to $(d-1)s$ sample points when compared to the standard EMG signal. As the length of a sample point depends on the sampling rate a higher sampling frequency will result in less delay for the same parametric values. When using the Cyton device with a sampling rate of 250 Hz the final delay value will be multiplied by 4 ms. This also means that a higher sampling rate allows for more precise fine tuning of the lag parameters as a change in parametric values corresponds to a smaller time step. Due to the nature of the EGTKE calculation, the parameter combination (a,b) is equivalent to the combination (b,a). The only difference between the two signal responses is a horizontal shift.

4.2.2 Morphological postprocessing operations

To process the obtained EGTKE signal the choice was made to use a single threshold-based onset detection system followed by two postprocessing techniques. To apply these techniques the onset activation index is seen as a 1D binary image and restructured using two morphological operations[16]. Firstly, a morphological closing operator (MCO) is used. MCO first dilates the 1D image and then erodes it, using a structuring element of $t1$ ms. This fills in the gaps in the activation detection that are smaller than $t1$ ms. Gaps larger than this value are unaffected, preserving the shape of the activation index but connecting the periods of muscle activity into one large activation segment. In operational form this step can be seen as $A \bullet B = (A \oplus B) \ominus B$. The second step is to apply a morphological open operator (MOO). MOO accomplishes the reverse, using a structuring element of $t2$ ms to firstly erode the signal before dilating it again. The resultant effect is that activation peaks that are shorter than $t2$ ms are filtered out of the signal, whereas peaks larger than this value are unaffected. The combination of these two operations serves as an additional measure of signal quality control, by removing the potentially remaining noise spikes and connecting the signal into a smooth activation sequence. In operational form the MOO can be written as $A \circ B = (A \ominus B) \oplus B$. A visualization of the operations can be seen in Figure 2. The combination of the EGTKE operator with the two postprocessing techniques results in six different parameters that can be altered to fine tune the EMG onset detection. Three of these parameters are related to the EGTKE preprocessing, a threshold detection value, as well as two values for the morphological operations. These parameters can be individually configured per obtained signal, enabling the selection of different values based on the muscle group.

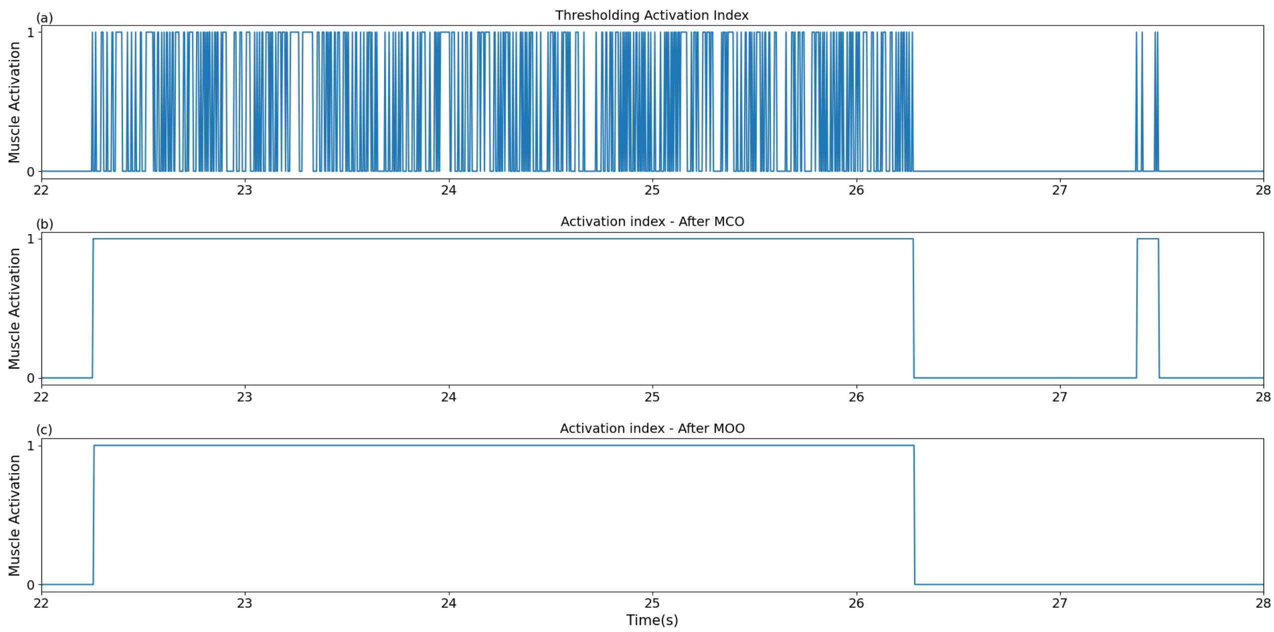

Figure 2: Effects of the postprocessing operations. a) the activation detection sequence. b)The resultant sequence after applying the MCO. c) the final detection signal after the application of the MOO.

4.3 Data Analysis

The six parameter values that affected the response of the system were optimized by hand. A visual inspection was conducted for each parameter set to determine whether an accurate muscle detection was obtained and whether the background noise and influence of other muscle groups was filtered out. This analysis was divided into two sections. In the first section of the analysis, the preprocessing algorithm was optimized in three phases. In the first phase the influence of the matrix size d and the lag parameters m and s were investigated separately to determine the effects of each parameter on the EGTKE response. The second phase consisted of optimizing the EGTKE response for all three parameters combined. For this phase a variable single threshold was used for activation detection. The magnitude of this variable depended on the size of the matrix used in the EGTKE calculation. Parameter d was used as an exponent to set the magnitude of the thresholds. Optimal values were decided based on visual inspection of this resultant signal, taking into account the increase in response time of larger parameters. In the third and final phase the optimal EGTKE values found were used for optimization of the postprocessing operations. A range of thresholds were selected to obtain a sequence of activation indexes. For each threshold the MCO and MOO values were swept with intervals of 20 ms. Optimization of the MCO was determined by finding the lowest parameter value that still connected the periods of muscle activity into one active segment. The optimal MOO was determined to be the minimum value that removed all of the remaining background noise. As the main goal of this study was to determine if the algorithm results in an improvement of EMG detection no quantitative parameter sweep was performed.

Due to the unexpected EMG results obtained from the triceps muscles measurements an interview was conducted with an expert in the field of EMG. Per his recommendation the choice was made to apply a Fourier transform on the signal to perform a frequency analysis, comparing the activity of the triceps muscles for different movements to determine if there was a visible difference between voluntary and involuntary contraction.

5 Results

5.1 EMG measurements

The signal processing algorithm was configured using the measurement files consisting of the basic isometric contraction of either the biceps or triceps muscles. Following this configuration the algorithm was applied to the different movement files to analyse the results. Slight changes were made to the parametric values where required.

5.1.1 EGTKE optimization

Figure 3 shows the effects of the EGTKE operation. The maximum amplitude of the EMG signal was 74 μV. The background noise had an amplitude around 5 μV, with spikes of 15 μV. These consistent spikes are an artifact created by the heartbeat of the participant. Application of the EGTKE operator resulted in an increase of the overall signal response, with the maximum amplitude increasing 77 fold to a value of 5700 μV^2. The background noise was amplified by a smaller margin, averaging out at around 20 μV^2 with the heartbeat spikes going up to an amplitude of 120 μV^2. Increasing the matrix size d leads to a proportional multiplication in signal amplitudes. The background noise gets amplified to a much smaller degree compared to the active signal, resulting in a cleaner signal with less noise. The choice of an odd matrix size results in a similar amplification of the negative values, resulting in a minimum-to-maximum ratio of approximately 1. Comparatively, the ratio between the minimum and maximum for even matrix sizes lies between 4 and 10. An increase in matrix size increased the computational complexity and the response time of the system.

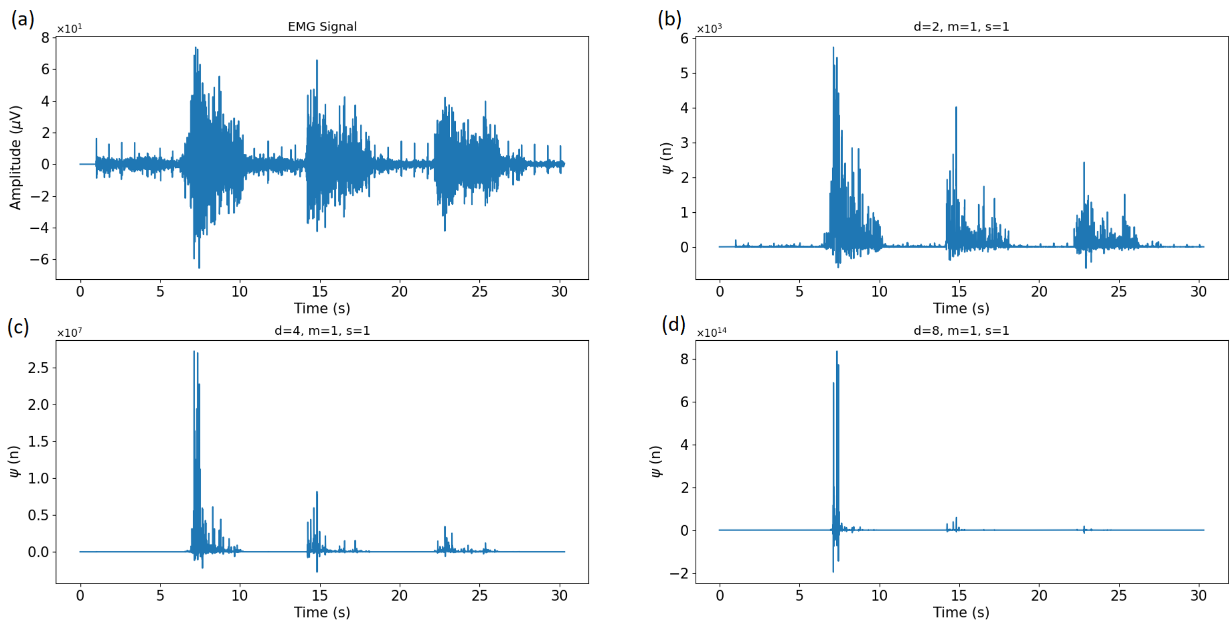

Figure 3: a) EMG response of the triceps during isometric contraction. b) Response of the EGTKE operator with default parameter settings. c, d) The effect of increasing the matrix size d on the EGTKE response.

To determine the activation detection for different parametric combinations a threshold of $0.75 \cdot 10^d$ was used. As can be seen in Figure 4 the default TKE parameters resulted in a large amount of noise detection. An increase of the matrix size resulted in a decrease of noise. Diminishing returns were found when increasing the matrix size, with matrix sizes above 6 detecting the same amount of background noise. For the lag parameters, an equal increase of both parameters resulted in an increase in noise when compared to the default values. The most amount of noise reduction was found when increasing one of the parameters, with the other parameter remaining fixed at 1. Additionally, an asymmetric increase of the lag parameters results in a decrease of overall signal amplitudes for both the background noise and EMG activation. This decrease was less noticeable for a larger matrix size due to the increase in amplitude multiplication.

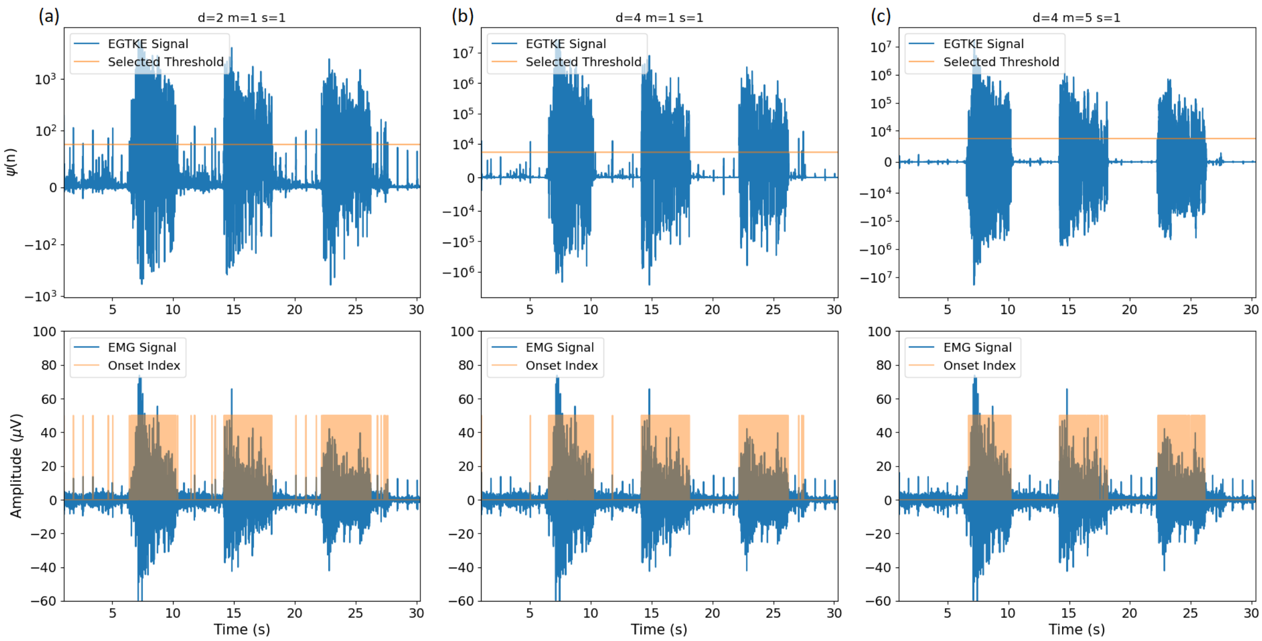

Figure 4: The EGTKE signal response and resulting activation index for three different parameter settings. a) The default TKE operator. b) Influence of the matrix size parameter d. c) Effect of the lag parameters.

5.1.2 Post processing operations

The postprocessing operations were performed on an EGTKE signal with the matrix size d set to 4, lag parameter m set to 5, and lag parameter s set to 1. These values were selected for both the triceps and biceps. Table 1 shows an overview of the selected thresholds and the required parameter values for the morphological operations to get a good signal response. A visualization the different thresholds can be seen in Table 1. The minimum viable threshold found was 1,000. Thresholds below this value resulted in complete noise detection, making it impossible to detect the EMG activation. Thresholds below 2,000 still detect some background noise, requiring the closing operation to filter out the remaining noise spikes. Thresholds of 5,000 or higher detected no background noise but required an increasingly larger MCO to connect the periods of muscle activity. When selecting a threshold of 50,000 or higher most of the EMG activation was no longer detected, and would therefore make it impossible to detect muscle activation.

Threshold setting	Threshold value	MCO value (ms)	MOO value (ms)
10^{d-1}	1,000	80	120
$2 \cdot 10^{d-1}$	2,000	120	20
$5 \cdot 10^{d-1}$	5,000	160	0
10^{d}	10,000	240	0
$2 \cdot 10^{d}$	20,000	450	0
$5 \cdot 10^{d}$	50,000	-	-

Table 1: Required MCO and MOO values for each selected threshold to get a smooth signal response to detect activation of the triceps muscles.

5.1.3 Biceps optimization

A similar signal analysis was performed for the activation of the biceps muscles. The same EGTKE parameter set of (4,5,1) was selected and a similar postprocessing procedure was performed. The amplitudes of the biceps activation were higher than those of the triceps, resulting in a higher range of viable detection thresholds. The range of viable thresholds found for the biceps muscles ranged from $5 \cdot 10^{d-1}$ to 10^{d+2}, with values outside this range either detecting a large amount of background noise, or are unable to detect the activation of the muscles. Threshold values of 200,000 or below required the MOO to filter out the remaining noise spikes, with thresholds below 100,000 picking up the tail end of the muscle activation sequence.

5.1.4 Application of optimized processing operations

The above process resulted in an optimized configuration of the processing algorithm for both the triceps and biceps. For both muscles the EGTKE parameters were set to (4,5,1). For the triceps a threshold of 2,000 was selected, and for the biceps the threshold was set to 500,000. These values were used to apply the processing algorithm to a different set of EMG measurements. In Figure 5 an overview can be seen of the processing algorithm when applied to different biceps measurements. A final MCO value of 120 was selected in combination with a MOO value of 80. During the isometric biceps contractions and elbow flexion a large response is visible due to activation of the biceps muscles. For the measurements of the triceps activation and the elbow extension some leftover noise is still being detected after application of the EGTKE operator and post processing techniques. Further increase of either the threshold or MOO values removes the remainder of the noise but alters the response of the real activation detection. Figure 6 depicts the EMG activity of the same movements but measured using the electrodes placed on the triceps muscles and shows that the movements relying on the triceps muscles, the isometric contraction and elbow extension, create clear periods of signal activity. However, during the movements that should only give rise to an activation of the biceps muscles a large activation is still observed in the triceps. Due to the large amount of activation detected it is not possible to alter the settings of the processing algorithm to filter this out, as these changes also resulted in complete filtration of the real activation.

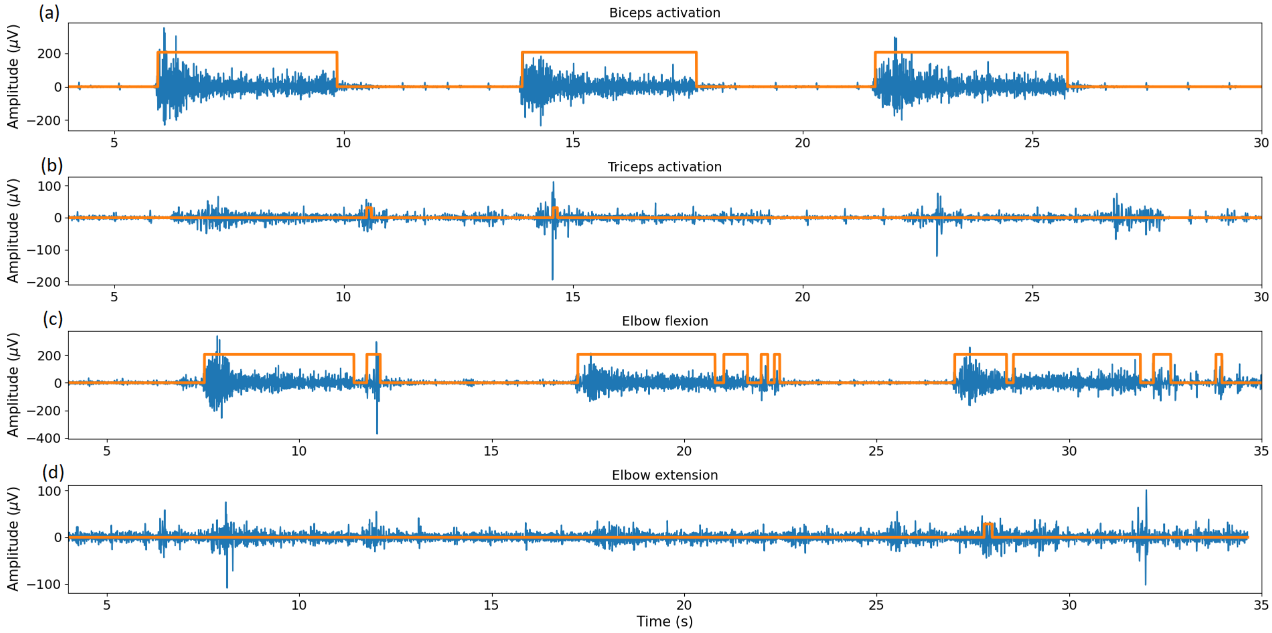

Figure 5: Application of the optimized processing algorithm to different EMG measurements of the biceps. a) Isometric biceps contractions. b) Isometric triceps contractions. c) Flexion of the elbow. d) Extension of the elbow.

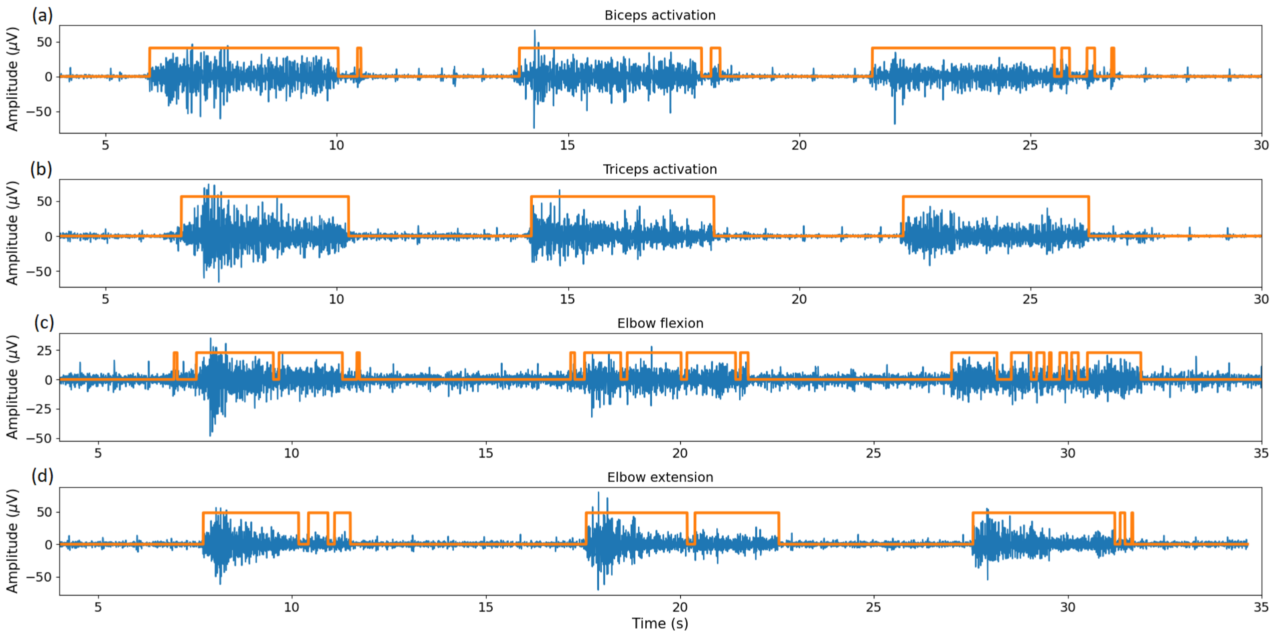

Figure 6: Application of the optimized processing algorithm to different EMG measurements of the triceps. a) Isometric biceps contractions. b) Isometric triceps contractions. c) Flexion of the elbow. d) Extension of the elbow.

5.2 Frequency analysis

To investigate the difference between the voluntary and involuntary activation of the triceps muscles a frequency analysis was performed. The power spectrum of the isometric triceps contractions was compared to the one of the isometric biceps contractions. The comparison was made using the Notch and high-pass filtered EMG measurements. Figure 7 shows the intensity of each frequency on a range from 0 to 125 Hz. Due to the sampling rate of 250 Hz it is not possible to analyze higher frequencies. The triceps activity during the isometric contraction of the biceps is seen as involuntary. Both frequency spectra have the highest activation in the range of 25 to 40 Hz. The power of the involuntary contraction appears to flat-line faster than that of the voluntary contraction, causing a higher amount of voluntary activity in the higher frequencies.

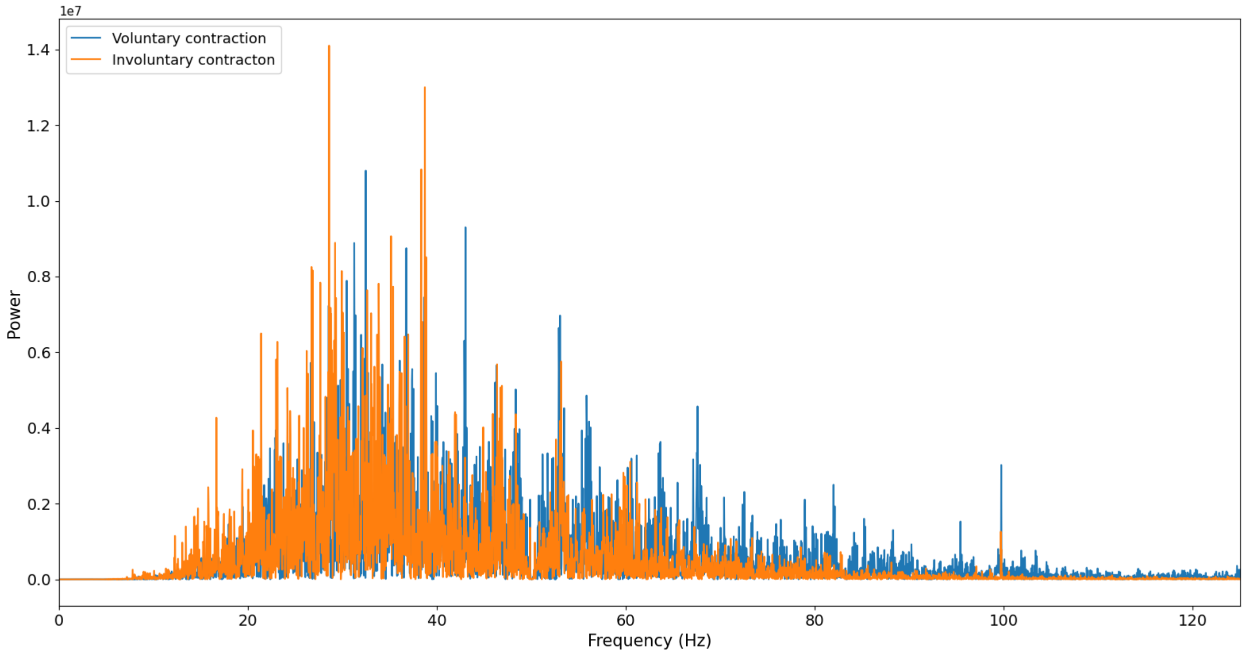

Figure 7: Power spectrum of the triceps muscle during voluntary and involuntary contraction.

6 Discussion

As discussed in the literature investigation, the original intention was to use tattoo electrodes for the EMG measurements, but the measurements in this study were conducted using conventional gel electrodes. Whilst the use of tattoo sensors could potentially solve the issues related to the loss of electrode contact initially described by the prosthetic user by preventing sweating and movement of the electrodes, it is unlikely that the use of tattoo electrodes would have affected the outcomes of this specific study. The measurements performed for this study were obtained in a single two hour session. Issues such as electrode shift and sweating tend to occur during longer periods of prosthetic use

The EMG measurements obtained could properly be analyzed, with a clear muscle activity response being visible during muscle contraction. The observed background noise during contractions was lower than expected, and for both the triceps and biceps a proper signal could be extracted. The amplitude of the biceps activity was higher, indicating that indeed the activity of the triceps muscles are weaker. A relatively large amount of background noise in the biceps signal was detected during contraction of the triceps muscles, with peak amplitudes as high as during actual biceps contraction. The choice was made to focus on the measurements obtained from the simple movements to allow for proper distinguishing between expected periods of muscle activity as the more esoteric movements such as picking up objects cannot be clearly divided into biceps and triceps contractions.

6.1 Signal processing algorithm

The implemented processing algorithm had the main goal of improving the EMG signal quality by being able to accurately determine the onset and offset of muscle activity. Application of the EGTKE operator resulted in an improvement of signal quality, boosting the amplitudes of periods of activity and filtering out the background noise. When combined with the two postprocessing operations a clear detection sequence was obtained that accurately determined the periods of muscle activity. However, while a relatively clean signal was obtained, proper optimization of the EGTKE operator was not achieved. Two main factors contributed to this lack of optimization. The first is that the optimization of both the preprocessing and postprocessing was done separately and by hand. This resulted in fewer total combinations being tested, so it is possible that more optimal parameter combinations exist. It is likely that a EGTKE parameter set that behaves worse at first glance and performs better after the postprocessing operations are applied.

To obtain a better optimized EGTKE operator a quantitative analysis would have to be performed to compare the results of different parametric combinations for a larger range of postprocessing values. The second major contributing factor the the suboptimal optimization of the EGTKE operation was the low sampling rate of the Cyton device. The sampling rate of 250 Hz results in measurement segments of 4 ms. As a result, a single change in either lag parameter value corresponds to a step size of 4 ms. A previous study investigated the effects of changing the lag parameters and found the values m=11 and s=8 to be optimal for signals with a low SNR[43]. In this study a sampling rate of 2048 Hz was used, meaning that a parameter change of 1 with a 250 Hz sampling rate corresponds to a parameter change of 8 for their conducted study. Due to this lack of precision it was not possible to optimize the lag parameters. Additionally, a higher sampling rate lowers the delay of the EGTKE operation assuming the same parametric values are used.

The final parameters chosen in this study were a matrix size d of 4, a lag parameter m of 5 and a lag parameter s of 1. This resulted in an overall preprocessing delay of 12 ms. The possibility of increasing the matrix size further was considered but despite increasing the response time due to the increase in window size an increase in computational time was observed. Increasing the matrix size further also yielded diminishing returns, with matrix sizes of 4 and higher picking up no background noise using the same variable threshold selection. The majority of the final signal delay came from the postprocessing operations. For the triceps the added delay was 140 ms, and for the biceps this added delay was 200 ms. These values are higher than desired and can make real-time prosthetic control feel sluggish and slow. It is likely that further optimization of the EGTKE preprocessing operator will allow for a reduction of these values and bring the overall response time down.

6.2 Muscle crosstalk

The observed EMG activity of the triceps muscles during periods of biceps contraction was unexpected. The original expectation was to see some influence of the biceps muscles in the triceps activation signal, but this was not the case. The muscle activity of the triceps was as strong during voluntary contraction as during periods of biceps contraction. To get a better understanding of the reasons for this an interview with an EMG expert was conducted. During this interview the measurement results were investigated and the possible reasons were discussed. It is likely the root cause of the problem is the co-contraction of both muscle groups during activation of the biceps. This means that normal signal processing methods are unable to filter out the resultant signal, as it consists of activity of the muscle itself and not background noise. Filtering out this signal would filter out actual muscle contractions, resulting in filtering of voluntary activation as well. The reason for this co-contraction is unknown and would have to be further investigated to find the source. A neurological issue or problems following the TMR surgery are two possible reason that could explain this. Following this interview the frequency analysis seen in the results was performed to determine if distinction between the two types of activity could be made. It is not possible to draw conclusions from this test due as it was performed using one set of data. Additionally, the lower sampling rate prevents the investigation of the higher frequencies.

6.3 Future improvements

An optimization study could be performed to further improve the quality of the EGTKE processed signal, using a larger dataset of EMG measurements sampled at a higher frequency. A quantitative optimization comparing the signal response for different parameter combinations against a predetermined optimal response could improve the onset detection. This would solve the two main issues encountered in this paper: A wider range of parametric combinations could be tested than if done by hand, and a more precise optimization could be performed with the higher sampling rate. The optimization would need to balance the increase in signal quality against the increase in computational time, finding the best signal response without severely increasing the lag of the system. As stated in the methods section, the TKE operator can be combined with different detection methods. It could be worth investigating if another onset detection method yields similar accuracies as the morphological operations without increasing the system delay as much.

To address the issue of muscle co-contraction, which is likely the primary cause of the user's problems, a completely different approach would need to be used. The possibility of co-contraction was not included in the scope of this research study. To accurately determine which muscles are active during specific movements a high-density EMG (HD-EMG) measurement study would need to be performed that could map all the areas of muscle activity for specific movements, investigating of the involuntary contraction of the triceps is the sole issue, or if different areas are also affected. An initial possible approach into solving the co-contraction issue was briefly investigated after the interview with the EMG expert. It could be possible to make a distinction between voluntary and involuntary contraction by analyzing and comparing the frequency spectrum of both types of activation. A previous study has shown that the use of larger high-pass filtering frequencies still results in a signal that can be used for muscle activation detection[45]. If the correlation of higher frequencies being more active during voluntary contraction is true, this method might make it possible to distinguish and remove involuntary contraction.

7 Conclusion

The primary goal of this investigation was to find a solution that would improve the quality of measured EMG signal for a specific prosthetic user with weak and noisy muscle signals. The implemented EGTKE operator and postprocessing techniques perform well in regard to noise reduction, obtaining a higher quality signal that filters out noise artifacts. However, the main control issue remains unsolved. This is due to a late discovery that the root cause of the problem is likely co-contraction, and not muscle crosstalk. This difference prevents the algorithm from properly filtering the signal, as the main problem is unintended activation of the muscles. To solve these control issues a different approach is needed, requiring a different investigation that investigates the cause of involuntary contraction as well as a method to differentiate between voluntary and involuntary contraction.

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8 Appendix

Added with this research report are three python files as well as twelve sets of EMG measurements. These files were used for the creation, testing and optimization of the signal processing algorithm. Ten sets of EMG measurements are the results of the tests with the prosthetic user and contain the EMG data of both the biceps and triceps muscles. The remaining two sets of EMG data are from tests conducted on myself and only contain data of the biceps muscles

8.1 Python code files

Three different python files are included. The “Realtime” and “Nonlive” processing algorithm files contain the code of the different processing steps used. The “NonLive” file applies these steps to a pre-existing raw EMG data file, processing the signal with each different technique used. By supplying a .csv file containing raw EMG data the the final processed signal can be obtained. The “Realtime” file performs the same signal processing steps but is designed to be used during real-time EMG measurements. The code for the different processing steps iterates for every measurement point, live processing the signal. A final “Live_plot” file is provided. This file can be run in tandem with the ”Realtime” file to have live visualization of the EMG signal or the signal of any of the processing steps. This was purposefully made separate from the live processing script to allow for any computer to run the processing script without causing lag due to outdated hardware.