Using Pattern Recognition for Refined Digit Control in Transradial Myoelectric Prosthetics

Grant Proposal

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Executive Summary (Eng)

Electromyographic (EMG) technology is commonly used to observe contractions in muscles throughout the body. This is especially useful for decoding the intended movement for amputees to map the movement to myoelectric prosthetics. However, fine motor movement is very difficult to interpret, especially while using surface EMGs (sEMG) that are not of a high density. This paper proposes a method to decode and map low density sEMG signals taken from the forearm to the intended fine motor movement in the fingers, specifically their contraction and extension. This study used X abled bodied subjects and had them perform ten different actions while six channels of sEMG data were collected at 125hz. The sEMG data was then used to train a compact convolutional neural network (cCNN), only using data from each individual subject, thus creating a specialized trained cCNN for each subject. Each subject was then connected to a myoelectric arm and asked to perform a modified block and box test as well as a clothespin test multiple times while time data was taken. The data shows that the low density sEMG signals processed with a cCNN can accurately map fine digit movement to a myoelectric device.

Keywords: myoelectric, orthotics, prosthetics, machine learning

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In the United States, over two million people currently experience a lack of limb due to amputations – the result of limb loss after birth- or amelia - being born without one or more limbs. This number increases by 185,000 per year on average (Zhu et al., 2022). Amputation constitutes a serious disability that can limit a person's ability to do everyday activities many take for granted. To help offset this disability, many patients elect to use prosthetics, which can be body powered or myoelectrically controlled. Over the past two decades there have been significant scientific advancements in surface electromyography (sEMG) controlled prosthetics. These prosthetics, often referred to as myoelectric prosthetics, use sEMGs to detect muscle contraction in residual muscles, which can then be mapped to the intended body function. The prosthetic then reflecting that intended body function. Many different types of programs exist to map these muscle contractions to prosthetic movement, where the most common commercial program is direct control (DirCon) (Resnik et al., 2018). DirCon works by reading EMG data from a single pair of antagonistic muscles, controlling one degree of freedom (DOF) at a time. DirCon can be quite cumbersome to control as users have to manually switch to a different DOF for full functionality. This difficulty results in many actions that require several DOFs taking a significant amount of time, leading some to abandon their prosthetics all together in favor of less effective body-powered prosthetics (Hargrove et al., 2017). Over the past few years, many prosthetics labs have begun experimentation with pattern recognition (PR) control methods, which use machine learning (ML) to decode residual muscle contractions to more accurately map the contractions to one or more DOFs at a time. PR has also been used in tandem with DirCon, using it to switch between DOFs, termed "adaptive switching" in research by Edward et. Al (2018).

Despite all these advancements many of these myoelectric arms are limited in the number of available outputs in each joint. In research conducted on pattern recognition in myoelectric prosthetics in 2022, Zhu et al were able to include two DOFs, the hand and the wrist, allowing for significant movement options. However, the hand was only proportional with all fingers at once, allowing them to contract the fingers part way though all fingers would be contracted the same amount. Many have conducted similar trials with more or less DOFs, different muscle groups, different types of amputees; however, almost all have a similar issue regarding hand contraction being every finger or none. While this works well for grabbing many objects and moving them, it does not allow for the finer movements people are able to achieve with biological hands. These movements could include grasping something fragile or holding delicate objects. The lack of individual finger control also severely limits possible gestures patients can make, which many of us use for communication. Some gestures include, thumbs up, pointing using your index finger to reference something or someone, and many other forms of nonverbal communication used daily by abled-bodied people. The goal of this project is to implement pattern recognition to allow for dexterous control of fingers in cases of transradial, below the elbow, amputations.

Section II: Specific Aims

This proposal's objective is to use pattern recognition to improve current control over individual finger movement in transradial prosthetics. Control in individual fingers is highly limited as other degrees of freedom are prioritized when developing new prosthetics. This project aims to address this issue using techniques used by modern myoelectric prosthetics. Should this project be successful, transradial amputees will regain access to controlling the grasping motion, with curling and uncurling each of their fingers. This motion will be independently calculated for each finger, allowing them each to be controlled individually. Allowing individual control would grant increased ability to perform daily tasks by amputees. Some of these tasks could include making gestures such as a thumbs up, manipulability of objects that are rounded, manipulability of small objects, and the manipulability of objects that require a specific fine force to be acted upon them, such as a clothespin.

Our long-term goal is to restore all motor functions to transradial amputees through the use of prosthetics. The engineering objective is to improve the flexion of individual fingers in transradial myoelectric prosthetics. The rationale is that most prosthetics, as mentioned earlier, only offer limited control over fingers, often acting as one unit, rather than five individuals. Providing evidence that this control is possible and helpful to amputees could lead to further development and, therefore implementation as prosthetics improve over time. This project would also provide evidence that five DOFs can work in tandem, opening up the door for more multi-DOF systems in the future. The work we propose here will use machine learning and sEMG data to give amputees the ability to control each of their fingers separately with significant improvement in dexterity.

Specific Aim 1: Allow transradial amputees to have dexterous control of each of their five fingers through myoelectric prosthetics.

Specific Aim 2: Provide significant evidence that dexterous control over the five fingers will significantly improve the everyday life of transradial amputees.

The expected outcome of this work is that transradial amputee subjects will gain accurate control over the five digits when using a myoelectric prosthetic with a pattern recognition trained model. Subjects will report significant benefits in having individual finger control and show improvements in standard prosthetics tests such as the block and box test, which will be modified to use a sphere instead of a block, and the clothespin test.

Section III: Project Goals and Methodology

Relevance/Significance

This project aims to use sEMG data from amputee's lower arm muscles and machine learning to provide amputees with the ability to control the fingers on their prosthetics individually. This goal is relevant as the lack of control of these digits constitutes a serious disability for amputees, and this project could assist in alleviating that disability.

Methodology and Innovation

The proposed methodology would result in a new machine learning model built for recognizing patterns in muscle contractions that would facilitate to different finger movements. This project proposes that this goal be accomplished through a multitude of steps. First, a program for a neural network will be written using the pytorch library. This library was chosen as a very simple and highly abstract way to write a neural network. Its flexibility allowed us to make it highly flexible, opting to create a design that could easily be altered using parameters when creating an object of the neural network. A convolutional neural network (CNN) was chosen due to their specialty in pattern recognition applications across multiple dimensions, similar to what is being proposed in this study. A CNN, in very simple terms, begins with the full input layer and then passes through filter layers, called convolutions, before proceeding to the normal feedforward layers. The goal of these filters is to find what data is significant in modifying the outcomes of the neural network. This allows the data to be weighted for significance and then giving that data more effect on the outcome. It is expected that the model will be able to determine the finger movement, and to what degree, based on the input EMG signals. When creating an object of neural network, we can set, through parameters, the number of input channels (sEMG signals being processed), the number of convolution layers, the number of output channels for each convolutional layer, the kernel sizes for each convolution (the size of the filter), the number of feedforward layers, the number of output channels for each feedforward layer, and finally the number of output channels. This modularity will allow for testing many different model structures to find which combination of settings grants the most accurate return. The model will use the ReLu activation function in each of its feedforward layers, as studies have shown it to produce the most accurate results (Sharma, 2022). ReLu will also be used in the final layer as this model is meant to be used for regression, not classification. (Neilson N.D)

The OpenBCI Cyton Board with Daisy Chain or the sEMGs within the amputee's prosthetic will be used to gather data (Harath 2023). A single pair sEMG will be attached to most residual muscles, with two pairs being attached to the flexor digitorum profundus, one for the muscle belly controlling the middle, ring, and small finger, and the other for the muscle belly controlling the index finger. Similarly, four pairs of sEMGs will be placed on the flexor digitorum superficialis, one for each muscle belly controlling each individual finger with the exception of the thumb. This data will be streamed and processed through the python brainflow library (Harath, 2023). While training, the subject will place their hands in multiple different positions. Once all of the positions are captured, the subject will remove and reapply the sEMGs and repeat the process. The removal process is to account for slight errors when applying the sEMGs, allowing the trained model to expect some variation (Harath, 2023). The process will be repeated a minimum of four times, giving the model 4 10 second timestamps to be trained on for each position. The samples will then be filtered and denoised, which will also happen to the live signals, to improve the input data, making it more consistent (Parajuli, 2019). The resultant data will then be placed into a numpy array and fed to the neural network for training (Parajuli, 2019). Three of the datapoints from each position will then be fed into the model to train it, and the fourth will be used to test the model. Using different data will allow us to use the scalability of the model described earlier to test many different forms of the model and find the most accurate. Finally, a live test will occur where the subject will perform multiple of the trained positions as well as some untrained positions to visually judge the model's outputs to ensure they match the user's intents.

The subject will then attach their prosthetic, and a program will be uploaded, allowing the model to affect their hand movement. The subject will then be given time to get comfortable and familiar with the new program. Once they find themselves comfortable, they will complete two tests. Both of these tests will also be performed prior to the testing of the new program to provide a baseline for comparisons. The first test they will complete is a modified box and block test. Here, they will have to move 5 a 2” diameter balls from one side of a box to the other with a dividing wall in between. The modified block and box test aims to test their grip control over the rounded object. This test will be repeated 3 times per subject, and a timer will be set to find how much time was spent moving the 5 balls. The timer will start when contact is made with the first ball and end when the fifth ball is placed on the other side of the wall. The second test that will be performed is the clothespin test. Here, a horizontal and vertical bar will be set up with 5 clothespins located on the horizontal bar. The subjects will move each clothespin from the horizontal bar to the vertical bar and back again. The clothespin test is to test the dexterity of the pinching motion between the index finger and thumb. The subjects will be timed from the moment they touch the first clothespin to the moment they let go of the last one in the correct location. This test will also be repeated 3 times per subject with improved finger control and without. Once time data has been taken from all subjects in both tests, the means will be compared using a matched pairs t test to see if their difference is statistically significant, thus making one program most likely more beneficial than the other for the tested amputees.

Specific Aim #1: Allow transradial amputees to have dexterous control of each of their five fingers through the use of myoelectric prosthetics.

Justification and Feasibility**.** The methods described above sufficiently support this aim as the machine learning model is specifically designed and trained with this goal in mind. Its outputs are also specially designed to fit the motion of fingers.

Summary of Preliminary Data. My preliminary data will be gathered from my own arm. I will go through the process described in the methodology above, training the model on a fully functional arm. I will then go through a set of test positions, some of which are being trained and others not, to observe the accuracy of the model given the training done.

Expected Outcomes. The expected outcome is that there will be rudimentary control of the independent fingers. It is expected that the machine learning algorithm will correctly find the finger positions 70% of the time within 5% of the actual value. These expected results will allow some room for growth in the methods to better the accuracy.

Potential Pitfalls and Alternative Strategies. We expect the selected hand positions for training will not work as intended on the first try. We expect that this will have to be consistently reworked until the goal of correctly finding finger positions 70% of the time within 5% of the actual value is achieved.

Specific Aim #2: Provide evidence that dexterous control over the five fingers will creates a significant improvement in the everyday life of transradial amputees.

Justification and Feasibility. Specific aim #2 should be easily proven using the methodology above. If subjects find a statistically significant improvement in time from the standard control method to the improved finger control method, it will be shown that it could significantly impact their life for the positive. Taking less time on the tests shows that they will be better suited to do daily tasks and thus, that this is a worthy area of research to be further developed.

Summary of Preliminary Data. Unfortunately, this specific aim cannot be backed up by preliminary data as it relies on the testing of amputees.

Expected Outcomes. We expect to see an improvement in the timed test when subjects use the improved finger control algorithm.

Potential Pitfalls and Alternative Strategies. The biggest pitfall here is the worry about acquiring human volunteer test subjects. Should I not be able to find human test subjects with transradial amputations and preexisting myoelectric prosthetics with fingers, I will attempt to partner with the WPI robotics lab. Here, I will use abled-bodied participants with no experience using myoelectric prosthetics to complete the tests. They will train the model in the same way as done before; however, they will be connected to a myoelectric arm separate from their own. They will also be given additional time to get used to the arm in both settings, with and without improved finger control, before completing the tests. This has been done in other studies when they could acquire volunteer subjects and when they could not.

Section III: Resources/Equipment

The two major resources needed for this project that are not typically available are EMG electrodes, a board capable of collecting data from EMG electrodes, a computer capable of processing training for a machine learning algorithm, and transradial amputee human subjects who use myoelectric prosthetics. The EMG electrodes and board have already been provided for this research by the Massachusetts Academy of Math and Science at the Worcester Polytechnic Institute. The researcher also already owns a computer that will most likely be powerful enough to run the machine learning algorithm. Should this computer prove to not be sufficiently powerful, the Massachusetts Academy of Math and Science has a computer that is sure to be sufficient. Regarding amputee subjects, I have reached out to a prosthesis at Next Step Bionics and Prosthetics located at 85 Prescott Street in Worcester, MA, to hopefully partner with them to find volunteer participants.

Section V: Ethical Considerations

The biggest ethical concern stems from the use of human participants in this trial. Throughout the trials, data will be taken from their muscle movements to train the neural network and data regarding the time it took to complete both tests with and without the improved finger technology will be taken. Every precaution will be taken to ensure that this data remains private and secure to offset any concerns. Before beginning any testing, all participants will be required to sign an informed consent form which would describe in detail what would occur during the testing. These informed consent forms would be scanned and stored in a password protected folder to ensure privacy. Any data collected by the participants during the testing would also be stored in a password protected folder and would not contain the names of any participants, referring to them as participant1 and so on. Finally, in the final paper, the participant's data will be averaged with no information linking any participant to their data. Their names will also not be included in the final paper unless it is requested by the subjects.

Section VI: Timeline

https://trello.com/invite/b/6720c6c23306d0c87ad8dae2/ATTI74626ed312a7ec2643813136220a7b1d3587F445/stemi

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