Surface-EMG Processing & Classification for Muscle Interfaces

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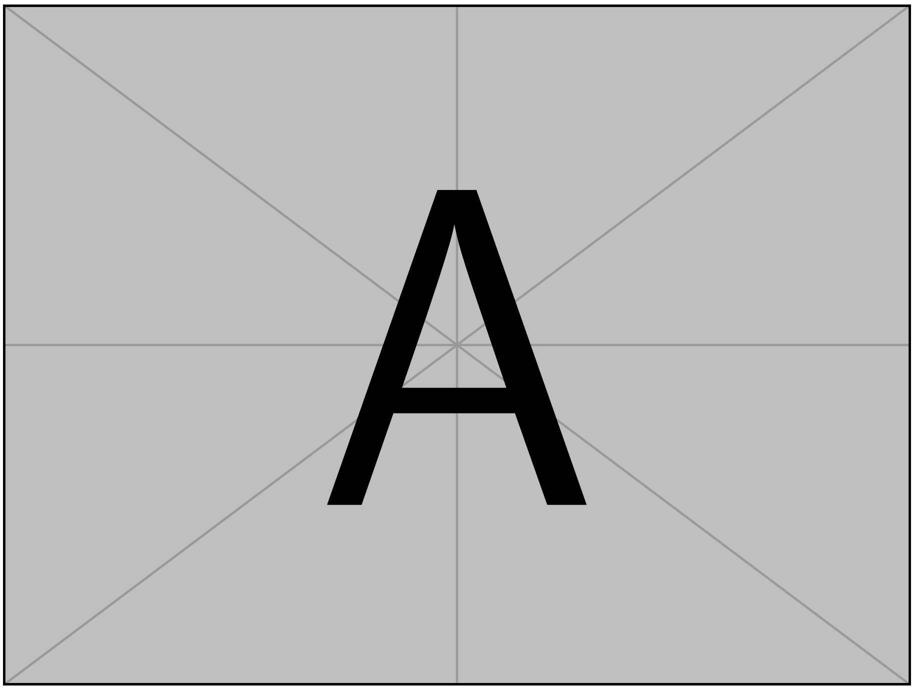

1 Abstract

Hello, this is my abstract...

2 Acknowlegdements

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Glossary

abduction/adduction Movement away/towards the midline of the hand. 14, 15

Congential A disease or physical abnormality present from birth. 6

flexion/extension The bending movement of the finger. 14

phalange Bone in the finger. 14

sEMG surface-electromyography. 8

traumatic A disease or physical abnormality due to trauma. 6

Contents

3 Introduction

The human hand is one of the most important factors of the human identity. The hand allows a person to perform complex muscolatory combinations to interact with the surrounding world, express complex emotions during speech, and aid in defining a person's individuality and personalty [???]. The hands are controlled by a complex combination on precise muscles designed to perform gentle, precise control of the fingers. This allows a person to grasp objects in many different ways, perform complex tasks such as writing, playing musical instruments, or even constructing a house. The hand also acts like a sensory device allowing us to perform precise observations through feeling and touch. This allows a person to understand the environment without seeing it, the hand is able to sensor heat/cold, create complex understanding of geometries and texture through touch and manipulation.

Missing limbs, either Congential or traumatic amputation severely reduces a person's ability to interact with- / understand the world, express themselves and perform simple day-to-day tasks. In order to alleviate some of the drawbacks of missing a limb, amputees are often able to aquire a prosthetic replacement of their lost limb. The aquired prosthetic tries to imitate the movements of the lost limb, through muscle-activated interfaces, that is then used to control the movements of the prosthetic. In the case of hand prosthetics, the prosthetic allows the user to perform simple, day-to-day tasks, and is able to alleviate some of the stress caused to the non-amputated hand through overusage.

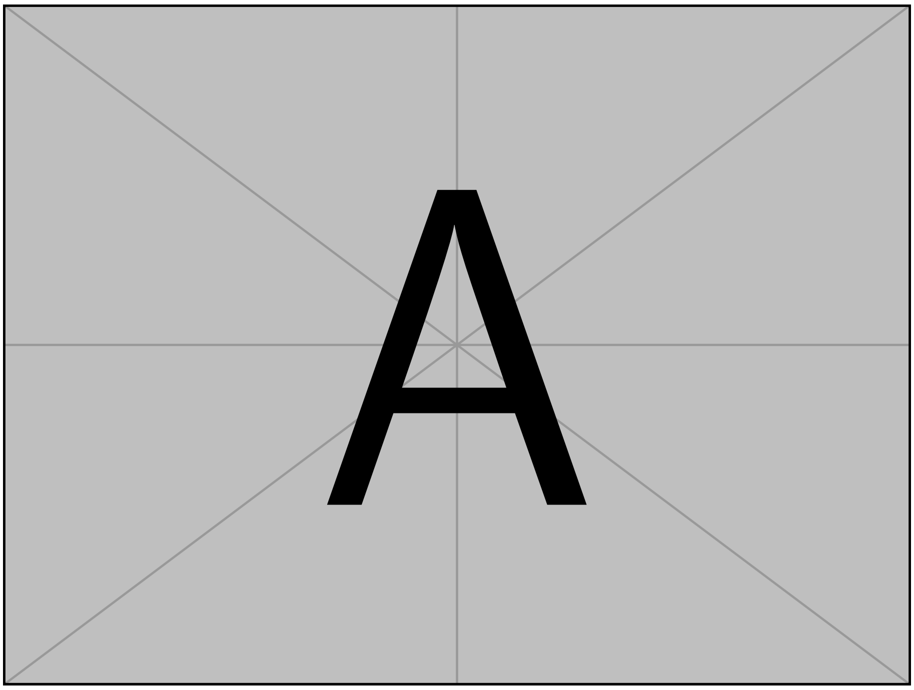

Figure 1: Example figure text

This thesis aims to summarize, and elaborate on current state-of-the-art research and products in the field of prostetics devices, and products the control of prosthetics and the existing limitations of these state-of-the-art products.

This thesis aims to contribute to the world of prosthetics control, by researching effective methods of collecting sensory data from the lower-/upper-arm, and by doing so, creating an state-of-the-art Artificial Intelligence (AI) based controller, that is able to imitate the intent and movements or a real hand. And by doing so, by improving sEMG controller design to increase functionality and the controllable DoF of the prosthetic, to provide a more true-to-life experience to the prosthetics user, and thus reduce the amount of patients that disregard prosthetics.

This thesis also aims to explore efficient methods of designing a network to identify lower-/upper-arm muscolatory intent, with the purpose of controlling a simulated prosthetics device, and by doing so, increase the controllable Degree-of-Freedom for the prostetics user.

4 Problem Specification

There is a large need for new technology that improves the effectiveness and ergonomics of human hand prosthetics.

Current state-of-the-art products on the market exhibits a severe reduction of controllable Degree of Freedom (Dof) compared to their biological counterparts. These products often rely on simple, grasp control based on 2 or more surface-electromyography (sEMG) interfaces, to classify "open/close" signals for the control scheme. The prosthetics user is then manually required to change grip control-scheme, creating very crude control dynamics that is very different from biological hand-control. A indebth explanation of "open/close" control can be seen in section **??** This is a great pitfall in the field of Research and Creation of prosthetics, as unsatisfactory function of prosthetics lead to amputees, that exhibit a great deal of stress douring the rehabilitation process.

This can cause the patient to repel the rehabilitation process and the prosthetic all-together. The repelling of the prostetic increase in the cases of the most severe cases of amputation, where the largest amount of control muscles are lost. These amputations are often located further up the limbs, where the loss of mobility and controllability are greatest. The amount of muscles leftover from amputation also dicates the type of prosthetic a patient is able to recieve. Patients of lower-arm amputation has less control over their prosthetic than patients of hand amputation, due to the loss of the muscles in the lower-arm. The loss of control increases as the amputation severity increases, and this is a problem in prosthetics design because it is impossible to create a standardized controller that suits most patient's needs.

State-of-the-art commercial prosthetics further decrease the controllable DoF in order to increase robustness of the control experience, this is further elaborated upon in **??**.

4.1 Motivation

The main goal of this thesis is to provide a meaningful contribution to the world of prosthetics design and control. In order to confine the workload done in this thesis, a set of development goals has been made:

1. Create a software-based, biology-inspired, anatomically realistic simulation of a humanoid lower-arm/hand that is able to imitate the movements of the humanoid limb.
2. Make the prosthetics simulation controllable from a widely-used robotics-software.
3. Design a sEMG muscle pre-prossesing pipeline for a prosthetics controller.
4. Design a state-of-the-art prosthetics controller based on AI, to control a simulated prosthetics device.
5. Create a custom dataset to train AI based controllers for prosthetics.

6. Test and Validate the created prosthetics controller against state-of-the-art methods.

5 Literature Review

As sensors capability for for biological sensoring increases in state-of-the-art prosthetics development and research, there becomes a larger need for translating sensor data into usable input data for prosthetics controllers. A lot of reserach has been done in this area, this research elaborates on different Machine learning or AI-based methods of understanding muscle-based sensor data. The pipeline for converting EMG sensor data to usable input data often contains a pre-processing step, where data is de-noisified, and cleaned of potential errors. The pre-processing step can also contain feature extraction such as ... The pre-processing step is then followed by a processing step, this step encompasses the use of a Machine-learning algorithm or a Neural Network, designed to either Classify a grip type, or Regress the angle of the joints. After Classification or Regression a post-processing step can be added where the actual kinematic data is created, and used as input to the prosthetic controller. Popular methods of processing EMG signals will be researched, and elaborated upon, with the aim of identifying robust, effective and implementable methodologies.

5.1 Introduction to Literature

Human Machine Interfaces (HMI), are control systems that enables humans to interact and control a mechanical or robotic system. As explained in the paper [1], researchers and prostecisists have been developing mechanical prosthetics for many years. One example of such devices would be the ankle-foot-orthoses, a support device strapped to the angle, used to relieably adjust the pressure applied by the body while walking, to help impared individuals with walking in a more natural way. [1] proposes that EMG signal based control research are a ongoing topic in rehabilitation and prosthetics. Generally, EMG is an experiment-based method of evaluating and recording electrical signals from muscles. Specifically, EMG signals eminate from the exiciability of muscle fibers through neural control, causing action potentials that cause depolarization and repolarization of the muscle membrane. These polaziration changes can be detected using EMG sensors, either through non-invasive or invasive techniques. Invasive EMG signal recording requires the use of a penetrating needle electrode to be placed in the muscle tissue, this method reduces the signal-to-noise ratio (SNR) but can be a cause of discomfort and infection. As an alternative, non invasive EMG sensors, placed at the surface of the skin are called sEMG sensors, they provide much less discomfort and propose no risk of infection to the amputee, at the cost of having an increased SNR. [1] explains that the muscle fiber membrane has a resting potential of -90 to $-90mV$ when resting. The paper also explains that the amplitude of sEMG signals have a voltage range from 0 to $10mV$, and a frequency range from 10 to $500Hz$.

5.2 Noise in EMG signals

The paper [1] poposes different noise types that contaminates EMG signals, these noises are defined as electrical signals that are not part of the decired EMG signal. The different noise types found in EMG signals are

- Inherent Noise in Electronics Equipment,
- Ambient Noise,
- Motion Artifacts,
- Inherent Signal Instability,
- Electrocardiographic (ECG) Artifacts,
- & Cross Talking.

Noise in Electronics Equipment exists in all electronic devices, this noise has been proved to be reduced by using electrodes made of silver. **Motion Artifacts** affects EMG signals when the skin and electrodes move in relation to the movement of the underlying muscle. This can cause artifacts due to inconsistent displacement. **Inherent Signal Instability**, The amplitude of EMG signals are quasi-random. Frequency components less than 20 Hz are unstable and affected by firing rate of the motor units. This range is considered unwanted noise. Muscles change based on their active motor units, therefore the EMG signal changes too. **ECG Artifacts** is the electrical activity of the human heart is a huge interference component of EMG signals recorded from the Shoulder Girdle (Shoulder muscle groups). It is very hard to remove ECG artifacts from EMG signals, due to their relative charactaristics in the frequency spectrum! **Cross Talk** is undecired EMG signals from muscle groups not commonly monitored. i guess its a form of EMG leak from undecired muscles.

5.3 sEMG Sensors for Prosthetics

The usage of sEMG sensors propose a lot of obstacles because of noise, but that does not stop sEMG sensors from being part of the state-of-the-art research in prosthetics. In the paper [2] proposes that the usage of sEMG sensors are of great importance in upper-limb classification for prosthetics devices. The paper uses sEMG sensors to classify reaching-to-grasping tasks using a Convolutional Neural Network (CNN) after pre-processing the signal with Principal Component Analysis (PCA) to reduce noise. The processing combination method of PCA-CNN proved to show higher accuracy than Machine Learning methods, such as Support Vector Machine (SVM) with an accuracy of $70.1 \pm 9.8\%$ based on 9 subjects. The paper proposes that the sEMG sensors are placed on the upper-body in combination with the upper-arm for grasping intention classification, specifically, the muscles *Pectoralis*, *Trapezius*, *Latissimus Dorsi* & the *Biceps/Triceps*, see section **??** for placements. In [2], the *Southhampton Hand Assessment Procedures (SHAP)* [3] was used to create a dataset. SHAP is designed for the assessment of musculoskeletal and neurological conditions, and can be used to test the effectiveness of prosthetics.

Another paper that proposes the usage of sEMG sensors for prosthetics is [4]. The paper The paper proposes the usage of different sEMG devices, two of those are the wearable product “Myo Armband”, [5] a discontinued sEMG product consisting of 8 sensors that can be placed below the elow joint, and the “Delsys Trigno” [6], a set of individual sEMG sensors that can be worn and record most muscle groups.

[4] proposes the pre-processing of the sEMG data using a Notch filter of 50Hz. Furthermore, the target angles obtained as ground truth targets were reduced in dimensions through PCA, thus having the 6 dominant PC's be the targets. Then, using an "Inverse PCA algorithm", they compute the final control output for the prosthetic. In order to process the sEMG data, [4] proposes the use of a time window of $200ms$, with feature extraction for root mean square (RMS) & zero crossing (ZC). The extracted features were used as input to a nonlinear autoregressive exogeneous (NARX) network, that consists of a fully-connected multilayer-perceptron (MLP) network combined with a recurrent neural network (RNN).

5.4 Adaptive Grasping Methods

Most state-of-the-art methodologies consist of using sEMG data to predict grasp type classification or joint angle regression. The paper [7] proposes that this method becomes a burden for the HMI user, as the severity of the amputation increases and the loss of muscle recording arears become greater. [7] takes inspiration from evolutionary robotics, and propses the use of evolutionary computation to predict stable grasping methods based on touch sensor input. This is done by having a mapping between the touch sensor input of the fingers and the motorcontrol of the joints. [7] uses a simulation to train a RNN network, this RNN takes sEMG sensor data, Touch sensor data, distance to the object & object height into account. It is possible to compute distance to / height of object because grasping and training is done entirely in simulation, using a simulated target object, but that the method used would be realiseable for prosthetics. The paper concludes that alongside sEMG sensors, touch sensors could be used to appropiate joint motion could be predicted using contact states between hand and object.

The paper [8] proposes a passive solution to adaptiveness when grasping. Their method uses an underactuated, compliant linkage mechanism, where the joint rotation of the finger joints can be driven by a single motor. This allows the fingers to not rely on touch sensors, as the method in [7] does. [8] proposes the use of a sliding window with a size of $250ms$. The window is then processed using feature extraction of integral myoelectric value (iEMG), RMS, mean absolute value (MAV) & ZC with a threshhold to eliminate low signal fluctuation from noise. The extracted features are used for linear discriminanr analysis (LDA) to classify grasping intent. The paper proposes that LDA showed the highest accuracy out of different Machine Learning methods.

5.5 Grasping Intention from the Upper-arm

Another way of reducing the usage of lower-arm muscles when designing hand prosthetics would be to predict the intent of the user's actions based on upper-arm grasp prediction. The focuso of the paper [9] on recording and classification of upper-arm. The paper proposes a learning approach that decodes grasping intention during the reaching motion for upper-limb prosthetics. For pre-processing, a 30-350Hz bandpass filter is used on 12 muscles, 7 located in the upper-arm and 5 located in the lower-arm. These muscles are passed through a buttersworth filter with cut-off at

$20Hz$. Furthermore, the elbow joint angle was measured using a goniometer. [9] proposes that a sliding window of $150ms$ should be used, and they use no dimensionality reduction method such as PCA. The paper tests 2 different machine-learning methods, LDA and Support Vector Machine (SVM), that utilize feature extraction of the average activation, waveform length and the number of slope changes for each window. Additionally, the paper tests an echo state network (ESN) using the given window of data with no feature extraction.

5.6 Alternatives to sEMG-based prosthetics

Research of prosthetics control interfaces expand into a multitude of areas. The paper [10] proposes the use of a brain-computer-interface (BCI) as an alternative to HMI. BCI is a type of technology that uses brain activity and the brain's neural information to control machine interfaces such as computers, assistive technology & prosthetics. BCI's have great benefit in areas where access to muscolatory information such as sEMG is impossible due to loss of muscles in the target recording area, or due to paralyzation where it becomes impossible for the patient to activate the targeted muscle groups. One dominant method of acheiving a BCI interface is electroencephalography (EEG). The purpose of [10] is to detect individual finger control using EEG sensors. EEG functions similarly to EMG but with the focus on recording brain activity instead of muscle activity. EEG is a non-invasive, portable and low-cost sensoring type, that provides a high temporal resolution in comparison to other methods that detects brain activity, according to the paper [11]. [11] explains the great need for assisted rehabilitation devices and prosthetics, and that the need will increase in the future. Brain Computer Interfaces using EEG sensors needs to be further researched to increase overall performance of the system. [11] proposes that that the most used method of controlling a prosthesis or a rehabilitation device using EEG is to pre-process/filter the recorded data before segmenting it using a sliding window. Using the windows, feature extraction in both time & frequency domains are used as input to a feature reduction algorithm. These features are then subject to a classification network in order to transform the EEG data into motorcontrol for the BCI. It can be noted that the EEG sensor contains artifacts from other parts of the brain, such as eye movement, cardiac activity or contraction of the scalp muscles. Overall performance of using EEG for prosthetics control is low compared to more conventional methods such as EMG [11] . Furthermore, the setup for EEG recording is more complicated than EMG.

6 Summary of Literature

The state-of-the-art literature spans different methods of creating human machine interfaces. The main areas of creating interfaces are Muscle-/neuron-based recording and brain-based recording. Due to the large amount of cross-talk noise from brain-based sensoring, it is apparent that to increase overall controlability and robustness of a prosthetics device, the prosthetic is required to use EMG based sensoring for its contro. By reviewing the state-of-the-art literature in sEMG-based hand prosthetics, it is apparent that if a Machine-Learning & Neural Network (except RNN), are to be used, we need to use a sliding window technique with a size of $150ms$ to $250ms$. It can be noticed that all methods use a pre-processing filter step on the raw EMG data, but that the choise of filter varies greatly. Amongst the most used filters are Buttersworth & lowpass filters with diffent frequency responces. 3 different methods of classification/regression of sEMG data are used: **Machine Learning**, **Window-Based Neural Networks**, **Recurrent Neural Networks**. algorithms such as LDA, SVM & ... As an alternative to ML, most literature proposes the use of **Neural Networks**, on the sliding window. Alternatively, methods not using a sliding window are recurrent networks, such as the echo state network or the NARX network. These Recurrent methods would also be applicable due to the continorous nature of the data.

7 Methodology

7.1 Design of a Prosthetic Hand

In order to design a state-of-the-art simulated prosthetic hand, a number of anatomical design choises needs to be considered. This thesis tries to create the most anatomically-correct hand simulation available, this will hopefully have a number of positive effects on prosthetics research. By having access to an advanced simulation, it would in turn be able to test and visualize more advanced movement controllers that can facilitate more DoF than current commercial prosthetics. By creating an anatomically correct prosthetic hand simulation, it is hoped that prosthetics users can have more advanced rehabilitation, and learn to have more natual control of their prosthetics. This would create a more natual usage experience, and decrease the percentage of users that reject the usage of their prosthetic alltogether.

A set of requirements The simulated anatomically correct hand should be determined in order to create a state-of-the-art prosthetics simulation.

The simulated prosthetic should:

1. Facilitate the same DoF as an anatomically correct hand.
2. Have porpotions that closely resemble that of an anatomically correct hand.
3. Be simulated and be controllable in a commonly used robotics software to increase accesability for researchers.

7.1.1 Brief of used Software

Coppeliasim see [12].

7.1.2 Anatomy

The hand is an anatomically-complex appendage designed to facilitate a large amount of control in different usage scenarios. The hand consists of 27 bones, 14 of these are called phalnages, and make up the 4 fingers and the thumb. These bones, alongside a complex set of ??? muscles facilitates 24 DoF (Not counting Translation of the entire hand).

The individual finger consists of 3 bones called phalange, arranged linearly from the palm of the hand. The 3 finger bones are called the proximal phalange, middle phalange and distal phalange. The joints between the phalanges are able to do flexion/extension movement, while the base of the finger is further able to do abduction/adduction movement.

7.1.3 Simulated Hand Articulation design

In order to translate the biology and anatomy of a real hand into an robotics simulation, we start by denoting the relative lengths of the wrist bones and phalnages by refrence, as can be seen in figure 2.

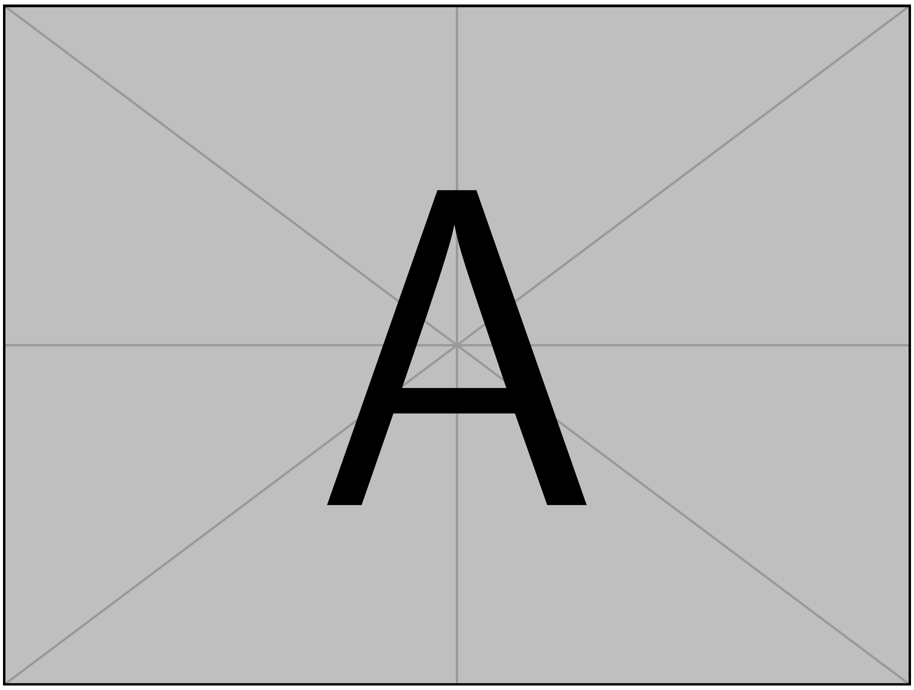

Figure 2: Example figure text

The porpotions of the refrence is used to denote the bone lengths for the model. The model is implemented in Coppeliasim **??**, The model is created in a hierachy, the bones are created with cylinders and the joints are created using 1 DoF Revolute joints. As specified in section 7.1.2, some joints of the human hand facilitates 2 DoF of rotation. This is needed in order for the wrist and finger base joints to be able to do abduction/adduction. To simulate this, two 1 DoF revolute joints were placed in series, thus allowing 2 DoF.

7.2 Dataset Creation

In order to train a simulated hand prosthetic, a sofisticated dataset containing the measured relation between muscle activity and the finger placements is needed. The recording of the dataset is done using the software explained in section 7.1.1, namely Motive [13] & EMGworks [14].

7.2.1 Motion Capture Glove

In order to get precise recordings of the motion of the hand and fingers, using Motive [13], flourecent 3D markers were placed on a glove. The pattern of the marker positions were carefully closen in order to calculate the angles of the individual finger bones. The precise positions of the 3D markers on the recorder glove can be seen in figure 3.

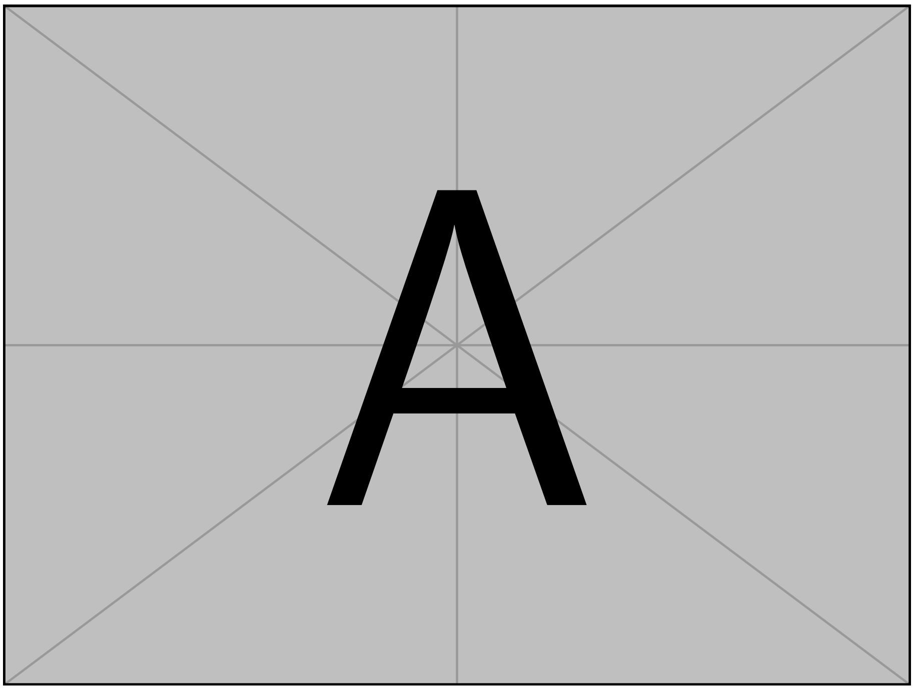

Figure 3: Example figure text

7.2.2 Sensor Locations etc.

The muscle recording sensors are located along the muscles of the forearm, the exact positions can be seen in figure 4.

7.2.3 Trial/motion overview

7.3 Implementation

7.3.1 Data Pre-Processing

7.3.2 Network Design

7.3.3 Software Hand Design

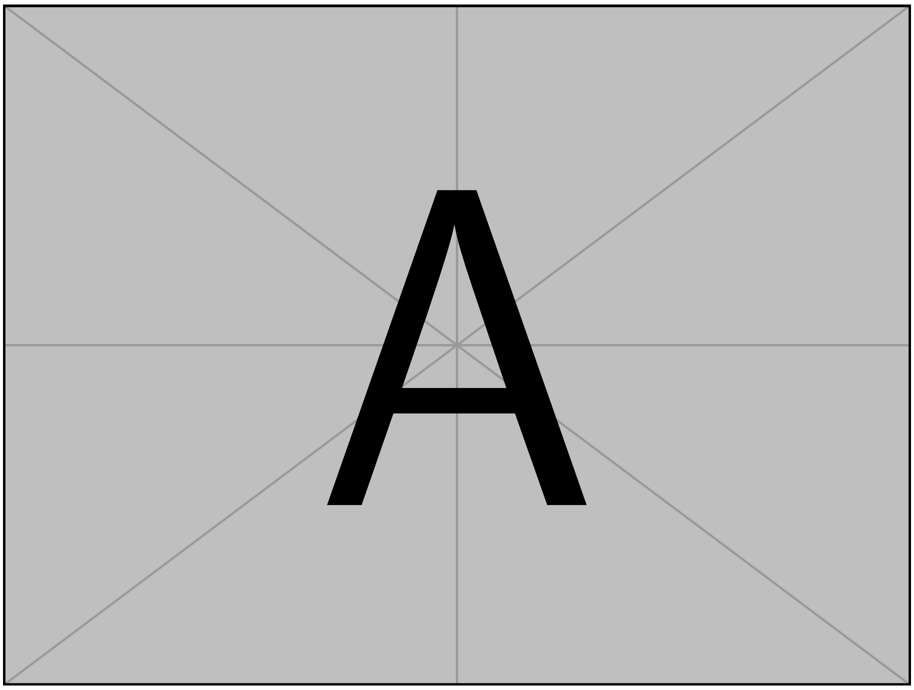

Figure 4: Example figure text

8 Tests & Results

9 Discussion

10 Conclusion

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10.1 Future Work

11 Bibliography

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