AALBORG UNIVERSITY
STUDENT REPORT

Simultaneous and proportional control of reaching and grasping

P7 Master project - Autumn 2017

Group 17gr7404

AALBORG UNIVERSITY
STUDENT REPORT

7th Semester, Master Project

School of Medicine and Health

Biomedical Engineering and Informatics

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Titel:
Simultaneous and proportional control of reaching and grasping

Theme:
Biomedical signals and information

Project period:
P7, Autumn 2017
01/08/2017 - 19/12/2017

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17gr7404

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Pages: 9000
Appendixes: maybe
Afsluttet: 19/12/2017

Abstract

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Preface

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1 | Introduction

In recent years the development of EMG controlled prosthetics have advanced considerably, due to an increased interest in the area along with a higher demand for better prosthetics and more precise control. [1] In the early years most EMG prosthetics functioned by only controlling one DOF by *on-off control*, mostly by linking antagonistic muscles to one DOF. This along with *mode switching* provided users a way to control more than one DOF, but never simultaneously. However, as demands would rise, more complex methods was introduced to the EMG scene, and proportional control was introduced with pattern recognition methods. This effectively enabled simultaneous control of more than one DOF, but gave rise to new problems; a wider range of control would give less accurate movements, and training the pattern recognition methods proved difficult, as the training could overfit, causing extended use of the prosthetics to degrade in performance. [2] More advanced prosthetics have also been developed making it possible to control several more DOF, especially for individual finger movements. However, no EMG-based control scheme has been able extract an adequate amount of information to effectively control these advanced prosthetics. [3]

A study by Fougner et al. [4] have addressed the problem that most studies test their algorithm/method on only one position. This proves a problem when it have been shown that muscles create muscle-synergies to perform movements, and so a change can be seen in recorded EMG signals from muscles when the arm is positioned in different positions. [5] [6] [4] In order to overcome this problem Fougner et al. [4] has suggested to combine recording of EMG signals with data from an accelerometer to provide arm position data, would be beneficial in increasing the accuracy of EMG controlled prosthetics. Fougner et al. used linear discriminant analysis with four time domain features (mean absolute value, zero crossing, number of turns, waveform length) to analyse the EMG signals. They used the acquired position data to form feature vectors to represent different arm positions. They then classified the data in four different training schemes, with results showing improvement in classification, reducing average error from 18% to 5%. [4] A novel approach to improve on these findings would be to include data from inertial measurement units (IMU) to the training of the regressor.

It is possible to do proportional and simultaneous control of two DOFs in a lower-arm prosthesis, while having the arm in different positions, using simple/multiple linear regression on recorded surface EMG signals and inertial measurement units.

2 | Background

2.1 Anatomy of the lower arm

This project will focus on the lower arm as the Myo armband will be used extract information from this part of the body. The anatomy of the lower human arm will briefly be described in this section along with a description of relation between lower arm muscles and hand movements for selected gestures.

The human arm is designed to give humans a manoeuvrability and dexterity to coordinate and execute complicated and precise hand and finger movements with ease. Each movement happen on an axis, and each axis denotes one degree of freedom (DOF). The arm posses six DOFs as shown in 2.1.

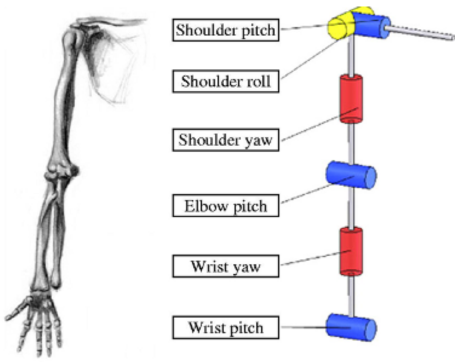

Figure 2.1: Visualisation on the arms six degrees of freedom. [7]

The number of DOFs is defined as the number of possible input parameters to a movable mechanism, where each input controls an independent movement in one axis. Several bodies can work together in relation to each other, but to total number of DOFs will be the number of possible independent movements that can be performed between the bodies. [8]

The great dexterity of the human arm is achieved through the use of several muscles which intertwine and make synergies to perform all the different gestures of the hand [9] [5]. Muscles in the lower arm is arranged in layers, having an outer, middle and inner layer. These muscles are used to rotate the forearm, flex and extend the hand at the wrist as well as performing ulnar and radial deviation. The muscles control extension and flexion of the fingers at each separate joint and the movements of the thumb, so that hand can be opened and closed. This enables movement in six DOFs of the arm and several more at the hand and fingers.

The aim for this project is to translate ulnar and radial deviation along with extension and flexion of the wrist via EMG signals to control a robotic arm. Therefore, only selected muscles will be relevant to further investigate.

PICTURES DEPICTING adduction and abduction and flexion and extension)

Muscles involved with radial and ulnar deviation includes several muscles in the arm. Most of these muscles extend throughout the whole forearm as most of them originates from the distal lateral surfaces of humerus or the proximal portions of radius and ulnar, and extends towards the wrist and fingers to fixate on the metacarpal bones in the wrist and through tendons fixate on the different phalanges bones of the fingers and thumb. Radius and ulnar deviation is depicted in 2.2.

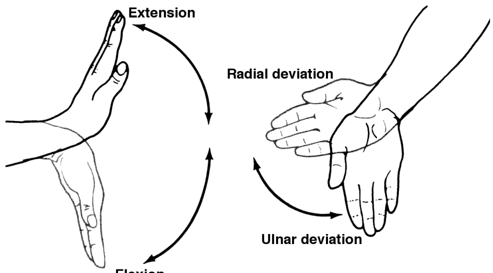

Figure 2.2: Flexion, extension and radial and ulnar deviation of the hand. Modified from [10]

Several more muscles in addition to those responsible for ulnar and radial deviation are involved with the flexion and extension of the wrist. Like the other muscles, the flexor and extensor muscles also extend through the whole forearm from the distal part of humerus and proximal parts of radius and ulnar to the metacarpal bones in the wrist. Many of these muscles are included in movements of both radial/ulnar deviation and flexion/extension, though flexion/extension have one muscle who is only used for flexion at the wrist, the palmaris longus muscle. This can be explained as more force is usually needed in flexion at the wrist than in extension or radial/ulnar deviation. Though several of the same muscles are included in both types of movement, studies have shown that it is possible to differentiate between recorded EMG signals form these muscles when performing radial/ulnar deviation and flexion/extension at the wrist. [3]

2.2 Origin of electromyography

write head: head also make sure Martin is not lying about origin of the EMG signal (motor unit action potential VS calcium release from the SR)

The electric potential detected with electromyography is an action potential causing the muscle to contract. Certain mechanisms are involved for this to happen. The motor unit of the muscle needs to be activated alongside with its associated alpha motor system, which is the lower motor neuron, its axon, and the muscle fibers the motor unit innervates. The muscle fiber is an excitable cell with a resting potential of between -90mV and -70mV. A threshold of approximately -55mV needs to be reached for an action potential to be generated. The sarcolemma, the membrane covering the muscle fibers, has sodium and potassium ion channels that maintains the resting potential, depolarize the muscle fiber if the threshold is exceeded or repolarize the muscle fiber. [11]

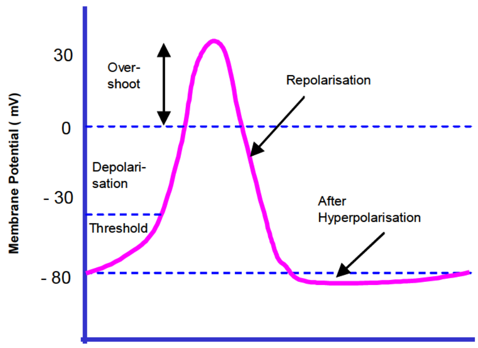

Figure 2.3: Illustration of the action potential exceeding the threshold for it to be generated and the following depolarization and repolarization. [12]

The lower motor axon is branching out so that it can attach to the muscle fiber at the motor end-plate and create neuromuscular synapses. The action potential traveling down the axon reaches the synapses and releases Acetylcholine (ACh). ACh raises the permeability of the cell membrane where sodium ions influx and causes the membrane to depolarize. Calcium ions are released and binds with troponin and exposes the active sites on the thin filaments which allows the muscle to contract. The action potential travels along the whole muscle fiber through t-tubuluses. This happens in both directions from the motor end-plate to the tendentious attachment. When the peak of the depolarization of about 30mV is reached a rapid efflux of potassium ions causes the muscle fiber to repolarize and reach its resting potential again. [11]

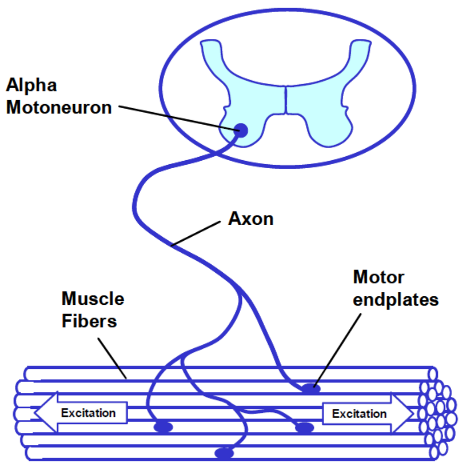

Figure 2.4: Illustration of the action potential exciting the muscle fiber, which causes the release of calcium ions and the muscle to contract. [12]

Depending on the force that needs to be applied for a given task more or less motor units are activated and therefore more or less muscle fibers are contracted. The bigger the force the more motor units are activated. Furthermore, the number muscle fibers per motor unit varies between muscles in the human anatomy. The finer the movement the higher the innervation, e.g. the lower arm muscles has a higher innervation than those in the quadriceps. [11]

As mentioned this project focuses on the mapping of different hand gestures. This mapping relies on that the generated EMG from the different hand gestures are differentiable. For a prosthetic user a good performing prosthesis must perform hand gestures as well in an elevated limb position as in a seated position to be able to support the user in daily tasks, e. g. taking a cup from a cupboard and pouring water into the cup. However, changes in the EMG occurs when performing the same hand gestures in different limb positions. These signal alternations can occur for different reasons. Changing the limb position can lengthen the muscles and result in a change in the signal source relative to the electrode from which the EMG signal is obtained, and even the lengthening of the muscles itself due to changing limb position will alter the EMG activity caused by a degree of overlap of the thick and thin filaments. Other findings has shown that the activity of certain muscles' is depending on angles of joints besides those primarily actuating the contraction of these muscles. Thus, this limb position effect must be seen as an important aspect to take into consideration in the mapping of hand gestures to control a prosthesis for the user to receive a good performing support device.

2.3 Electromyography acquisition

The following section will contain an explanation of the main component of acquiring EMG signals using surface electrodes.

When acquiring EMG signals the electrodes act as a transducer by converting the differences in ion distribution on the skin surface caused by ion exchange under muscle activity, into an electric current. Surface electrodes used to aquire EMG signals comes both with and without gel covered surfaces, where the the Myo armband employs dry electrodes. Using dry electrodes will often be more practical in use, while the gel covered electrodes will aquire more exact readings of the signals. [13] [11]

The most commonly used electrodes for EMG are made of disposable silver-impregnated plastic, and in order to keep the electric potential on the skin surface stable and reduce impedance between the surfaces, they are often covered in a silver chloride gel. Using dry electrodes will result in a higher surface impedance, which means that the signal contains more noise compared to a gel covered electrode. However, when using dry electrodes the skin will itself provide a "gel" by sweating which will increase readings and decrease the impedance. [11]

2.4 Myo armband

Myo armband is a interactive gesture system developed by Thalmic Labs capable of identifying the movements of hand and arm in order to interact and control different electronic devices.

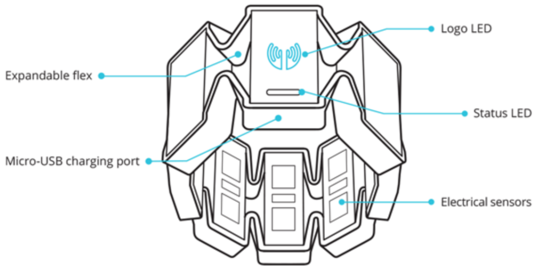

Figure 2.5: Main components of the Myo armband. **SOURCE**

The Myo armband has eight medical grade stainless steel EMG sensors, responsible of recognizing each gesture. These electrodes are dry and therefore not covered in silver chloride gel to reduce impedance between the electrode and skin. However, it has been shown by Mendez et al. SOURCE that the EMG recorded with the Myo armband is a suitable acquisition system for mapping hand gestures compared to conventional EMG acquisition. The only mapping method used in that study was linear discriminant analysis, and it is noted that other mapping methods should be investigated to further validate the quality of mapping the EMG obtained by the Myo armband.

In addition, it has a nine axis inertial measurement unit (IMU) which enable the detection of arm movement. The IMU includes a three axis accelerometer, a three axis accelerometer and a three axis magnetometer. An IMU is an electronic device that provides information concerning position and orientation for navigation and stabilization purposes. The accelerometer measures the physical acceleration experienced by an object, where the object in this case is the body part where the Myo armband is placed. It gives information about the acceleration experienced relative to free fall and expresses this in g-force. One g-force being when the accelerometer is at rest on the Earth's surface. That is since all points on the surface of the Earth is accelerating upwards relative to an object in free fall near the surface. For the g-force to change from one g-force the accelerometer must be exposed to motion. The gyroscope has the property of measuring angluar velocity. The magnetometer has the property of measuring magnetism. (something about the actual data the myoband provides and how many axes a magnometer actually has). **SOURCE more text on the data types we are going to get from the IMU's**

The Myo armband is capable of pulling sEMG data at a sample rate of 200Hz while the remaining data (accelerometer, gyroscope and magnetometer) is pulled at a sample rate of 50Hz. Thus, the Myo band arm supplies two kinds of data, which is spatial and gestural. The spatial data provides information about the orientation and movement of the user's arm given by two data types: orientation and acceleration. Thes are provided through the accelerometer and gyroscope. Gestual data provides information about the users hand gestures and is provided through EMG recordings. The recorded signals can be send to other devices using Bluetooth 4.0.

2.5 JACO2 robotic arm

In this section a briefly description of the JACO^2 robotic arm will be given. It is a 6 DOF robotic arm with a three fingered hand developed by Kinova Robotics. It is lightweight ($4.4kg$), which makes this machine specially usable in assistive and collaborative applications. It is designed to help people with upper body disabilities in order to gain more autonomy in ordinary daily tasks.

Figure 2.6: 6 DOF JACO^2 robotic arm from Kinova Robotics. [14]

new more exciting picture of the same thing

The JACO^2 is a serial manipulator, which means that this kind of robotic arm is designed as a series of links connected by motor-actuated joints that extend from a base to an end-effector. Any movement in a joint affects all the following joints and links in the chain. The arm can by default be controlled with the help of a joystick, but it can be programmed in C++ to be controlled by other means, using the software development kit (SDK) provided by the manufacturer.

include picture of JACO arm with all the names of things on/in it.

2.6 Preprocessing of EMG

Surface EMG is emitted up to 500 Hz and depending on the area of the EMG acquisition, it is recommended to implement a bandpass filter from 25 to 500 Hz in order to avoid low frequency movement artifacts in the recorded signal. If the EMG is acquired from an area close to the heart, it would be preferable to filter from 100 Hz in order to avoid recording artifacts from the heart. A downside to this bandwidth is that fatigued muscles will fire at a lower rate, which means the performance of the system will be affected when the subject gets tired. [11]

In order to achieve a higher signal to noise ratio (SNR) it is common practice to implement preprocessing methods, including input impedance, differential amplification and filtering. The raw EMG signals has to be preprocessed due to them being sensible to noise elements from the surroundings, since the range of the signal is in the order of millivolts to microvolts. Input impedance is determined by a simple rule in order to avoid defeating the common mode rejection of the EMG amplifier. The rule states that the input impedance of the EMG amplifier has to be between 10 and 100 times higher than the impedance of the skin-electrode interface. [11]

Differential amplification is used in EMG in order to amplify the original signal and remove common signals from two or more electrodes, in order to avoid common noise from more electrodes in the amplified signal. The amplifier must have a build in gain as well [1], which determines the final strength of the signal, and both of these features are implemented in order to avoid the SNR. Basic filtering should be implemented in order to avoid electrical noise. This filter would be implemented as a notch filter, in order to reject the electrical noise and achieve a higher SNR. Furthermore the filtering should include a bandpass filter with a bandwith chosen depending on where the EMG is performed. This is done in order to make sure the final signal doesn't contain irrelevant high and low frequencies.[11]

2.7 Feature extraction

Following preprocessing of the recorded EMG signal, features can be extracted and used to map different hand gestures. When analyzing EMG signals there will be three different signal components to be extracted, which are the frequency and time domains, as well as the time-scale representation. Frequency domain features require a Fourier transformation of the signal, which requires more processing than the direct extraction of time domain features. [15]

[1] FiXme Note: check what the preprocessing properties are for the Myo armband - this should be mentioned in the myoband section. If we start writing it here, we're mixing stuff from different sections which causes confusion when reading the project..

Based on the study af Hahne et al. [3], we will choose logarithmic variance as the feature to be extracted from the recorded EMG signal. Hahne et al. finds that the cross-validation performance improves significantly with the use of linear regression combined with logarithmic variance, compared to combining the linear regression with variance or RMS. [3].

2.8 Regression methods

Regression methods are widely used is statistics as a method to determine relationship between variables. It can be used to extract relations to predict future developments or tendencies in a given data set. It is also a commonly used method to evaluate EMG signals to determine different parameters.

The most basic form of regression is linear regression, which is a test for linear dependency between two variables. In simple linear regression it is investigated how one, dependent variable, is related to another, independent variable. The term *simple* denotes that only two variables are being considered simultaneously. The equation for simple linear regression is: [16]

$$Y_i = \alpha + \beta X_i \tag{2.1}$$

Performing simple linear regression finds the correlation between the tested variables, and is expressed by the correlation coefficient. This coefficient describes how the two variables relate to each other by how the development of one variable is dependent on the the other. Thus a positive correlation represent that a change in one variable will resolve in a similar change in the other variable as well. On the contrary, a negative correlation imply that change in one variable will resolve in an opposite change in the other variable. If no correlation is present between the two variables no change in either variable will resolve in change in the other, and it can therefore be determined that the two variables has no relation to each other. [16] The simple correlation coefficient is calculated as: [16]

$$r = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \tag{2.2}$$

Furthermore a coefficient of determination can be calculated to express how much of the variability of the dependent variable is accounted for when regressing upon the independent variable. This coefficient is denoted r^2 and can be calculated by simply squaring the correlation coefficient (r). Both r and r^2 can be used to determine the strength of the relationship between the two tested variables. [16]

A variant of the linear regression is the multiple linear regression, which can be used in cases where the relationship between three or more variables is wished to be investigated. Here it is considered that one of the variables are dependent on two or more independent variables. Multiple linear regression can be used in cases where two or more variables are expected to have a linear correlation to a dependent variable and it is wished to find which of the independent variables who has the biggest influence on the dependent variable, so to say the highest correlation coefficient. Since multiple linear regression is based upon simple linear regression, it is modelled after the equation for simple linear regression. However, as Y can be dependent on more than one other variable at times, another can be added to the equation: [16]

$$Y_i = \alpha + \beta_1 X_1 i + \beta_2 X_2 i + \epsilon_i \quad , \tag{2.3}$$

, where the sum of the error (ϵ) is zero and is assumed to be normally distributed.

When three variables are present in the equation, the visual representation of the regression is in the 3rd dimension, and will no longer be presented as a line in 2D, but as a plane in 3D. Having more than three variables will resolve in a regression in the m-dimension, where m is the number of variables. This plane of regression is called the hyperplane. However, regression is not a perfect fit to every sample point, and thus the equation for three or more variables is only complete when the error is also calculated, denotes as ϵ.

There exist ofcourse cases where the relationship between more than three variables is wished to be investigated. In such cases, each new variable can be added to the equation, and the final can be expressed in a summed up equation: [16]

$$Y_j = \alpha + \sum_{i=1}^{m} \beta_j X_i j + \epsilon_j \quad , \tag{2.4}$$

where m is the number of variables.

There exist no limit to the number of variables which can be tested, however there should always be at least two observations more than the number of variables, so that $n \geq m+2$. Otherwise multiple linear regression is not possible. [16]

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