sEMG analysis of the forearm muscles to determine force and grip type

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I hereby declare and confirm that this thesis is entirely the result of my own original work. Where other sources of information have been used, they have been indicated as such and properly acknowledged. I further declare that this or similar work has not been submitted for credit elsewhere.

Linz, 20. Dezember 2016

Richard Schmidt

Acknowledgements

At first I would like to thank my advisor Prof(FH) Priv. Doz. Dr. Thomas Haslwanter of the University of applied science of upper Austria. In all my questions about research he supported me and added new aspects to think about.

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Finally I want to thank my wife for the great and unconditional support through the years of study.

Kurzfassung

Diese Masterarbeit befasst sich mit der Entwicklung eines geeigneten Paradigmas, zur Griff-Kraft Bestimmung bei unterschiedlichen Wiederholungsfrequenzen und Griff-Klassifizierung aus den Oberflächen Elektromyogramm (sEMG) Signalen des Unterarmes. Dies wurde im Rahmen einer Machbarkeitsstudie durchgeführt. Zu diesem Zweck wurden die sEMG Signale und die Griff-Kraft bei drei Griffarten (Präzisions-, Kraft- und Zangengriff) von fünf Teilnehmern untersucht. Um die bestmögliche Platzierung der sEMG Elektroden zu bestimmen, wurden mit zwei Elektroden Konfigurationen gemessen. Das entwickelte Paradigma enthält für jeden Griff eine Anordnung mehrerer Kraft-Messungen bei unterschiedlichen Kraftniveaus und unterschiedlichen Wiederholungsfrequenzen. Zur Überprüfung des entwickelten Paradigmas wurde die Griff-Kraft mittels linearer Regression aus den RMS gefilterten sEMG Signalen berechnet. Die Griff-Klassifizierung wurde mittels linearer Diskriminanzanalyse der sEMG Daten umgesetzt. Die Ergebnisse der Kraftbestimmung und Griff Klassifizierung weisen darauf hin, dass sich mit den präsentierten Elektroden Konfigurationen und den verwendeten Auswerteverfahren keine zufriedenstellende Genauigkeit erreichen lässt.

Abstract

This master thesis deals with the development of an appropriate paradigm to determine the grip force and the performed grip type, at different repetition frequencies, from the surface electromyography (sEMG) signals of the forearm. This was done in the framework of an exploratory study. For this purpose sEMG signals and the corresponding grip force were recorded for three different grip types (precision, force and pinch grip). The study involves five subjects. To determine the best electrode placement two electrode configurations were recorded. The developed paradigm includes for every grip type an arrangement of several force measurements with different repetition frequencies. For validation of the developed paradigm the force was determined with a linear regression model from the root mean square (RMS) filtered sEMG signals. The grip classification was determined with a linear discriminant analysis of the sEMG signals. The results of the force determination and grip classification indicate that the presented electrode configurations and the used evaluation methods cannot achieve a satisfaying accuracy.

Executive Summary

In the context of an exploratory study this master thesis deals with the development of a paradigm which determines the grip force and grip classification, based on sEMG signals of the forearm.

The developed paradigm involves three grip types (precision, force and pinch grip). Each of these grip types is represented in one dedicated measurement block. The measurement blocks consist of a calibration section at the beginning followed by 23 force and frequency tasks (section of interest) and another calibration section at the end. The calibration section consists of maximal voluntary contraction (MVC) tasks for every grasp type and one special maximum sEMG exertion task. The force and frequency tasks have six different MVC levels (5%, 10%, 20%, 35%, 50% and 66% of MVC) and five different repetition frequencies (0.1Hz, 0.25Hz, 0.5Hz, 1Hz and 2Hz).

A measurement procedure which provides video instructions for the contraction timing was developed. The measurement devices, required for the setup were arranged into a portable system.The portable kit is able to record the grip force and ten sEMG signals simultaneously. The measurement system provides live monitoring of all channels.

Five healthy male subjects were selected using convenience sampling. For an easier reproduction the results were documented in a structured way. The file labels follow a strict convention to ensure easy data excess to the required data for the analysis.

To validate the developed paradigm the measurements were analyzed regarding the force determination and the grip classification.

The force determination is based on a linear regression model of the sEMG signals. The sEMG signals and the force were root mean square (RMS) filtered and a training set of the MVC tasks was presented the regression. The force was predicted with the calculated coefficients of the model of the sEMG channels from the validation dataset. The validation dataset was represented with the force and frequency tasks. This was done for each grip type and every subject.

The grip classification was determined with a linear discriminant analysis (LDA). Seven features of the sEMG raw data were calculated. The resulting feature vector consists of ten features per channel. The data were spread into a training and a validation dataset. Both datasets were represented with a feature matrix containing the corresponding feature vectors. The feature matrixes were presented to the principal component analysis (PCA) to reduce the dimensionality of the matrixes. The reduced training feature matrix and the corresponding labels were presented to the LDA. A trained model was the result of LDA for the classification. To determine the overall accuracy a leave-one-out cross-validation was used.

Table 0.1 shows the averaged over all error of grip force determination. The electrode configuration two comes to smaller values. The result data shows, that special placed electrodes predict the force more exactly. The overall relative RMS-error was with 100% and 106% very high. This values are too high for a practical use of a simple linear regression model as force prediction model.

over all		error	precision grip	force grip	pinch grip	average
el.config. 1	mean	abs. [kg]	0.72	3.89	0.83	1.81
		rel. [%]	115	100	99	105
	σ	abs. [kg]	1.18	7.17	1.47	3.27
		rel.[%]	15	5	24	14
	rms	abs. [kg]	1.38	8.16	1.69	3.74
		rel.[%]	117	100	103	106
el.config. 2	mean	abs. [kg]	0.70	3.87	0.82	1.79
		rel. [%]	104	99	95	99
	σ	abs. [kg]	1.17	7.14	1.46	3.25
		rel. [%]	10	4	16	10
	rms	abs. [kg]	1.36	8.12	1.69	3.72
		rel. [%]	104	99	97	100

Table 0.1: averaged over all error of grip force determination

The overall accuracy of the grip classification was 55.7% for electrode configuration1 and 60.28% for electrode configuration2. The accuracy of both configurations is currently not ready for practical use and has to be improved. The results of the force determination and grip classification indicate that the presented electrode configurations and the used evaluation methods cannot achieve a satisfaying accuracy.

Contents

List of abbreviations

AR autoregressive coefficients (time domain feature)

EMG electromyography

IEA international ergonomics association

LDA linear discriminant analysis

MAV mean absolute value (time domain feature)

MNF mean frequency (frequency domain feature)

MNP mean power (frequency domain feature)

MVC maximum voluntary contraction

PCA principal component analysis

RMS root mean square

sEMG surface electromyography

SM2 second spectral moment (frequency domain feature)

WL waveform length (time domain feature)

WMA world medical association

ZC zero crossing (time domain feature)

1 Introduction

To get into the topic of this thesis, let's have a look at ergonomics, what it is and why we should address this topic. The International Ergonomic Association defines "ergonomics" as following:

> "Ergonomics (or human factors) is the scientific discipline concerned with the understanding of interactions among humans and other elements of a system and the profession that applies theory, principles, data and methods to design in order to optimize human well-being and overall system performance.
>
> Practitioners of ergonomics and ergonomists contribute to the design and evaluation of tasks, jobs, products, environments and systems in order to make them compatible with the needs, abilities and limitations of people. IEA [2016]"

This definition draws a very rough image of what ergonomics is.

> "The interaction among humans and other elements of a system IEA [2016]"

This formulation suggests that nearly every single interaction between humans and their environment has ergonomic aspects to consider. From work to home and everything in between. This thesis addresses especially the physiological interactions of the human- forearm and the hand with our environment. Our hands are precise, powerful and preserving high end tools which allow us to interact with our environment. But such sophisticated tools have physical and physiological boundaries which have to be respected.

> "in order to optimize human well-being and overall system performance IEA [2016]"

The scientific proposal to optimize these interactions, is the quantification and evaluation of the movements and the applied loads for the body. The quantification process should impair the actual task of interest as little as possible to avoid systematical measurement inaccuracy.

For the quantification of the movement there are practical solutions available. Such as goniometers which provide the joint angel. The sensors are placed at the joints of interest on the skin, with an individual model, the motion of the hand can be tracked. Another example is 3D visual tracking, which works with visual markers on the body and a fixed camera system triangulat the markers position. These are just two examples for motion capturing.

For the quantification of the body loads or grip strength solutions are also available. Perpetrated knobs or tolls with integrated force sensors which measure the grip strength / body load. These techniques are very precise, but for every individual task of interest, a whole measurement device has to be designed. This yield to long development cycles and expensive investigations. Another approach places the force sensors between the hand and the environment like hand gloves with integrated force sensors. The advantages of this approach is, precise force measurement and the capability to accomplish different tasks. The main disadvantage is the intervention to the given task. With gloves in-between the hand and the environment the haptic perception gets nearly completly lost.

In many real life situations repetitive movements for the hand occur. Especially in industrial work environments, like assembly bets or machine work, the effort to the body due to repetitive moments with strong loads is very high. Investigations in this field show a need of a practical and non-influencing load or force measurement device for the hands. J.Kappelusch [2012]

1.1 Problem statement

The problem this thesis is associated with is the need of an accurate and non-influencing measurement technique for grip force measurements. The presented approach deals with grip force prediction from recorded sEMG data and the classification of the performed grip.

1.2 Background information

1.2.1 Surface electromyography principals (sEMG)

The surface electromyography (sEMG) is a sub method of the electromyography (EMG). They differ in the location and the kind of the used electrodes. The EMG and sEMG both measure the electrical activity of the skeletal muscles. The measured electrical activity of the muscles may not be mixed up with the action potential of the nerves.

As the name let suggest, the sEMG records this electrical activation at the surface of the body, at the skin. So the electrical potential of the muscle have to pass the connective tissue to reach the skin. This yield in an electrical resistance for the signals. This resistance depends on the contact pressure of the electrode, the humidity of the skin and the thickness of the connective tissue between muscle and skin. This leads to the fact that muscles which are located near the bone have more or less no influence to the potential at the surface.

Actually measured were the differential potential between a pair of electrodes, with a differential amplifier. Differential amplifiers have a very high common mode rejection ratio, which is important to eliminate the much higher common mode interferences on the skin. The range of sEMG signals were from µV up to several mV. Such low signal amplitudes require a very high input resistance of the amplifier, to minimize the influence to the signal. The measured differential potential can't be assigned to a singular muscle, rather to the region beneath the surface electrode.

After the differential amplifier the analog voltage signal is digitalized and stored. Bischoff et al. [2005]

1.2.2 Anatomy of the forearm

The anatomy of the forearm muscles is an important issue which has to be considered during sEMG measurements. The figure 1.1 shows the surface near muscles and their position on the forearm. The electrode positioning was chosen regarding the placement of the forearm muscles. Gray [2007]

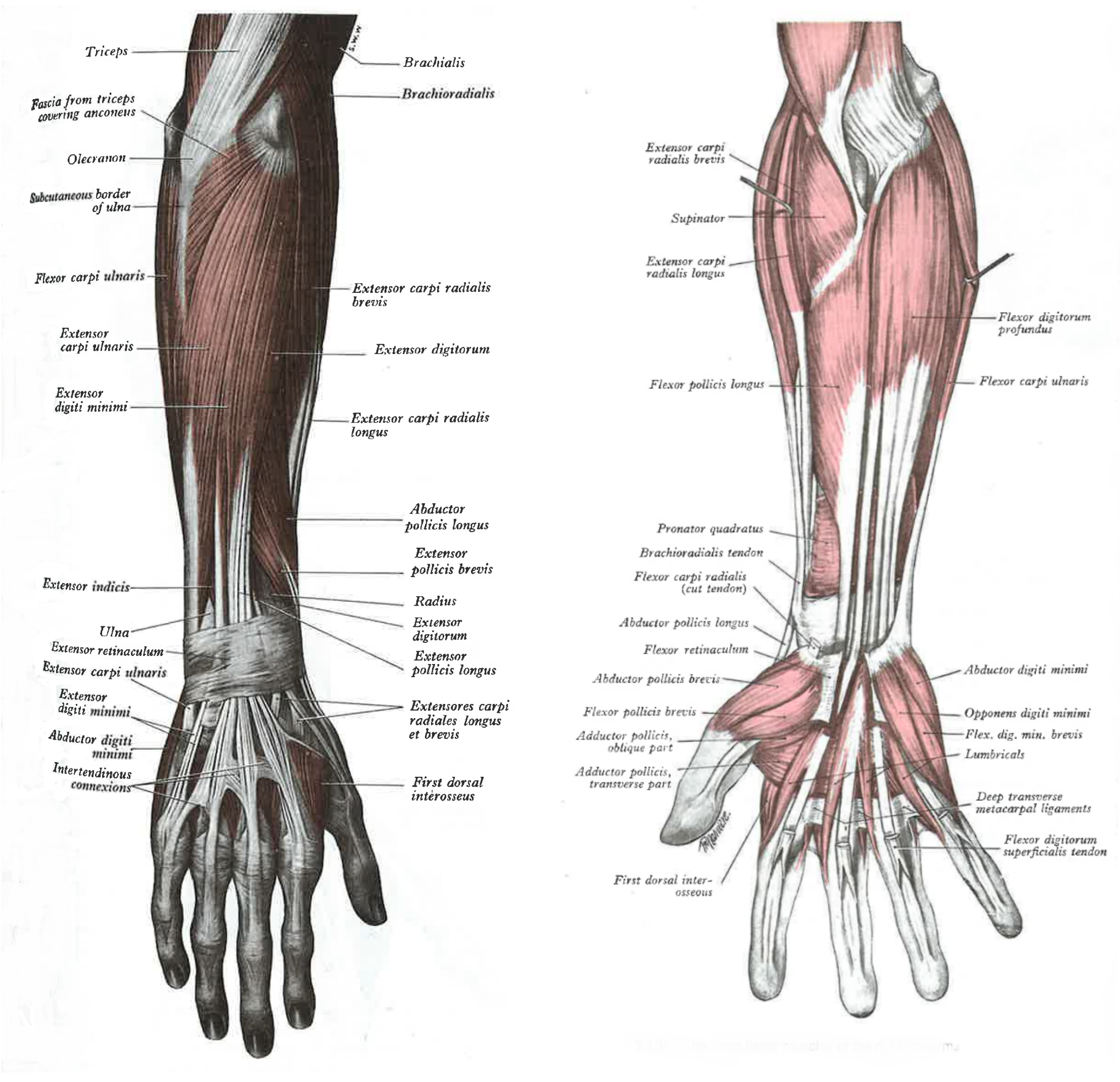

Figure 1.1: Anatomy of the forearm muscles Gray [2007]

1.3 Goals

1. Development of a paradigm to determine the grip force and grip type during several force levels and repetition frequencies

2. Set up a measurement system to fulfill the paradigm
3. Perform test measurements with five subjects
4. Documentation of the measurements for further research
5. Analysis:
   a) Determine the grip force out of the sEMG
   b) Determine the grasp type from the sEMG

2 Material and methods

2.1 Subjects

This is an exploratory study in the course of education. The reporting obligation from the convention of Helsinki should have been done. WMA [2013] The subjects were recruited using convenience sampling. Five right-handed healthy males between 24 and 28 years with a mean of 26 years were recorded. All subjects were informed verbal to the risks and purpose of the exploratory study. All subjects agreed voluntarily to the participation and the publication of the recorded data.

2.2 Grip types

Hands are able to fulfill many different kinds of movements, however the most everyday tasks can be represented with a few basic grip types and their derivations Feix [2008-2012]. Three basic everyday life grips were selected for the investigation: precision, force and pinch grip. Figure 2.1 shows the selected grip types on the associated force sensors.

Precision grip Involves the thumb and the index finger. The thumb flexes toward the index finger and the index finger flex toward the thumb until both come together. The grip force occurs between the fingertip of the index finger and the tip of the thumb. This grip is used for writing with a pencil, picking up small items and countless tasks which require little force and high accuracy.

Force grip Involves all fingers and the thumb. The fingers flex in direction of the palm of the hand and the thumb flexes in direction of the flexed fingers. The main grip force is provided from the fingers. The primary function of the thumb is the guidance of the object, the secondary function is applying grip force. The grip force occurs along the inside of the fingers, the hand palm and the thumb. This grip is used to grasp heavy objects.

Pinch grip Involves mainly the thumb and the index finger. The primary function of the other fingers is supporting the index finger. The fingers flex approximately 90 degree to the hand palm and the thumb flexes to the side of the index finger. The grip force occurs between the tip of the thumb and the outside of the index finger. This grip is used to hold a sheet of paper and other objects.

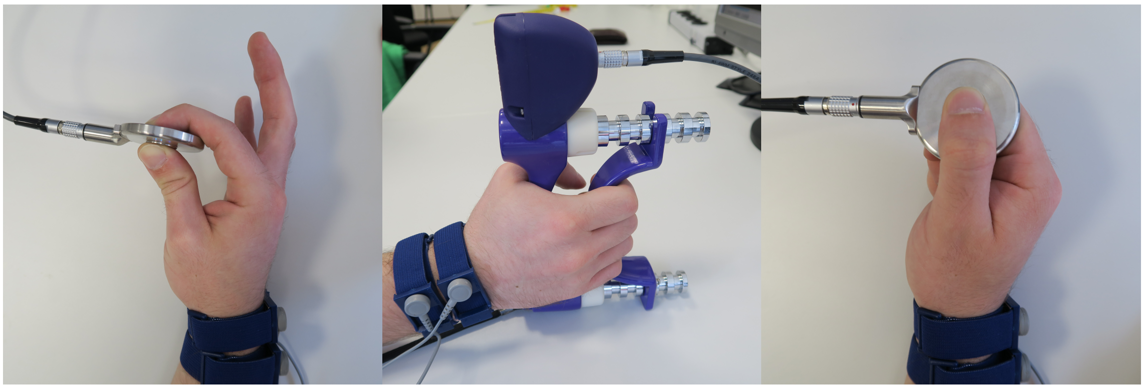

Figure 2.1: From left to right, precision, force, pinch-grip

2.3 Paradigm

The records consist of three identical blocks, with the same structure and sequence of the measurements. The blocks vary just in the performed grip type (pinch, force and precision grip). So at the first block the pinch grip, at the second block force grip and at the third block precision grip were performed. The placement of the electrodes and instruction of the subject at the beginning takes about half an hour. Between the measurement blocks was an intermission of half an hour. Every block lasted approximately one hour. So the whole measurement approximately lasted 4.5 hours. The sequence of the paradigm is shown in figure 2.2. The arrows indicate the position of the calibration tasks.

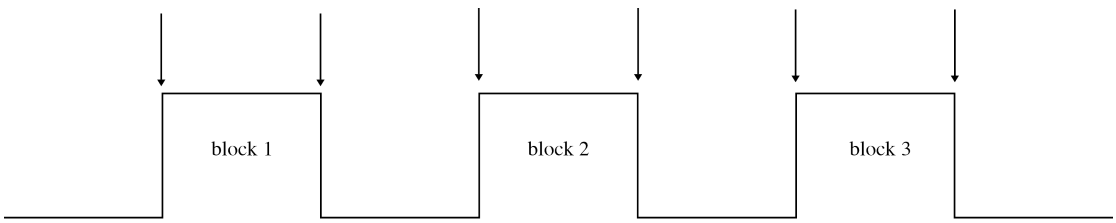

Figure 2.2: Sequence of the paradigm, the arrows indicate the position of the calibration tasks

Each block consists of 31 tasks. At the beginning and at the end of each block four calibration tasks take place. The calibration tasks were maximum force tasks for every grip type and in addition one task with resisted maneuvers of the forearm in neutral position. The maximum force tasks for the three grips contain one maximum contraction over 2 seconds. The four maneuvers were: pushing upwards from neutral, pushing away from the body, pushing downwards from neutral and pushing inwards from neutral. Every subtask was performed for 2 seconds following 3 seconds rest.

For the calculation of the force levels in every block, the corresponding calibration file which contain the maximum voluntary contraction (MVC) of the subject was used as 100%. From this all other force levels were calculated.

Table 2.1: All measurements from the paradigm. (The order of the MVC tasks was the same for all subjects)

Force level	Block 1 precision grip	Block 2 force grip	Block 3 pinch grip
calibration	MVC force grip	MVC pinch grip	MVC force grip
	MVC pinch grip	MVC precision grip	MVC precision grip
	MVC precision grip	MVC force grip	MVC pinch grip
	Subsequential tasks	Subsequential tasks	Subsequential tasks
5% MVC	0.1 Hz	0.1 Hz	0.1 Hz
	0.25 Hz	0.25 Hz	0.25 Hz
	0.5 Hz	0.5 Hz	0.5 Hz
	1 Hz	1 Hz	1 Hz
	2 Hz	2 Hz	2 Hz
10% MVC	0.1 Hz	0.1 Hz	0.1 Hz
	0.25 Hz	0.25 Hz	0.25 Hz
	0.5 Hz	0.5 Hz	0.5 Hz
	1 Hz	1 Hz	1 Hz
	2 Hz	2 Hz	2 Hz
20% MVC	0.1 Hz	0.1 Hz	0.1 Hz
	0.25 Hz	0.25 Hz	0.25 Hz
	0.5 Hz	0.5 Hz	0.5 Hz
	1 Hz	1 Hz	1 Hz
35% MVC	0.1 Hz	0.1 Hz	0.1 Hz
	0.25 Hz	0.25 Hz	0.25 Hz
	0.5 Hz	0.5 Hz	0.5 Hz
	1 Hz	1 Hz	1 Hz
50% MVC	0.1 Hz	0.1 Hz	0.1 Hz
	0.25 Hz	0.25 Hz	0.25 Hz
	0.5 Hz	0.5 Hz	0.5 Hz
66% MVC	0.1 Hz	0.1 Hz	0.1 Hz
	0.25 Hz	0.25 Hz	0.25 Hz
calibration	MVC precision grip	MVC force grip	MVC pinch grip
	Subsequential tasks	Subsequential tasks	Subsequential tasks
	MVC pinch grip	MVC pinch grip	MVC precision grip
	MVC force grip	MVC precision grip	MVC force grip

After the calibration the force and frequency tasks were executed. Table 2.1 shows an overview of all the performed measurements. The tasks were performed at six different force levels (5%, 10%, 20%, 35%, 50% and 66% of MVC) and five repetition frequencies (0.1Hz, 0.25Hz, 0.5Hz, 1Hz and 2 Hz). By increasing the percentage of MVC the number of recorded repetition frequencies decrease. This was done to prevent the subjects from excessive fatigue. At 5% and 10% MVC all five repetition frequencies were performed. At 20% and 35% the slower four repetition frequencies were performed. At 50% MVC the slower three repetition frequencies were performed. And at 66% MVC the slower two repetition frequencies were performed.

All subjects were instructed to avoid alcohol, nicotine and caffeine 12 hours before and during the measurements. In total there are 93 records per subject. Each record contains the measured force and both electrode configurations.

2.4 Data aquisition

2.4.1 Recording devices

All measurements were recorded with a wireless data logging device from Biometrics ltd. This system enables a whole biomedical research platform which provides sensors like goniometer, surface EMG electrodes, accelerometer, force sensors and switches. This system was selected because of the ease of use and standardizes measurements which alleviate data exchange with scientific partners. The used system is based on two MWX8 Datalog devices. To ensure synchronously recording, they were connected with the SL100 synchronization cable. Ten SX230 surface EMG electrodes were attached to the measurement inputs. The electrodes were perpetrated with sensor tapes T350. The ground for each Datalog device was provided with the R506 wrist straps. To measure the grip force, the P200 pinchmeter and the G200 dynamometer were used. For the communication, settings and life data viewing a software front end named “Biometrics Datalog” is provided. The MWX8 Datalog device can stream the recorded results via Bluetooth to a personal computer and simultaneously save them to a micro SD card. The generated files have the extension “.RWX” and have to be converted to plain text (“.txt”) with the delivered front end application. The following list show an overview of the used devices and materials for the data acquisition.

- Biotronic, MWX8 Datalog
- Biotronic, G200 Dynamometer
- Biotronic, P200 Pinchmeter
- Biotronic, Wrist Strap R506
- Biotronic, EMG Sensor SX230
- Biotronic, EMG Sensor Tapes T350
- Biotronic, Synchronization Cable SL100
- Personal computer
- Separated monitor for the subject
- Alcohol wipes

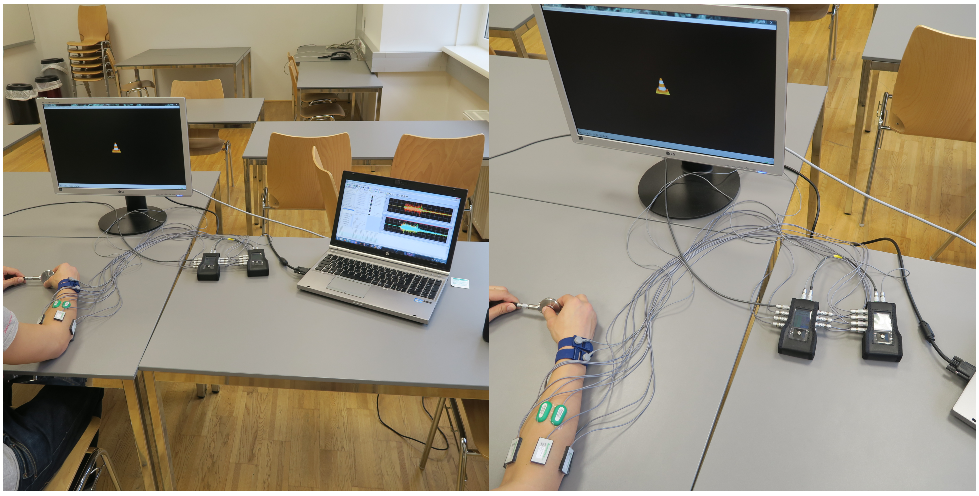

Figure 2.3: Measurement setup

2.4.2 Measurement preparation

The measurements were performed in free lecture rooms to avoid disturbances during the measurements. This was important for the concentration of the subjects because the audio signals of the force threshold and the video instruction have to be heard. Before the subject came over, the room was configured in the following way: Two big desks stand side by side. At the left desk a separate monitor provides the subject with the video instructions and gives enough room for the forearm to execute the tasks. The force sensors were cleaned with alcohol wipes and put in front of the subject monitor. At the right desk were the Biometrics measurement units and a personal computer for video control and measurement documentation. Figure 2.3 shows the measurement setup.

The sEMG electrodes were cleaned with alcohol wipes and prepared with sensor tapes. The two measurement units were provided with new batteries and linked together with a synchronization cable at the digital ports. The measurement units were adjusted in a way that the records were streamed via Bluetooth to the personal computer and simultaneously saved to the micro SD card to avoid data loss. Both measurement units where set to the personal computer time to prevent different record times at the raw files. Then the channel configuration, amplifier sensitivity and the used sampling frequency were set. At the end of the preparation the whole measurement setup and data transmission were tested.

2.4.3 Measurement procedure

After preparation of the measurement setup, the subjects were taken to the measuring room. The subjects were informed about the measurement setup, the associated risks and the duration of the measurement. All subjects agreed verbally to the participation and publication of the data.

The subjects were asked to sit down and to free the right forearm. The sEMG electrodes were attached successively to the forearm and the cables were passed to the measuring device without crossing each other. The two ground wrist straps were attached to the right wrist. Finally, all cables were connected to the measuring device.

The subjects were shown the correct execution of the movements on the sensor and the video instruction files to get familiar with the correct movement and repetition frequencies. They were given the opportunity to practise and were corrected if necessarily. The subjects have to relax the forearm on the table for one minute. After one minute the sEMG sensors amplitude was set to zero.

After this the actual measurement starts. The order of the measurements strictly follows the table 2.1. The calibration sections at the beginning and at the end of each measurement block were instructed verbally. All other tasks were instructed with the video files.

To calculate the force level of the individual measuring blocks, the maximum force from the corresponding MVC files was used. The calculated force levels were set as audio alarm on the measuring device. Every time the subject reached this value the alarm occurred.

Due to the different positions of the sEMG electrodes, different amplitudes were obtained for the individual channels. The measuring range of each channel was adapted corresponding the obtained sEMG amplitude. After each measurement the internal filename of the measuring units were copied into a excel sheet to identify the file later on. After the block one and two a break of 30 minutes was taken. For this time, the measuring instruments were attached to the belts of the subjects so that they could move cautiously free.

After the break the measuring devices were placed again. The setup was checked again and the next measurement bock began. At the end the surface electrodes were removed from the subject.

2.4.4 EMG channel configuration

To record all sEMG signals the whole measurement is repeated with two different electrode configurations. The first configuration are six radial distributed sEMG electrodes on the forearm. The second configuration are 4 sEMG electrodes in asymmetric position on the forearm. Table 2.2 and 2.3 show the channel configuration and placement of the electrodes. Figure 2.4 show the electrode placement on the forearm of one subject.

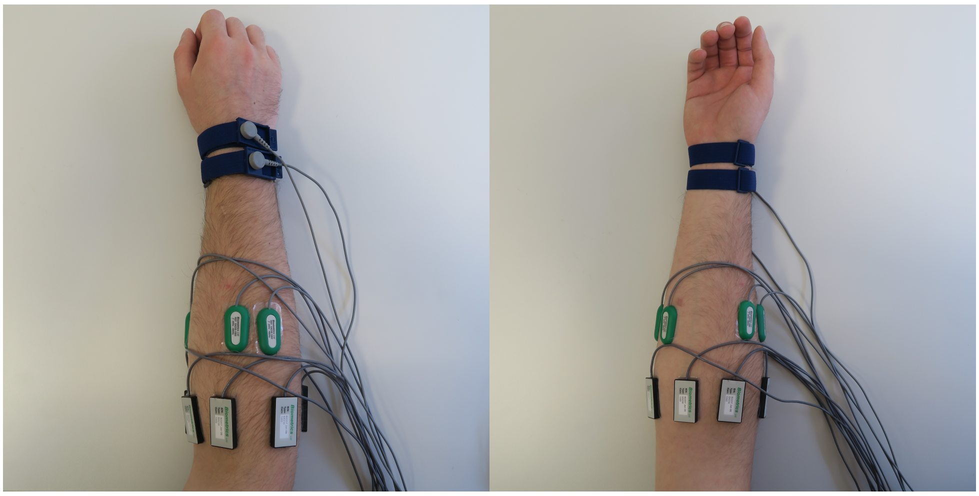

Figure 2.4: sEMG sensor placement

Table 2.2: Radial channel configuration MWX8, (Clockwise mean hand at pronation with direction lateral)

Channel	Purpose	Placement
Ch1	force sensor(G200, P200)	Hand (grip, depending)
Ch2	EMG electrode (SX230)	Start point (flexor digitorum)
Ch3	EMG electrode (SX230)	Clockwise uniformly distributed
Ch4	EMG electrode (SX230)	Clockwise uniformly distributed
Ch5	EMG electrode (SX230)	Clockwise uniformly distributed
Ch6	EMG electrode (SX230)	Clockwise uniformly distributed
Ch7	EMG electrode (SX230)	Clockwise uniformly distributed
Ch8	-	-
D1	EMG ground (R506)	wrist
D2	Synchronization cable	-

Table 2.3: Asymmetric channel configuration MWX8

Channel	Purpose	Placement
Ch1	EMG electrode (SX230)	Extensor capri ulnaris
Ch2	EMG electrode (SX230)	Extensor digitorum
Ch3	EMG electrode (SX230)	Flexor digitorum profundus
Ch4	EMG electrode (SX230)	Flexor pollicis longus
Ch5	-	-
Ch6	-	-
Ch7	-	-
Ch8	-	-
D1	Synchronization cable	-
D2	EMG ground (R506)	wrist

2.4.5 Video instruction

The timing instructions for the subjects is a very important duty. To ensure that all subjects were instructed right during all performed tasks, video files were created. The files contain a rectangular signal which is zero for no contraction and one for contraction. Figure 2.5 shows two screenshots of the video instruction files. During the signal is one, an audio signal with 440 Hz appears. At the beginning and at the end of the actual task a five second lash was added. Table 2.4 shows the timing information of the created video files. The videos were created with "Matlab" and compressed with "ffmpeg". For every repetition frequency one file was generated.

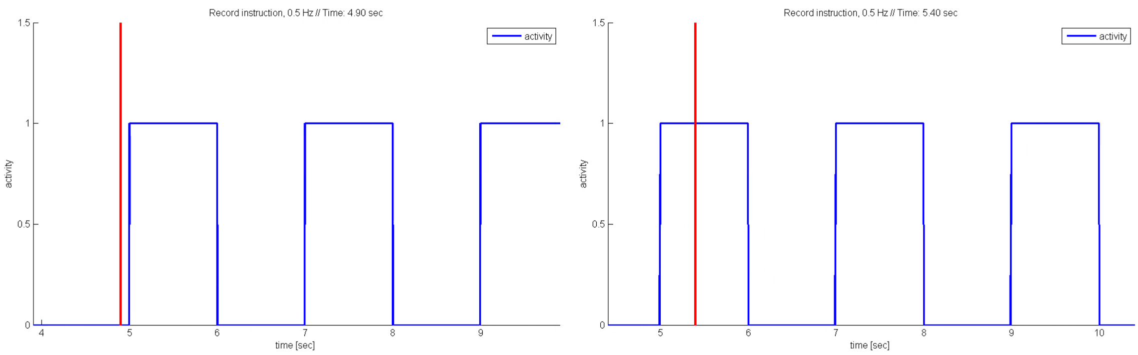

Figure 2.5: Screenshot's from the vide instructions

Table 2.4: Video instruction timing

Frequency [Hz]	Period [sec]	Contraction [sec]	Repetitions	Advance / Backlash [sec]	Duration [sec]
0,1	10	2	10	5	110
0,25	4	2	10	5	50
0,5	2	1	10	5	30
1	1	0,5	10	5	20
2	0,5	0,25	10	5	15

2.4.6 Record labeling and data format

The raw data was saved in ".RWX" format from the biometrics data logger to the micro SD card. With the included software "Biometrics datalog" and the notes during the measurement all RWX files were exported as comma separated values into a ".txt" file. Every ".txt" file contains a header where the filenames, recorded channels, number of samples, engineering units and filter information is stored. Each data channel belongs to one column.

For automated file processing the labels follow a strict convention. The filename consists of up to 6 sections. Each section is separated with an underscore and the filename ends with ".txt". Table 2.5 show an overview of the sections, there possible entries and two examples. The first section corresponds the subject number (02, 03, 04, 05 and 06). The second section identifies the measurement block (1, 2 and 3), the third section corresponds to the performed grip (precision, pinch, force and sub), the fourth section contains the MVC level (05, 10, 20, 35, 50, 66 and max). The fifth section contains the repetition frequency for all force and frequency tasks (010, 025, 050, 100, and 200) and a single “C” for all calibration tasks. The sixth section is only represented at the calibration tasks and indicates if the calibration was done at the beginning of one block or at the end of one block (1, 2).

Table 2.5: Label sections and possible entries

Section nr.	1	2	3	4	5	6
Section name	subject	block	grip	MVC	freq.	cal. nr.
Possible entries	'02'	'01'	'precision'	'05'	'010'	'1'
	'03'	'02'	'force'	'10'	'025'	'2'
	'04'	'03'	'pinch'	'20'	'050'	
	'05'		'Sub'	'35'	'100'	
	'06'			'50'	'200'	
				'66'	'C'	
				'max'		

File name	description
02_01_precision_05_010.txt	subject 2, block 1, precision grip, ... 5% MVC, 0.1Hz
02_01_pinch_max_C_1.txt	subject 2, block 1, pinch grip, 100% MVC, ... calibration file, calibration at beginning of block

(a) Examples, record labeling

Data access

To facilitate data access, the file names contain all informations about the performed task. This gives the opportunity of automated file selection. The following steps show a comfortable way to address the required data.

1. Read in all filenames and save them to a cell array *'fileNames'*
2. Find all indices for all delimiters, *find(filename '_ ')*
3. Spread *'fileNames'* with the delimiter indices and save spread pieces into a struct called *'fileParts.(subject, block, force, . . .)'*

Once this two struct's were calculated the file selection can be automated, like the following examples.

1. *fileIndex = ((fileParts.subject == '02') & (fileParts.force == '50'));*
   a) Get all indices from subject 2 with 50% MVC level
2. *requiredFileNames = fileNames(fileIndex);*
   a) Get required file names

2.5 Data analysis

2.5.1 Force prediction

The goal of the force prediction is the accurate force prediction from the sEMG signals for every subject and grip. Three regression models per subject (one model for precision, force and pinch grip) were calculated (15 models in total). The force prediction was done in three major steps. Preprocessing, calculation of the regression models and validation of the models. Accuracy is defined as the root mean square of the residuals between measured and calculated force of the validation data. Figure 2.6 shows the process steps from the force prediction

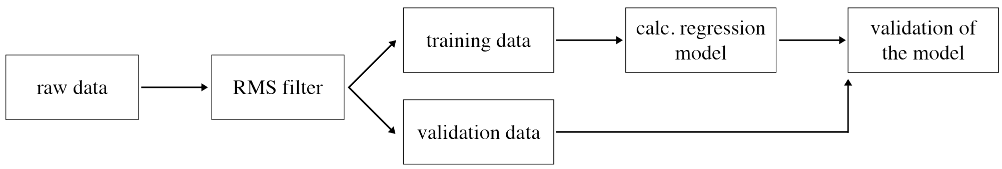

Figure 2.6: Process steps, force prediction

2.5.1.1 Preprocess

Regarding the big amount of data, the raw data were filtered with a root-mean-square filter and saved to a new directory. The RMS filter works with a window size of 197.

The following steps were executed for every subject. For each grip type a training set and a validation set were prepared. The training set consisted of all MVC tasks of the corresponding grip. The validation set consisted of the force and frequency tasks. After the separation into training and validation sets, the normalization took place. At first the training set was normalized. The validation set was normalized with the same coefficients as the training set.

2.5.1.2 Linear regression

Linear regression is a way for modelling a dependency of one output variable y, from one or more variables x in a linear manner. In this case the force represents the output variable and the sEMG channels represent the input variables. The linear model behind this regression is shown in equation 2.1. The result of the linear regressions are the coefficients for the model. Bishop [2011]

$$force = \sum_{i=1}^{N} c_i * sEMG_i \tag{2.1}$$

2.5.1.3 Validation

The validation data set and the calculated regression coefficients were used to calculate the force out of the sEMG input. This was done for both electrode configurations.

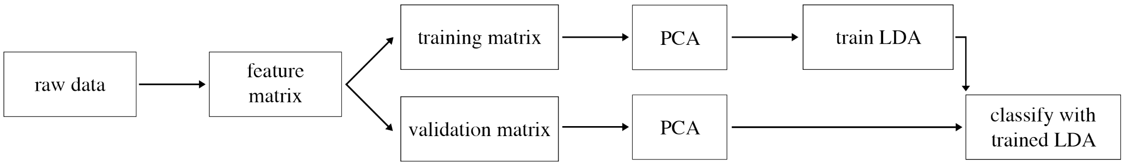

Figure 2.7: Process steps, grip classification

2.5.2 Grip classification

The grip classification was done in three major steps: preprocessing, dimension reduction with principal component analysis (PCA) and classification with linear discriminant analysis (LDA). This section covers the detailed procedure for the grip classification. Figure 2.7 shows the process steps from the grip classification.

2.5.2.1 Preprocess

For the classification the data have to be spread into active and non-active regions. One active region consisted of one full muscle exertion and is called event. To find the indices of the single events, a function was developed. This function plotted the RMS filtered force and required a user input on the graph for threshold selection. The regions of the active events were marked in the graph by changing the color. The result of this function was a logical vector which is one for active and zero for non-active regions. All indices were saved to a cell array corresponding to the file names.

After the preparation of the event indices a feature vector for every single event was calculated. The feature vector consists of 10 features per sEMG channel. In total 10 sEMG channels were recorded so each vector consists of 100 entries. Simultaneously the labels for every event were created.

Since all feature vectors were calculated, they were saved as a feature matrix, where the columns represent the events and the rows correspond to the features. The feature matrix was spread into a training and a validation matrix. The training matrix was normalized for every row (this means for every feature). The validation matrix was normalized with the coefficients from the training matrix.

2.5.2.2 Principal component analysis (PCA)

The principal component analysis is a statistical way to reduce the dimensionality of a large multivariate dataset. This was done by replacing the N–original variables to n-derivate (principal components) by using orthogonal projection. The PCA is sensitive to the relative scaling of the original data. Bishop [2011]

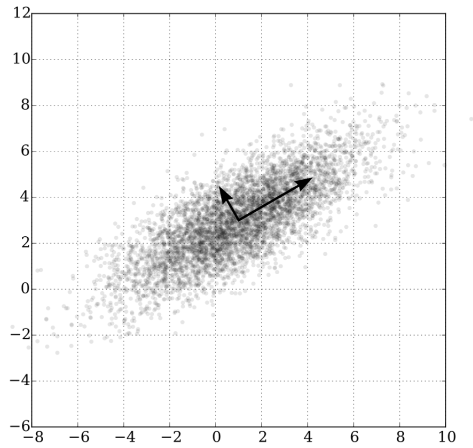

Figure 2.8: A scatter plot of samples that are distributed according a multivariate (bivariate) Gaussian distribution centered at (1,3) with a standard deviation of 3 in the (0.866, 0.5) direction and of 1 in the orthogonal direction. The directions represent the Principal Components (PC) associated with the sample. Nicoguaro [2016]

The PCA was trained with the training matrix. After this both, training and validation matrix were reduced in dimensionality. To find the best number of principal components all possibilities from 1-100 were calculated. The best overall accuracy was found at 5 principal components. The used functions for PCA were programmed by Stephan Salzmann.

2.5.2.3 Linear discriminant analysis (LDA)

Linear discriminant analysis explains a set of categorical data with a set of continuous variables. The categorical data is represented with the three investigated grip types (precision, force and pinch). The continuous variables are represented from the calculated features. LDA came from the field of supervised learning, which means that the classifier has to be trained. In order to train the classifier, a training set with the continuous variables and the associated labels must be provided.

After the training the classification takes place, where just continuous variables were provided. As a result the classifier calculated the corresponding labels for the data. The used functions for LDA were programmed from Stephan Salzman.

Accuracy of the grip classification is defined as percentage of correctly predicted labels.

2.5.2.4 Feature description

In the following section the calculated features for classification are mathematically defined. All features except the autoregressive coefficients (AR) were implemented straight forward in Matlab. AR were implemented with the Matlab function 'arburg()'. The mathematical definitions and selection of the features are based on

Limsakul [2012]. The first four features (MAV 2.2, WL 2.3, ZC 2.4 and AR 2.5) are time domain features, the last three features (MNP 2.6, MNF 2.7 and SM2 2.8) are from the frequency domain. All features are calculated from the raw EMG data.

Mean absolute value (MAV)

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{2.2}$$

Waveform length (WL)

$$WL = \sum_{i=1}^{N-1}|x_{i-1} - x_i| \tag{2.3}$$

Zero crossing (ZC)

$$ZC = \sum_{i=1}^{N-1}[sgn(x_i \times x_{i+1}) \cap |x_i - x_{i-1}| \geqslant threshold] \tag{2.4}$$

$$sng(x) = \begin{cases} 1, & if\ x \geqslant treshold \\ 0, & otherwise \end{cases}$$

Autoregressive coefficients (AR)

$$x_i = \sum_{p=1}^{P} a_p x_{i-p} + w_i \tag{2.5}$$

Mean power (MNP)

$$MNP = \left(\sum_{j=1}^{M} P_j\right)/M \tag{2.6}$$

Mean frequency (MNF)

$$MNF = \left(\sum_{j=1}^{M} f_j P_j\right)/\left(\sum_{j=1}^{M} P_j\right) \tag{2.7}$$

Second spectral moment (SM2)

$$SM2 = \sum_{j=i}^{M} P_j f_j^2 \tag{2.8}$$

3 Results

3.1 Raw data

This section shows a brief overview of the recorded raw data. The figures show the measured force and the sEMG signal amplitude. For better reading only a representative selection of the collected data is shown.

The different positions of the electrodes on the forearm result in different strong amplitudes in the sEMG signals. In order to view all signals, a uniform scaling of the different channels was omitted. This means that the specified scaling must always be considered when looking at the individual figures. All figures use the same order of magnitude of the unit, kg for the measured force and mV for the sEMG amplitude.

3.1.1 Fixed force and frequency [50% MVC, 0.5Hz], all grip types

The figures 3.1, 3.2 and 3.3 show the measurements of subject two, at a constant force level of 50% MVC and a repetition frequency of 0.5Hz for both recorded EMG channel configurations. This figures should visualize the impact of the performed grip to the EMG.

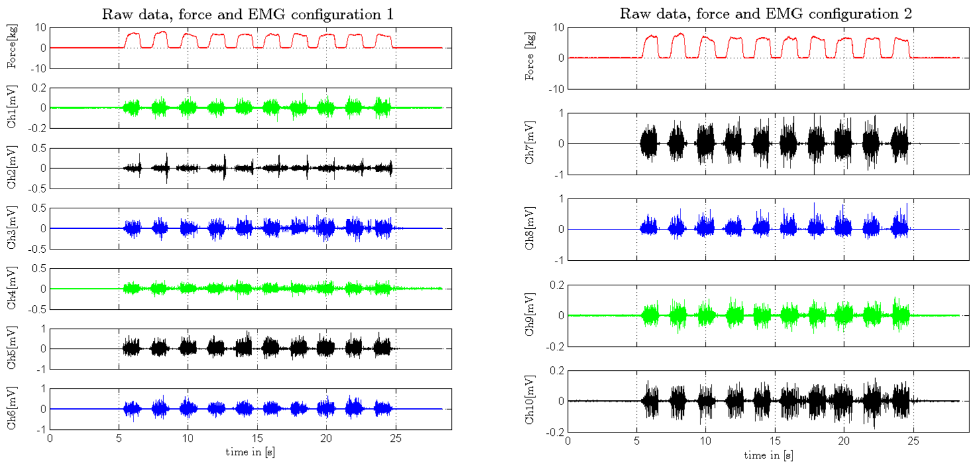

Figure 3.1: Subject 2, precision grip, 50% MVC, 0.5Hz, EMG configuration 1 and 2

Figure 3.1 shows the precision grip. All channels show activity, but they differ in the range of measurement. This comes from different positions on the forearm. The differentiation between active and non-active is possible with visual inspection. The precision grip is the weakest of all measured grip types, according to the grip force.

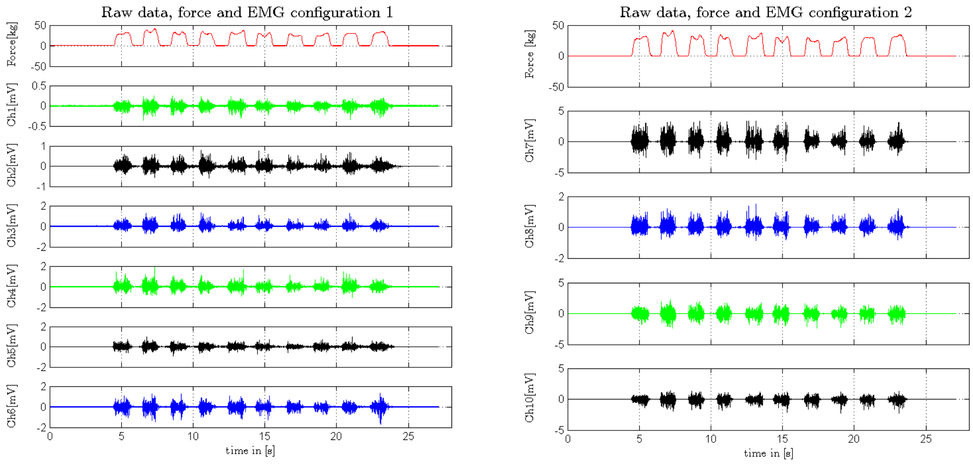

Figure 3.2: Subject 2, force grip, 50% MVC, 0.5Hz, EMG configuration 1 and 2

Figure 3.2 shows the force grip. All channels show a higher activity in the sEMG signals than the other grips at the same MVC level. This means there are more muscles with a higher innervation involved, than in pinch and precision grip.

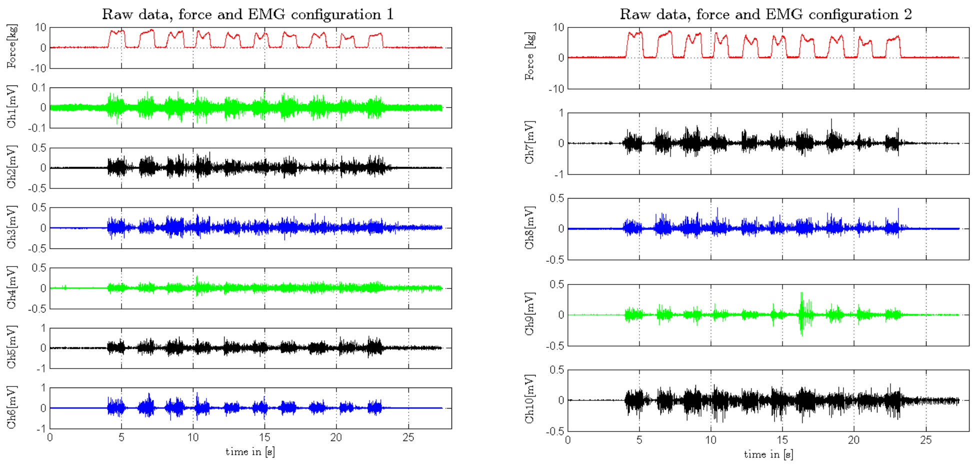

Figure 3.3: Subject 2, pinch grip, 50% MVC, 0.5Hz, EMG configuration 1 and 2

Figure 3.3 shows the pinch grip. Over all subjects the pinch grip is the second strongest grip, regarding the grip force. The differentiation between active and non-active is not that easy for all channels.

3.1.2 Force grip, fixed force 10%MVC, all frequencies

The figures 3.4, 3.5 and 3.6 show the measurements of subject two, during force grip at a constant MVC level of 10%. This figures should visualize the impact of the repetition frequency to the sEMG signals. The muscle activation stays almost the same for all frequencies. The differentiation between active and non-active regions of the sEMG signals become more challenging by increasing the repetition frequency.

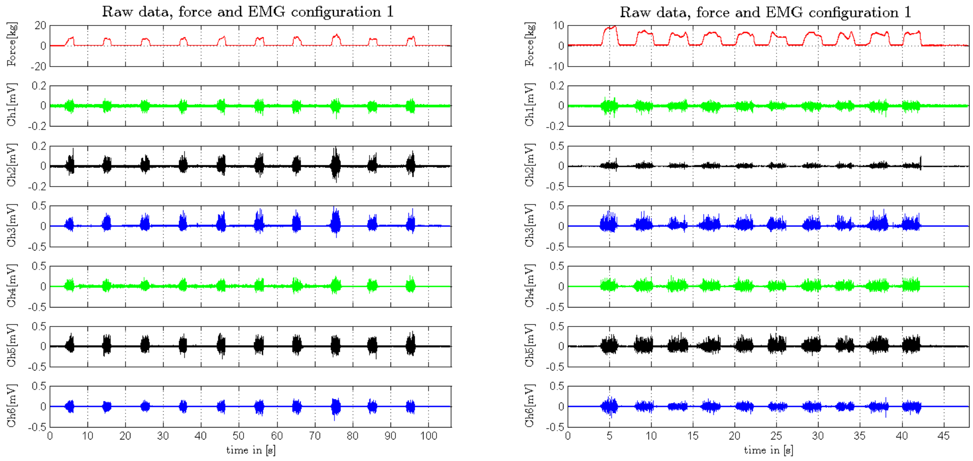

Figure 3.4: Subject 2, force grip, 10% MVC, left graph 0.1Hz, right graph 0.25Hz

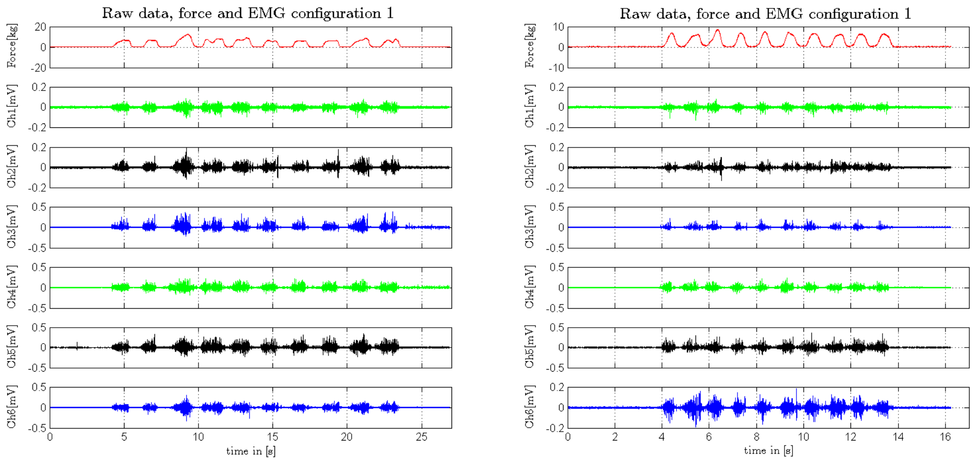

Figure 3.5: Subject 2, force grip, 10% MVC, left graph 0.5Hz, right graph 1Hz

Figure 3.4 and 3.5 show the force grip with 10% MVC and repetition frequencies 0.1Hz, 0.25Hz, 0.5Hz and 1Hz. During the low repetition frequencies all subjects had problems to stay exactly at the target MVC level. This is caused by the long exertion duration of two seconds. The differentiation between active and non-active regions on the sEMG signal is possible with visual inspection. In figure 3.5 the effect of holding the MVC level can be obtained. The measured force looks smoother at 1Hz than at 0.5Hz. This is caused by the shorter exertion duration.

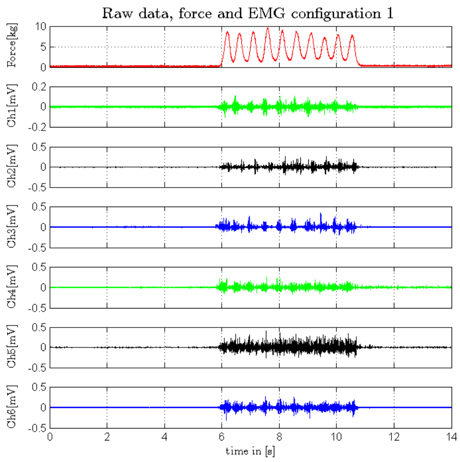

Figure 3.6: Subject 2, force grip, 10% MVC, 2Hz

Figure 3.6 shows the force grip with 10% MVC at 2Hz. The short period duration of 0.5 seconds and the exertion duration of 0.25 seconds didn't allow the force relaxing to zero anymore. That leads to a difficult differentiation of the active and non-active regions in the sEMG signals. This can be obtained in figure 3.6 at channel 4 and 5.

3.1.3 Pinch grip, fixed frequency, all forces

The figures 3.7, 3.8 and 3.9 show measurements of subject 2, during pinch grip at 0.25Hz repetition frequency. These figures should show the impact of the MVC level to the sEMG signals. For low MVC levels the sEMG amplitude doesn´t overcome the noise level. Especially during the pinch grip this effect can be obtained.

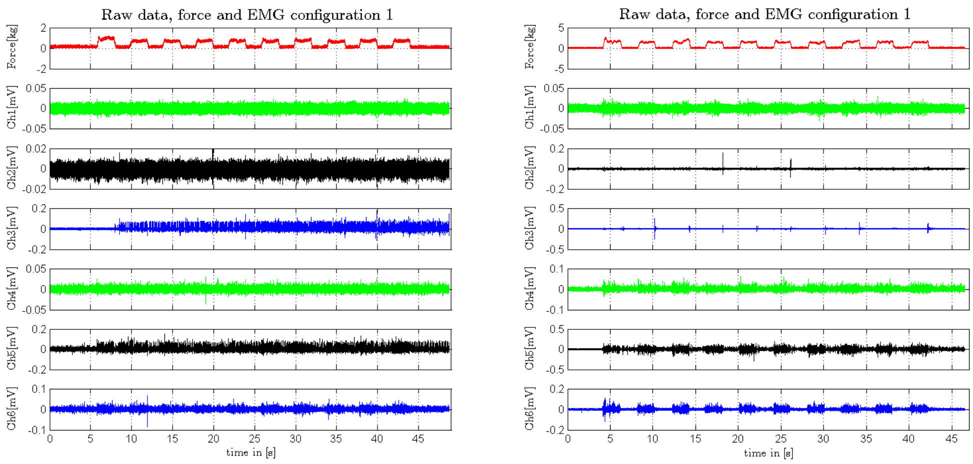

Figure 3.7: Subject 2, pinch grip, 0.25Hz, left graph 5%MVC, right graph 10%MVC

In figure 3.7 on the left graph (5% MVC), an increase of the amplitude after the first contraction can be seen. After this event the amplitude remains approximately the same. This can be explained with a small movement of the electrode or with a different contact pressure of the electrode.

Figure 3.7 shows the pinch grip at 0.25Hz repetition frequency at 5% MVC and 10% MVC. In the left figure at 5% MVC level the sEMG amplitude doesn´t overcome the noise range. Therefore the visual differentiation between active and non-active sEMG level can't be made due visual inspection. The graph corresponding to the 10% MVC level shows a slight better differentiation, but still not at all channels.

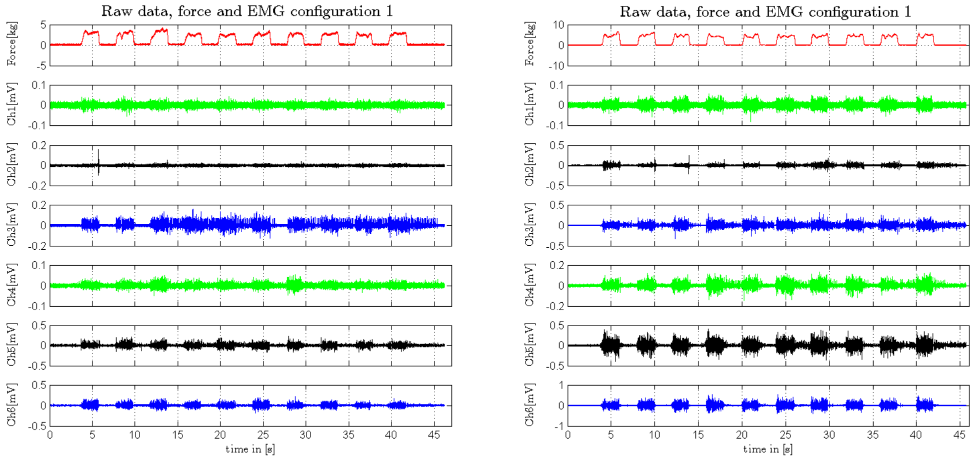

Figure 3.8: Subject 2, pinch grip, 0.25Hz, left graph 20%MVC, right graph 35%MVC

Figure 3.8 shows the pinch grip at 0.25Hz repetition frequency at 25% MVC and 35% MVC. At 35% MVC the sEMG signals overcomes the noise level in every channel. The fact that the sEMG signals can't be differentiated with visual inspection up to 20% of MVC, leads to the assumption that the presented electrode configurations didn't capture the sEMG signals of the pinch grip well.

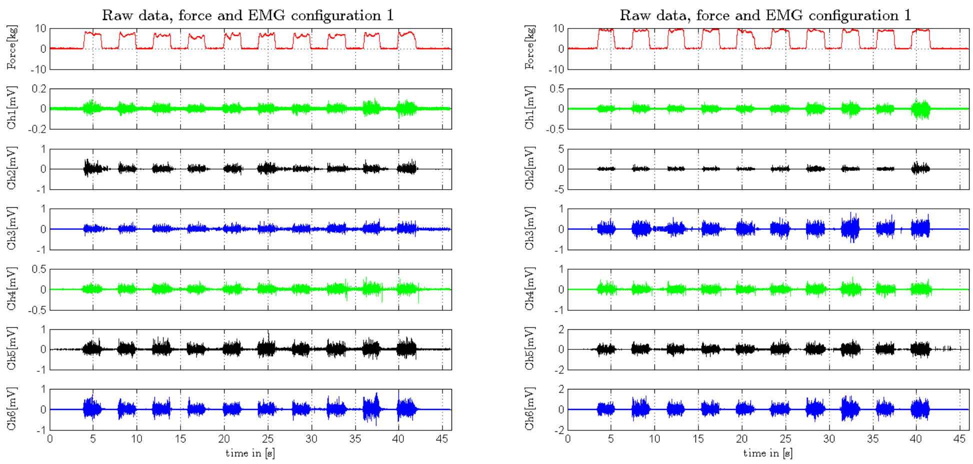

Figure 3.9: Subject 2, pinch grip, 0.25Hz, left graph 50%MVC, right graph 66%MVC

Figure 3.9 shows the pinch grip at 0.25Hz repetition frequency at 50% MVC and 66% MVC. The sEMG amplitude overcomes the noise level visible.

3.1.4 Precision grip, 5% MVC, 2Hz

The figure 3.10 shows measurements of subject 2, during precision grip at 5% MVC and 2Hz repetition frequency at both channel configurations. This figure shows the difficult situation for low MVC levels at high repetition frequency tasks. The sEMG amplitudes are quite near the noise level.

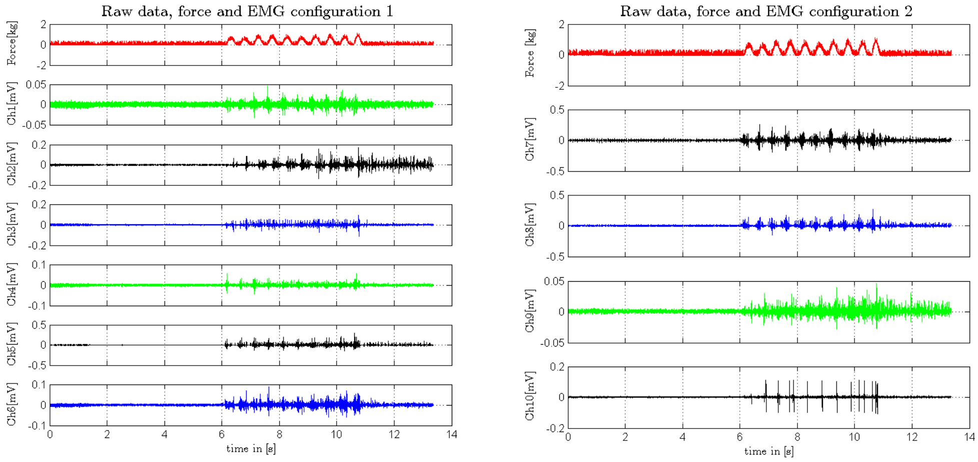

Figure 3.10: Subject 2, precision grip, 2Hz, 5%MVC, EMG configuration 1 and 2

3.2 Force estimation

This section shows the results from the force estimation. Table 3.1 shows the r^2 value for the individual regression models for both electrode configurations and all subjects. The r^2 value or coefficient of determination is a measure of the performance of the model. Values near to 1 mean good correlation and values near 0 less than ideal. Haslwanter [2016] In both configurations the force grip has the highest r^2 value, followed by the precision grip and the pinch grip. This means that the model of the force grip, explains the force data better than the other grips. Only for subject 2 the precision grip has a higher r^2 value.

Table 3.1: r^2value, from regression models

		sub. 2	sub. 3	sub. 4	sub. 5	sub 6	average
el.config. 1	r^2precision grip	0.98	0.92	0.95	0.96	0.92	0.94
	r^2force grip	0.97	0.97	0.98	0.96	0.96	0.96
	r^2pinch grip	0.91	0.93	0.82	0.89	0.94	0.89
	average	0.95	0.94	0.92	0.94	0.94	

el.config. 2	r^2precision grip	0.96	0.78	0.91	0.95	0.88	0.90
	r^2force grip	0.97	0.97	0.96	0.97	0.95	0.96
	r^2pinch grip	0.88	0.93	0.82	0.91	0.88	0.88
	average	0.94	0.89	0.90	0.94	0.90	

The tables 3.2, 3.3, 3.4 show the calculated error statistics for all three grip types. This was done for the absolute error ($abs.err = calculatedforce{-}measuredforce$) and the relative error ($rel.err = abs.err/measured.force$). From this two values the mean, the standard deviation and the root mean square error was calculated. All values were rounded to three significant values.

Table 3.2: Precision grip, calculated error statistics from the validation dataset

precision grip		error	sub. 2	sub. 3	sub. 4	sub. 5	sub. 6	average
el.config. 1	mean	abs. [kg]	1.08	0.49	0.62	0.79	0.64	0.72
		rel. [%]	100	122	105	128	121	115
	σ	abs. [kg]	2.02	0.9	0.98	1.09	0.89	1.18
		rel. [%]	3	19	12	20	22	15
	rms	abs. [kg]	2.29	1.02	1.16	1.34	1.1	1.38
		rel. [%]	100	124	106	130	123	117
el.config. 2	mean	abs. [kg]	1.08	0.46	0.63	0.72	0.61	0.70
		rel. [%]	96	106	112	101	103	104
	σ	abs. [kg]	2.02	0.87	0.99	1.08	0.89	1.17
		rel. [%]	6	20	14	4	7	10
	rms	abs. [kg]	2.29	0.98	1.17	1.3	1.08	1.36
		rel. [%]	96	108	113	101	104	104

Table 3.3: Force grip, calculated error statistics from the validation dataset

force grip		error	sub. 2	sub. 3	sub. 4	sub. 5	sub. 6	average
el.config. 1	mean	abs. [kg]	4.68	3.07	3.93	3.49	4.26	3.89
		rel. [%]	96	106	94	103	99	100
	σ	abs. [kg]	9.07	6.23	7.08	5.88	7.59	7.17
		rel. [%]	4	9	5	3	3	0.05
	rms	abs. [kg]	10.2	6.95	8.1	6.84	8.7	8.16
		rel. [%]	96	107	95	103	99	100
el.config. 2	mean	abs. [kg]	4.62	3.08	3.92	3.47	4.26	3.87
		rel. [%]	93	105	98	100	98	99
	σ	abs. [kg]	8.96	6.24	7.04	5.88	7.57	7.14
		rel. [%]	5	8	4	1	4	4
	rms	abs. [kg]	10.08	6.96	8.06	6.82	8.69	8.12
		rel. [%]	93	105	98	100	98	99

Table 3.4: Pinch grip, calculated error statistics from the validation dataset

pinch grip		error	sub. 2	sub. 3	sub. 4	sub. 5	sub. 6	average
el.config. 1	mean	abs. [kg]	1.09	0.53	0.71	0.83	0.97	0.83
		rel. [%]	66	156	49	123	99	99
	σ	abs. [kg]	2.12	0.91	1.33	1.36	1.64	1.47
		rel. [%]	23	36	36	19	4	24
	rms	abs. [kg]	2.39	1.06	1.51	1.59	1.91	1.69
		rel. [%]	70	161	59	125	99	103
el.config. 2	mean	abs. [kg]	1.08	0.51	0.76	0.81	0.96	0.82
		rel. [%]	58	128	80	113	94	95
	σ	abs. [kg]	2.13	0.9	1.34	1.35	1.64	1.46
		rel. [%]	29	20	14	11	5	16
	rms	abs. [kg]	2.39	1.03	1.54	1.58	1.9	1.69
		rel. [%]	65	130	81	113	94	97

Table 3.5 shows the averaged over all error for all grip types. The electrode configuration two comes to smaller values. This means that the special placed electrodes predict the force more exact.

The overall relative RMS-error was with 100% and 106% very high. Too high for a practical use of a simple linear regression model as force prediction model.

Table 3.5: Over all error, calculated error statistics from the validation dataset

over all		error	precision grip	force grip	pinch grip	average
el.config. 1	mean	abs. [kg]	0.72	3.89	0.83	1.81
		rel. [%]	115	100	99	105
	σ	abs. [kg]	1.18	7.17	1.47	3.27
		rel.[%]	15	5	24	0.14
	rms	abs. [kg]	1.38	8.16	1.69	3.74
		rel.[%]	117	100	103	106
el.config. 2	mean	abs. [kg]	0.70	3.87	0.82	1.79
		rel. [%]	104	99	95	99
	σ	abs. [kg]	1.17	7.14	1.46	3.25
		rel. [%]	10	4	16	10
	rms	abs. [kg]	1.36	8.12	1.69	3.72
		rel. [%]	104	99	97	100

3.3 Grip classification

This section shows the results from the grip classification. Accuracy is defined as (accuracy = number of right predicted labels / number of predicted labels * 100). To determine the overall accuracy a leave-one-out cross-validation was used. For every iteration one subject was separated from the training dataset. This separated dataset was used to validate the model and calculate the accuracy of the iteration step.

To test the whole classification process, a dummy dataset was used. This dataset consists of the same structure and amount of data as the recorded dataset. The force was reconstructed with a rectangular signal which is one during the activation and zero for non-activation. The sEMG channels were simulated with random noise around zero for non-active regions and random numbers between -0.5 and 0.5, for active sEMG regions. At first all sEMG channels contain non-active noise. The distinction between the grasp types were implemented with active regions in different channels. Precision grip has an active sEMG in channel 3 and 8. Force grip is active in channel 1 and 7 and the pinch grip is active in channel 3 and 9. An example provides figure 3.11. The whole classification process was done with this dummy data. The overall accuracy for the dummy data were 100% each.

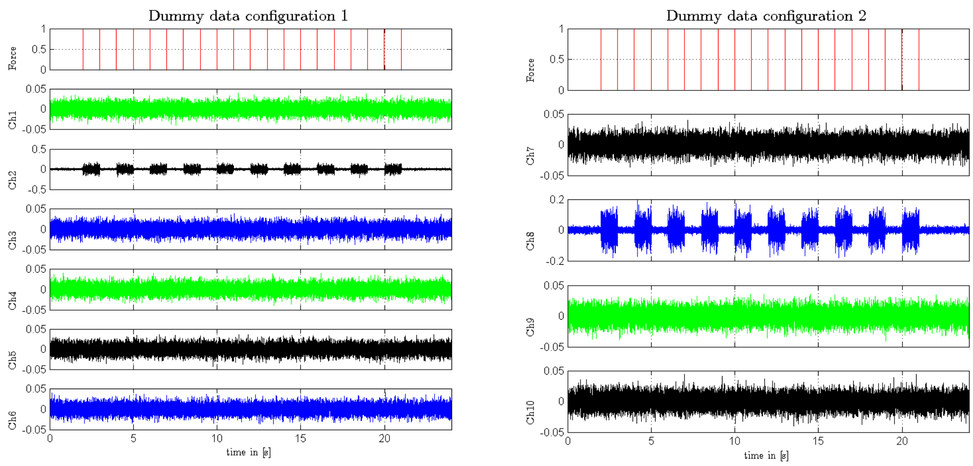

Figure 3.11: Dummy data

Table 3.6 and figure 3.12 show the accuracy of both electrode configurations for every iteration step and the overall averaged accuracy. For this calculation all available files were used. (All grips, all MVC levels during all repetition frequencies, including the max MVC tasks). The overall accuracy for electrode configuration one (six radial distributed sEMG electrodes) is 55.7%. For the second configuration (four asymmetric placed sEMG electrodes) the overall accuracy is 60.28%.

Table 3.6: Accuracy of grip classification, for all files

	accuracy	sub. 2	sub. 3	sub. 4	sub. 5	sub. 6	average
el.config. 1	[%]	64.1	62.5	53.2	47.2	51.5	55.7
el.config. 2	[%]	58.6	61.4	56.6	62.7	62.1	60.28

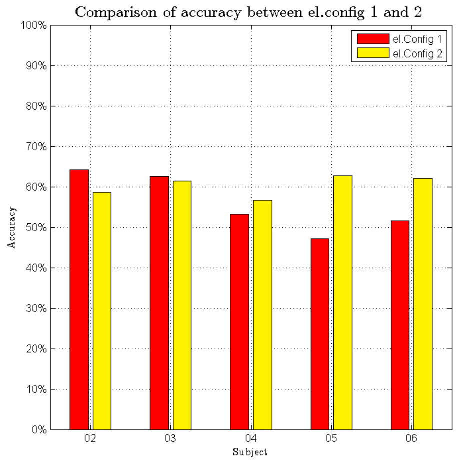

Figure 3.12: Accuracy of grip classification, for all files, spread for each subject

To test the impact of high and low MVC measurements to the overall performance of the classifier, they were excluded from the following calculations.

Table 3.7 and figure 3.13 shows the accuracy of both electrode configurations, by excluding the 5%, 10% and 100% MVC tasks. The overall accuracy increases for both configurations to 63.94% and 63.5%. An impact on the difficult low MVC tasks can be obtained.

Table 3.7: Accuracy of grip classification, for files 20%, 35%, 50%, 66% MAV

	accuracy	sub. 2	sub. 3	sub. 4	sub. 5	sub. 6	average
el.config. 1	[%]	65.1	70.8	60	59	64.8	63.94
el.config. 2	[%]	62.3	54.1	66.9	67.4	66.8	63.5

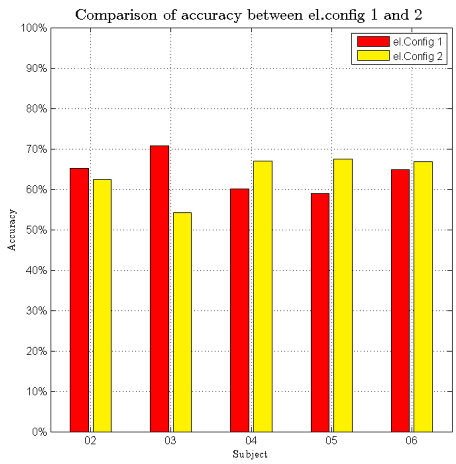

Figure 3.13: Accuracy of grip classification, for files 20%, 35%, 50%, 66% MAV, spread for all subjects

4 Discussion and outlook

This section covers the discussion and outlook for each chapter. At first all chapters are discussed, at the end of each paragraph the outlook is presented.

4.1 Materials and methods

4.1.1 Subjects

The number of selected subjects is not representative. Due to the fact that this thesis is an exploratory study, five subjects are sufficient. The selection method and convenience sampling are appropriate for such tasks and commonly used. For further investigations the number of subjects should be increased according to Altman [1990]. The eligibility requirements for the future subjects have to be written and reported to the Austrian federal office for safety in health care (basg). This can be done at their hompage (https://applicationform.basg.gv.at).

4.1.2 Grip types

The three selected grip types (precision, force, pinch grip) represent many everyday life tasks. Adding an additional grip type (e.g. large diameter or power sphere, Feix [2008-2012]) would increase the recording duration per subject by one hour and probably lead to concentration issue of the subject.

4.1.3 Paradigm

Holding the required MVC level with simultaneously precise timing involves a high level of concentration. It showed up, that the concentration and physical strength of the subjects comes close to exhaustion during the observation. The sequence of the tasks within every block from low MVC levels to high MVC levels may support the strength exhaustion.

Further measurements should adapt the paradigm in the following way: At the beginning of the measurement one big calibration block for all grip types should be performed. This calibration block should consist of the following tasks:

- Slowly increasing the force up to MVC and then slowly decreasing to zero. This task should be used to train the linear regression models.
- Another task with successive maximum force exertions and fast increasing rates has to be added, to get the maximum MVC level more accurate.

Within a block the order of the tasks has to be inverted. Starting at the highest MVC level to the lowest.

This modification came as feedback from the subjects. Because at the end of each block the exhaustion began to appear, so it should be easier to do the weak forces at the end.

The calibration files at the beginning and at the end of each block should be reduced, to the MVC task of the corresponding grip. With this changes the measurement duration can be slightly decreased without a major loss of information.

4.1.4 Recording devices

The used recording devices worked without issues during all measurements. The possibility of Bluetooth transmission to the personal computer, gives an important ability of live surveillance of the recorded data. For more detailed investigations a solution for automated data renaming would be very helpful.

4.1.5 Measurement preparation and procedure

The measurement preparation lasts in total about one hour. For more efficiency several subjects should be recorded in a row. This also improves the reproducibility of the measurements.

4.1.6 EMG channel configuration

The six radial distributed sEMG electrodes are comfortable to place on the skin and were a practical implementation for real life applications. For the force prediction and the grip classification the results were not as good as the results of the asymmetric electrode placement. During the development, multiple electrode configurations is easy to arrange and should be carried out for comparative purposes.

4.1.7 Video instruction

The generated video files were a great help during the measurements. The feedback of the subjects was very positive. The only criticism point was a little flickering on the edges of the video. This came from the compromising process and could be solved easily.

4.1.8 Record labeling and data format

The structure of the record labels allows an easy way to access the required data. The conversion of the RWX data format into comma separated text files should be automated for further investigations.

4.1.9 Data analysis

Working with a big amount of multivariate data is a challenging task. The chosen programming language 'Matlab' offers all needed tools for the analysis. The only drawback is the need of a Matlab license for transferring the algorithms to research or other partners. The alterative freeware solution, which doesn´t have this problems, is ‘Octave’, ‘Phyton’ or ‘R’.

4.1.10 Data analysis, force estimation

The approach of force calculation out of the sEMG data with a linear regression model was done according to the work of M.Kapellusch [2014]. Due to the fact that this master thesis covers three grip types causes the decision of calculating separate regression models for each grasp. The principal implemented procedure of the force estimation is working. The filtering of the data and the separate storage of the filtered data speeds up the following calculation steps tremendously. For further investigations an alternative method like multivariate linear regression could be used.

4.1.11 Data analysis, grip classification

The implementation of the grip classification was validated with a dummy data set. With the generated dummy data the accuracy of the classifier reaches 100%. The preprocessing step of generating a feature matrix for all datasets improves the classification speed substantially. For further investigations a larger set of features should be used, to improve the classification accuracy. The use of another classifier, like neuronal networks or support vector machines should be considered. As a further step the real time implementation of the algorithm should be considered.

4.2 Results

4.2.1 Raw Data

All 465 recorded files were inspected visually. The visual inspection leads to 2 main observations.

1) The signal to noise ratio of the pinch grip is higher than for the other grip types. This observation could be caused by the co-contraction of several involved muscles. The fingers from Index to little finger work as support for the thumb. To support the thumb sufficiently the fingers contract static. The force sensor had to be supported during the whole measurement, but the applied force differ over time. For further investigations the support of the sensor should be done with an external clamp, to prevent this effect.

2) Classifying the grip from the sEMG signals with visual inspection is not possible.

4.2.2 Force prediction

The r^2 values from the calculated models were between 0.88 and 0.94 for both electrode configurations. The interpretation of this result is, that up to 94% of the input data can be explained with the calculated models. In contrast to that, the averaged RMS error of the validation datasets were between 100% and 106%, with relative standard deviation between 10% and 14%. This results can be interpreted in 3 ways:

1) The implemented force prediction is not correct. The implementation was checked twice, but the implementation was not validated with dummy data. So there is still a chance that something does not work.

2) The data for the model calculation was chosen badly. To prove this statement the input files for model generation were changed in a way that every MVC level was represented once. The results of this second measurement were in the same range as the previous ones. Another approach to approve the quality of the input files for the recession is a modification of the paradigm. By involving files with small slew rate of the MVC level up to maximum and back to zero.

3) For this prediction a simple linear regression model is not appropriate. In the literature M.Kapellusch [2014] the same linear regression model is used to determine the force, out of the sEMG signal more accurate.

For further investigations I would proceed as following: Check the implementation and the results. If the implementation is correct, I would change the input files of the linear regression models in a maximization approach. If this was also not sufficient, a more sophisticated modelling approach (neuronal networks, support vector machines) should be chosen.

4.2.3 Grip classification

The classification process itself was validated with dummy data, which prove the principal correctness. Nevertheless, the accuracy of the grip classification with 55.7% to 63.94% was too low for a practical use. This yields to three major contrary assumptions:

1) There is no difference between the observed sEMG data. With 63.94% accuracy the classifier overcomes the random border of 33.3% for three grasps, by a factor of nearly 2. That's why this assumption will not match.

2) The difference between the observed sEMG data was not represented with the calculated features. The selected features were standard EMG processing features. They are used in many literature Limsakul [2012], Quaine [2014]. But there is no evidence that this features address the difference in the observed sEMG signals.

3) The LDA is not the appropriate method to address these differences. There are many methods for supervised learning available.

For further investigations I would proceed as following: Increasing the number of calculated features, and calculate their influence to the classification. With additional features the performance should also increase. If this was not the case than I would change to another supervised learning method. (Neuronal networks, support vector machines or other).

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