Continuous Estimation of Individuated Finger Movement for Prosthetic Control using Surface Electromyography

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Abstract

In this study we explored the possibility to estimate individuated finger movement and wrist movement in the purpose of controlling a prosthetic or robotic hand. The posture of the hand is determined by joint angles that are estimated continuously. The main benefits of this approach to control is that it provides natural control and allows for a wide variety of hand postures.

We estimate individuated movement of digits, using a 2-layered artificial neural network with input signals, derived from forearm surface electromyography, and joint angles as output. When estimating 7 degrees of freedom, flexion / extension in the wrist and metacarpal (MCP) and proximal interphalangeal (PIP) joints in thumb, index and longfinger, a low pass filtered EMG signal, reflecting the firing rate of motor neurons, outperforms an EMG representation based on the wavelet transform. Correlation coefficients between estimated and true joint angles varied, with higher coefficients for joints closer to the forearm, a result that partly is caused by difficulties measuring the muscle activity in deep muscles controlling the distal joints. When estimating five individually moving fingers, estimation of metacarpal phalangeal joints yields correlation coefficients to true angles at around 0.8, while estimation of proximal interphalangeal joints yield correlation coefficients between 0.6 and 0.75. The processing steps used allow for continuous real time control and the estimation results make it feasible to further continue the research. A possible continuation is to use independent component analysis on the EMG signal to separate muscle activity originating from different muscles.

Kontinuerlig estimering av individuerad fingerrörelse från ytlig elektromyografi i protokontrollsyfte

Sammanfattning

I denna studie utforskade vi möjligheten att estimera individuell rörelse av fingrar och handled i syfte att kontrollera en protes- eller robothand. Handens position bestäms av lederas vinklar, som estimeras kontinuerligt. De största fördelarna med denna ansats för kontroll är att den tillhandahåller naturlig kontroll och tillåter en stor variation av handpositioner. Vi estimeras individuerad rörelse av fingrar med ett 2-lagers artificiellt neuronnät med insignaler deriverade av elektromyografi från underarmen, och lederas vinklar som utsignaler. När 7 grader av frihet, flexion / extension i handled och de metakarpala (MCP) och proximala (PIP) leder i tumme, pek och långfinger estimeras jämfördes resultaten för olika EMG-representationer som indata. Dels användes en lågpassfilterad EMG signal, vilken reflekterar avfyrningstakten hos motorneuron och dets användes en representation grundad på Wavelettransformation. Den lågpassfilterade EMG signalen gav bättre resultat. Korrelationskoefficienter mellan estimade och riktiga vinklar varierade, med högre koefficienter för leder närmre underarmen, ett resultat som delvis är orsakat av svårigheter att mäta muskelaktivitet i de djupt belägna muskler som kontrollerar de distala lederna. När 5 individuellt rörande fingrar estimeras ger estimering av metakarpala musklerna koefficienter runt 0,8, medan de proximala lederna ger koefficienter mellan 0,6 och 0,75. Informationshanteringsstegen som används, tillåter kontinuerlig kontroll i realtid, och resultaten motiverar fortsatt forskning. En möjlig fortsättning är att använda independent component analysis på EMG-signalerna för att separera muskelaktivitet som hårstämmar från olika muskler.
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1 Introduction

Electromyography (EMG) is the electrical manifestation of muscle activity. The signal has been used in an array of medical applications, mainly as a diagnosis tool, for example to identify abnormal muscle activity[29] or to detect muscle fatigue[12]. Another large field of use is as human machine interface, especially for prosthetics control. Most EMG based prosthetics control systems use the EMG signal from a few muscles to extract features that are unique to certain movements in order to classify which action should be performed by the device[3, 17, 20]. More bio-mechanical approaches measure EMG from all muscles involved in a movement to estimate muscle tension to predict the movement through muscle torques[33][4]. Kое et al.[33] predicts the posture of the arm by estimating three degrees of freedom in the shoulder and one degree of freedom in the elbow. Furthermore are the degrees of freedom in the wrist estimated by DaSalla et al.[4]. In contrary to classifications approaches were the control is limited to a few states, the bio-mechanical approach allows for estimation of all possible postures enabled by the muscles.

The aim of this study is to explore the feasibility to use a bio-mechanical approach to estimate hand posture, for control purposes of a prosthetic or robotic hand, by estimating joint angles. The study will explore if it is possible to estimate individual finger movements and wrist movement continuously from surface electromyography signals only.

2 Background

2.1 Movement of Joints

Movement occurs at joints when contracting skeletal muscles act in coordination. Muscles act to rotate a joint by producing muscle torque, defined as the product of muscle tension and its moment arm. Tension is the total force output of a muscle and moment arm is defined as the shortest distance between the muscle line of pull and the joint center of rotation. As muscles exert force by contraction they cannot push. Therefore a joint must be controlled by at least two muscles producing opposing forces. Joint torque is the sum of muscle torques acting on the joint and when joint torque is non-zero, a force acts to rotate the joint. figure(1) shows how the forces of an extensor-flexor pair creates joint torque around a joint. In absence of a counteracting force the joint is perturbed. The perturbation causes the antagonistic muscle to stretch and generates a passive force. The joint is in equilibrium when joint torque is zero and opposing forces acting on the joint are equal.[13]

2.2 Skeletal Muscles and Contraction

Skeletal muscles are composed of bundles of muscle fibers A fiber is fused from several cells and has multiple nuclei but act as one unit and is encased by a sarcolemma, or cell membrane. The fiber is organized into a number of parallel myofibrils composed of repeating elements called sarcomeres. Within the sarcomere there are two types of overlapping protein filaments, thin and thick filaments as shown in figure(2). According to the crossbridge theory force is generated between the filaments by the formation of cross bridges. The sarcomere is
Figure 2: Sarcomere structure. The sarcomere is the contractile basis of muscles. The force generated by a sarcomere is dependent on filament overlap as that directly affect number of cross bridges formed.

the contractile basis of a muscle fiber and the level of contraction is decided by the degree of thin and thick filament overlap as this affect the number of cross bridges formed. Contraction of a muscle is achieved by rapid and asynchronous contractions and relaxations of muscle fibers throughout the muscle. Every muscle fiber is exclusively controlled by one motor neuron, and the bundle of fibers and their corresponding motor neuron is called a motor unit, which is the smallest controllable muscular unit. A muscle is constituted of several motor units, and fibers belonging to the same unit is scattered throughout the muscle, so no muscle part is individually controlled by one motor unit. All motor neurons innervating a muscle form a common motor pool [13].

A motor neuron axon splits and connects to muscle fibers in a muscle via chemical synapses called neuromuscular junctions. The postsynaptic portion, located on the fiber, is called an endplate and when neurotransmitter is released into the synaptic cleft the endplate membrane is depolarized. The depolarization caused by a neuronal action potential is called an end plate potential and if it surpasses a threshold it triggers a muscle action potential (see section 3.1.2) that propagates over the muscle fiber membrane, an event that is observable by the means of electromyography. The action potential causes release of ions that trigger muscular contraction that is maintained until the ionic concentration is restored. The connection between membrane action potential and muscle contraction is called the excitation-contraction coupling and the time from action potential and muscle tension is around 90 ms [7].

2.3 Electromyography (EMG)

When a muscle fiber action potential is triggered by a firing motor neuron a muscle fiber action potential is propagated in both directions along the fiber. This membrane depolarization generates an electromagnetic field in the vicinity of the fiber and electrodes located in the field will detect the potential difference. A firing from a motor neuron results in action potentials in all fibers belonging to that motor unit. The resulting field is called a motor unit action potential (muap), and is accompanied with single switch in the muscle. The measured muap can be seen as a superposition of individual muscle fiber action potential as in figure(3). Factors determining the shape of the

![Membrane pot Action Potential](image)

Figure 3: The left figure is a single fiber action potential (AP) and to the right is the muap which can be seen as a superposition of individual APs.

muap are primarily the diameter and geometrical arrangement of the muscle fibers, tissue filtering effect and properties of electrodes and recording equipment.

To sustain muscle contraction the motor
units must be repeatedly activated, and this results in a sequence of muaps called a motor unit potential train. The recorded EMG signal can be described as the summation of all observed muaps within the electrode take up area. The contribution of each motor unit or MUAPT is dependent electrode orientation and distance of the muscle fibers to the electrodes. [16]

The EMG signal amplitude has random characteristics that can be attributed to its composition of MUAPTS. Random properties of the MUAP can be contributed to the generation of action potentials in the motor neuron, and also a random nature in the release of signal substances in the neuromuscular junction causing the excitation of each muscle fiber belonging to a motor unit a random function of time. [16]

The recorded EMG signal has high noise characteristics resulting from various sources such as [16]:

Inherent noise in electrical components in the detection and recording equipment.

Noise from electromagnetic radiation from radios, power cables and power sources.

Motion artifacts from the interface between skin and electrode.

Inherent instability in the EMG signal caused by semi random firing of motor units.

EMG signals can be recorded by either surface electrodes located on the skin or indwelling electrodes located in the muscle. Indwelling electrodes are advantageous to surface electrodes in that they can reach deeper muscle layers and record selectively from small muscles. The main disadvantage of indwelling electrodes is that they are invasive, which can cause pain to the subject and are more difficult to setup. To avoid these issues surface electrodes are used in this project. Two negative issues with surface electrodes are (1) crosstalk, which occurs when electrodes detect activity from several muscles, resulting in a mixed EMG signal not corresponding solely to the activity of the intended muscle, (2) depth of measurement, which is limited to superficial muscles as the detectable potential difference quickly attenuates with distance.

Typically, surface EMG recordings are obtained using a bipolar electrode configuration, which uses two electrical contacts measuring potential to a common reference electrode. The difference of the two potentials is determined and amplified in a differential amplifier. The process is shown in figure(4). [10][15] Accord-

![EMG signal is differentially amplified and recorded.](image)

**Figure 4:** EMG signal is differentially amplified and recorded.

2.4 Muscle Contraction, Tension and EMG

2.4.1 Muscle Contraction

One of the most basic properties of a muscle is its ability to produce contractile force. The contractile force in a muscle is determined by the number of active motor neurons and their
individual firing rate and size of motor unit. Increased contractile force is achieved by either an increase in the firing rate of already active motor units or by the recruitment of more motor units. Motor units are recruited in increasing size order, that is, larger motor units with increasing muscle contraction force are progressively recruited.

2.4.2 Muscle Tension

The force output in a muscle is decided by passive and active tension in its muscle fibers. Passive tension is caused by elastic elements, and active tension is determined by fiber activation, length and velocity.

Active tension in a fiber is related to the rate of stimulation from the motor neuron. Low frequency stimulation causes separatewitches characterized by a rapid rise in force followed by a slower decline. When increasing the rate of stimuli within the time for force decline of a single twitch, remaining contractile force and newly generated force is summed resulting in a higher output force, creating a nonlinear relationship between firing rate and tension.

According to the cross-bridge theory, cross-bridges form between the different types of filaments and cause them to slide past each other. Each cross bridge is assumed to generate the same contractile force, and as the cross bridges are believed to be equidistantly formed between filaments, the total output of force is decided by the degree of overlap between filaments. When stretching the sarcomere so that there is no overlap of filaments no cross bridges can be formed and therefore no active force either. In contrast when the sarcomere is maximally contracted, passive elastic forces counter the active force and the total output is zero. This relationship is nonlinear and called the force-length relationship.

Molecular mechanisms underlying the formation of cross bridges causes the generation of active force to be dependent on the speed of change in muscle length. When actively

elargated more force is generated and when shortened the force generation decreases. This relationship is nonlinear and called the force-velocity relationship.[13]

2.4.3 EMG and muscle tension

There exists a relationship between EMG and tension. The EMG signal is composed of low and high frequency components and the they reflect different aspects of the signals. Low frequency components reflect the firing rate of motor neurons while high frequency components reflect the individual shapes of action potentials[16]. This was first explored 1973 by Mannard and Stein[2], who estimated muscle forces from EMG signals by lowpass filtering the signal.

2.5 Joint Torque, Joint Angles and Posture

Joint torque is as the sum of muscle torques acting on the joint:

\[ \tau = \sum_{i=1}^{n} \alpha_i T_i \]

where \( \alpha_i \) and \( T_i \) are moment arm and muscle tension for muscle \( i \) respectively. Moment arms depend on joint angles \( \theta \) and due to the length-tension relationship in muscle tension is as well. Joint torque can be expressed as:

\[ \tau = f(\alpha(\theta), T(\theta)) \]  

(1)

when joint torque is zero, \( \theta \) can be expressed as a function of muscle torque. This relationship is depicted in figure(5). The relationship is a many to one mapping as many levels of muscle torques give rise to the same joint angle: co-contracting muscles with matching increase in muscle torques do not change the joint angle.

Joint angles are of importance as they, with constant limb lengths define posture. If a finger is modelled as a 4-link system with known lengths of all links as depicted in figure(6), forward kinematics give the the position of each
2.6 The Hand

The hand and wrist has a very complex structure consisting of 27 bones and 39 muscles located in either the hand (intrinsic muscles) or forearm (extrinsic muscles). First the joints and muscles of the hand are described and next individuated control of digits.

2.6.1 Joints and Muscles of the Hand

The joints of the hand are the Metacarpal Phalangeals (MCP), Proximal Interphalangeals (PIP), Distal Interphalangeals (DIP) and the wrist. They are located as in figure (7) and their respective abbreviations will be used hereafter. When not refered explicitly, fingers are denoted by numbers: from 1 for thumb to 5 for little finger.

![Hand Diagram](image)

The degrees of freedom in the hand are:

Extension / Flexion: to increase or decrease the angle between bones. It occurs at DIP, PIP, MCP and wrist joints.
Adduction / Abduction: to move a bone closer to or away from the midline of the body (hand). It occurs at the MCP and wrist joints.

Muscles acting on the hand and wrist are either located in the forearm (extrinsic) or in the hand (intrinsic). There are 9 intrinsic muscles acting on the thumb and the rest of the digits. The intrinsic actions are extension/flexion and abduction/adduction of the thumb and adduction/adduction of the digits. Extrinsic muscles perform extension and flexion of all joints of the fingers, the thumb MCP and DIP and wrist and also adduction and abduction of the wrist.

As the intended human machine interface is supposed to control a hand prosthesis, only the degrees of freedom implemented by the extrinsic muscles are considered. The extrinsic muscles are organized into three layers depending on where they are located in the arm: deep, intermediate and superficial layers. Deep muscles are located in the center of the arm and are to some extent covered by the intermediate and superficial located muscles respectively. The 9 extensors and 6 flexors provide the degrees of freedom that will be estimated, are named in table(1) and hereafter they will be referred to by their abbreviations.

The muscles act on the digits and wrist according to[14]:

- Flexion digits: FDP and FDS, which both are multi tendoned and attach to all digits. The FDP attach to the distal phalanx affecting the DIP, PIP and MCP joints, and FDS is attached to the middle phalanx and affect only PIP and MCP.

- Flexion thumb: FPC, which is attached to the distal phalanx and affect the DIP and PIP.

- Flexion wrist: FCU, PL and FCR which are attached to metacarpals and remaining flexors participate.

Extension of digits: ED, which is multi tendoned and attach to all digits at the distal phalanx. The index finger and little finger both have muscles, EI and EDI, that act on them alone.

Extension thumb: EPL attached to the distal phalanx and EPI attached to the middle phalanx.

Extension wrist: ECU, ECRL and ECRB attached to metacarpals and remaining extensors participate.

2.6.2 Individuated Control of Digits

The extrinsic muscles controlling the fingers such as the FDP, FDS and ED are all multiten doned and attached to all four fingers. It is not clear how individual finger motion is achieved. According to Schieber [22], there are three possible explanations. The first possibility lies in neuromuscular compartmentalization: a muscle could be divided into functional sub divisions, each innervated by separate nerves, which would allow a multitended muscle to act separately on each tendon. A second possibility is that individuated finger movements are mediated by actions of the intrinsic muscles. The third possibility is that individuated finger movements are achieved by the combined actions of several multitended muscles. If the multi tendoned muscles produce different tensions at the digits it serves, various combinations of muscle activity could produce different degrees of individual freedom for every finger. Also could some muscles act to move a finger and others to stabilize the others.

The activation of motor units in different compartments of ED in force production of individual digits were explored by Keen et al.[9], and it was found that the motor units in different compartments showed unsynchronized firing, supporting the notion of compartmentalization. An electromyography study of the FDP reported by Reilly et al.[19] suggest an
incomplete compartmentalization. Recording EMG activity in different sites in the FDP showed high EMG activation for individual fingers, but also a lesser activation when adjacent fingers where active. Furthermore Shieb[22] reported that EMG recording in monkeys during movement of different digits show that a given multi tendoned muscle can serve as agonist, antagonist or stabilizer for the fingers it acts on. This supports the notion that individualized finger movement is achieved by the combined actions of several muscles. The same notion is supported by Wings et al. in [30] where synchronization of FPL and FDP during 5 digit grasping tasks is observed. The roles of intrinsic muscles have been studied through EMG by Basnajian [16], who shows that the intrinsic muscles primarily are involved in controlling the relative flexion/extension of the DIP, PIP and MCP joints, but not in individualizing digit movement.

Table 1: Extrinsic flexors and extensors with respective abbreviation

<table>
<thead>
<tr>
<th>Flexors</th>
<th>Extensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>deep layer:</td>
<td></td>
</tr>
<tr>
<td>Flex. Digits Profundus FDP</td>
<td>Ext. Indicis EI</td>
</tr>
<tr>
<td>Flex. Pollicis Longus FPL</td>
<td>Ext. Pollicis Longus EPL</td>
</tr>
<tr>
<td>Ext. Pollicis Brevis EPB</td>
<td></td>
</tr>
<tr>
<td>Intermediate layer:</td>
<td></td>
</tr>
<tr>
<td>Flex. Digits Superficials FDS</td>
<td></td>
</tr>
<tr>
<td>Superficial layer:</td>
<td></td>
</tr>
<tr>
<td>Flex. Carpi Ulnaris FCU</td>
<td>Ext. Carpi Ulnaris ECU</td>
</tr>
<tr>
<td>Palmaris Longus PL</td>
<td>Ext. Digits Minimi EDM</td>
</tr>
<tr>
<td>Flex. Carpi Radialis FCR</td>
<td>Ext. Digits ED</td>
</tr>
<tr>
<td>Ext. Carpi Radialis Longus ECRB</td>
<td></td>
</tr>
<tr>
<td>Ext. Carpi Radialis Brevis ECRB</td>
<td></td>
</tr>
</tbody>
</table>

2.7 EMG control

The EMG signal is used in many medical applications, especially as a diagnosis tool to determine muscle abnormalities [29][21] or muscle fatigue[12]. As the EMG signal reflects muscular activity, and the fact that the EMG signal can be observed before muscular action occurs has made EMG an interesting source for control of devices such as prosthetics[3, 17, 18, 4]. The idea of a human machine interface based on EMG dates back to ideas of Norbert Wiener in 1948[24] and there are many approaches for the use of myoelectric signals for control in the literature. As the aim of the thesis is to estimate joint angles of fingers and the wrist, I will briefly present results in the estimation of posture of the arm[32], classification of hand movements[3][17], classification of finger activation[8] and estimation of finger posture[27].

2.7.1 Classification of EMG Patterns

Classification of EMG patterns is to map an EMG pattern to into a certain movement or gesture. Engelhart et al.[17] describes the classification task as a 3-stage process involving signal measurement, signal representation and classification, as depicted schematically in figure(8). Signal representation is a crucial to classification performance, and is divided into feature
extraction and dimensionality reduction.

Feature extraction is a process to compute signal attributes that reflect different aspects of the EMG signal. Two basic approaches to extract features from the EMG signal are temporal and spectral approaches.

Dimensionality reduction is used to retain information important for class discrimination and discard irrelevant information. The purpose of dimensionality reduction is to provide the classifier with fewer inputs. A classifier with low input dimensionality has few number of parameters that have to be adapted, which leads to a classifier with better generalisation ability. Two strategies for dimensionality reduction are:

Feature selection, where a subset of features are chosen according to some class separability (CS) criterion.

Feature projection, which decides a linear combination of features through Principal Component Analysis (PCA) of the features.

The performance of the signal representation is dependent on the capabilities of the classifier. Two basic classifier approaches are artificial neural networks and statistic classifiers.

Engelhart et al. [17] compares classifier performance of features extracted as time domain features proposed by Hudgins[3], Short Time Fourier Transform, Wavelet transform and Wavelet Package Transform. Dimensionality reduction is performed with either PCA or feature selection, and classifiers explored are ANN and linear discriminant analysis (LDA).

2.7.2 Estimation of Arm Posture

When controlling a device that resembles a human joint or limb, it is desirable to have an intuitive generation of control signals. A natural way of generating these commands from EMG would be to mimic the behaviour of the limb. Koikey and Kawato[32] estimated arm posture in 3D space from surface EMG signals. Three degrees of freedom in the shoulder and one in the elbow was estimated and surface EMG signals were recorded from 12 muscles controlling flexion/extension, abduction/adduction and rotation of the shoulder joint. Hand, elbow and shoulder positions were recorded simultaneously with EMG signals at 35 different positions in 3D space. A low pass finite impulse response filter was used to capture the relationship between the EMG signal and muscle tension:

$$\hat{T}(t) = \sum_{j=1}^{n} (h_j \times EMG(t - j + 1))$$

where $h_j$ is the filter, $EMG$ the processed EMG signal, $\hat{T}$ is an estimate of the muscle tension and $j$ is the impulse response time $j$. A 3-layer artificial neural network with 30 hidden nodes was trained with joint angle data calculated from arm positions as targets and low pass filtered EMG signals as input. The back propagation algorithm was used for learning, and training was aborted before test data ex-
rror started to rise. The coefficients of determination for the 38,500 test samples were 0.69 for shoulder abduction / adduction, 0.92 for shoulder flexion / extension, 0.67 for shoulder rotation and 0.78 for elbow flexion / extension.

DaSalla et al. [4] estimated flexion / extension, adduction / abduction and pronation / supination of the wrist using similar methods to control a robot. EMG signals from 12 muscles and joint angles were recorded for 44 wrist postures. Correlation coefficients for estimated and measured joint angles for respective degree of freedom were 0.90, 0.85 and 0.86.

2.7.3 Individuated Finger Movement

The functionality of the human hand is to a large extent founded in the ability to combine individual finger postures to shape the hand to a tool suitable for a special task, such as holding a pencil or grasping a mug. When trying to reproduce the functionality of the hand, it is important to distinguish which fingers are active in a task.

Peleg et al. [8] classified which finger is active by measuring EMG signals. Subjects had their arm supported and hand fixed to a board of five micro switches that were pressed in random order with a delay between each push and EMG was recorded from 2 electrode pairs on the forearm. The data processing was divided into four stages:

Finger activation identification, where intervals of finger activation are identified without regard to finger identity. Muscles were determined to be active if the enveloped and bandpassed EMG signal for either of the electrode pairs exceeded a certain threshold.

Feature extraction, features were extracted from the previously identified intervals. Features were obtained from two sources: (1) Mean and variance of 20 frequency bands in the region 0-250 Hz, obtained from the Discrete Fourier Transform. (2)

Coefficients of an eleventh-order autoregressive model.

Classification, was done by a modified K-nearest neighbour algorithm.

Feature selection. A total of 102 features were calculated and a genetic algorithm was used to reduce dimensionality.

Average error percentage for classification of thumb activity was 7% (std: 5.5%) and 0.5% (std: 0.8%) for the other digits. A very good result, but a serious flaw for use in a real time system is that EMG samples used were 1.6 seconds long, creating an unacceptable delay in a real time control system.

2.7.4 Estimation of Finger Posture

The posture of the hand can be described by the individual postures of each finger, relative to the palm. Afshar and Matsuda [27] predict joint angles of the index finger. EMG signals recorded with indwelling electrodes from seven muscles in hand and forearm. MCP joint abduction, MCP joint flexion and PIP flexion were calculated with inverse kinematics from the fixed hand position and the fingertip position. DIP joint was estimated as a linear combination of PIP and MCP joint angles. EMG and positions were recorded simultaneously when the subject traced a line segment with the fingertip. For each subject this movement was recorded 120 times of which the first 60 were discarded as they may include adaptional change. The EMG signals was represented in two ways:

Lowpass filtered EMG signal.

EMG based torque estimate (EBTE). Assuming that the low pass filtered signal is proportional to muscle force, and measuring the moment arm of muscles around each joint, EBTE \( \tau_j \) for each joint is calculated as

\[
\tau_j(t) = \sum \hat{F}_m(t) \times r_{m,j}
\]
where \( \hat{F}_m \) is the force estimate and \( r_{m,j} \)
is the moment arm radius of muscle \( m \) at joint \( j \). 4 EBTEs corresponding to each
degree of freedom were calculated from
the 7 EMG channels.

A two layer ANN was used to estimate joint
angles with input data either as the lowpass fil-
tered signal of EBTE of each joint. Ten move-
ment sessions were used for training and 3 for
testing. The estimation using EBTE as input
yielded a average coefficient of determination
of 0.76 ± 0.14 and when using the lowpass fil-
tered EMG signal as input average coefficient
of determination of 0.70 ± 0.16 for the joint
angles.[27]

3 Mathematical tools

3.1 Artificial Neural Networks (ANN)

An Artificial Neural Networks (ANN) is a col-
lection of simple nodes that has the ability to
process information. The nodes are modeled
after the biological neuron, and they are inter-
connected in such a way that the information
processing of the collection resembles the
brain. The information processing is analogus
to that of the brain in the respect that the
ANN learns from experience, and store the
knowledge as weights in the interconnections.[28]

ANNs are robust to noisy data and has
good generalisation ability, properties making
the method suitable when working with the
unstable and noise prone EMG signal. Also,
to estimate joint angles from EMG we must
(1) estimate muscle torque from quasi tension
(i.e. find moment arms) and (2) estimate the
relationship between Joint torque and joint
angles. Due to the relations described in (2.4.2),
\( \alpha \) and \( T \) in equation (1) are nonlinear, so the
equation can not be solved analytically, but as
the transformation from muscle torque to
equilibrium angle is a many to one mapping
an ANN is suitable to learn the relationship.

3.1.1 Biological Neuron

The biological neuron is shortly described as
an introduction to ANN. The basic informa-
tion processing units in the nervous system are
the neurons, which have electrical properties
allowing to process and propagate information
to other cells.

The neuron has three distinct regions: axon
and dendrites and soma. The axon is a single
fiber that emanates from the soma and car-
rries information away from the cell to other
neurons or muscles. The information is en-
coded as electrical pulses, action potentials,
which originate in the soma. Dendrites are
protruding fibers that have a highly branched
structure and are specialized in receiving sig-
als from other neurons. Axons and dendrites
are connected through synapses, which trans-
fers action potentials electrochemically from
the axon to the dendrite. A neuron has mul-
tiple dendrites and receive information from
multiple neurons all causing electrical changes
in the neuron. The magnitude of the elec-
trical change is dependent on the strength of
the synapse. The electrical changes are spatio-
temporally summed in the soma and if the
resulting potential change exceeds the action
potential threshold an action potential is trig-
gered and propagated along the axon. See
figure(9) for a schematic view of the neuron.

3.1.2 The Action Potential

All cells are contained by a plasma membrane
that works as an insulator between the con-
ducting solutions on the inside and outside
of the cell, and ions pass the membrane is
through diffusion through ion channels or ac-
tively by the means of ions pumps. Because of
the membranes ion specific permeability through
ion channels and active transportation of ions
across the membrane, an electrical potential
difference exists across the membrane. At the
resting potential, electric and diffusion forces
are equal leading to a zero net movement of
ions. This equilibrium state is dependent on
ion permeability and changes in permeability leads to a new equilibrium.

Neurons and muscle fibers are said to be excitable as they have the ability to briefly alter their membrane potential. Coming sections describes the action potential focusing on neurons, but the generation of action potentials is also valid for muscle fibers. Muscle fibers differ from neurons in that they don’t have any axon or dendrites and that the input to a muscle fibers always exceeds the required action potential threshold.

The signals communicated in the neural system are fast and large changes in membrane potential, which are call action potentials. An action potential is triggered when the summation of synaptic input causes the membrane potential to exceed a threshold. At this threshold ion specific permeability changes giving rise to a series of ionic fluxes, which is manifested electrically as an action potential. An action potential is shown in figure(10). The amplitude of the action potential is constant for a certain neuron, and it does not reveal anything about the stimuli except that it was above threshold. This is usually described as the all-or-nothing-behavior of the action potential.

### 3.1.3 Artificial Neuron

In the same way neurons are the basic elements of information processing in biological neural networks, artificial neurons, are the building blocks of the ANN. A schematic artificial neuron, or node, is depicted in figure(11).

It is modeled after the biological neuron, and processes information in a similar way. Signals $x$ (stimuli) are weighted by weights $w_i$ (synaptic strength) and summed (summation in the soma), and the transfer function $\varphi$ determines output response. Knowledge is stored in the weights, which are updated through some learning algorithm. A unit with a step transfer function outputting a 1 if a certain threshold is reached and 0 otherwise captures the all or none behavior of the action poten-
Membrane pot.

\[ \text{mV} \]

\[ 0 \]

threshold

rest. pot.

\[ 0 \quad 1 \quad 2 \quad 3 \quad 4 \quad 5 \] ms

stim, puls

Figure 10: The action potential has three phases caused by different ion fluxes: depolarization (1-1.5 ms), repolarization (1.5-2 ms) and hyperpolarization (2-3.5 ms). The Action potential is only triggered if the stimulation pulse causes the membrane potential to exceed a threshold. Dotted line shows stimulation that does not rise above the threshold and is not propagated along the axon.

\[ \phi = \sum_{i=1}^{n} w_i x_i \]

\[ y = \varphi(\sum_{i=1}^{n} w_i x_i) \]

Figure 12: Examples of commonly used transfer functions.

3.1.4 Artificial Neural Network (ANN)

Typical ANN consist of a collection of nodes (artificial neurons) connected by links that are assigned with weights. The nodes are structured in such way that knowledge, relevant for a mapping from input data to desired output, can be updated and stored. Knowledge is stored in the weights and updated through a learning process. Learning is either supervised or unsupervised. In the case of supervised learning the ANN is presented with pairs of input data and target data, and in the case of unsupervised learning clusters are formed from the input data.

One of the most common ANN architecture is the Multiple Layer Perceptron (MLP), which also is used in this thesis. The MLP is a feed forward network, where nodes are organized into layers: input layer, hidden layer(s) and output layer. There are no loops and the nodes are only connected to the next layer, see figure(13). Signals flow through the input layer through the hidden layer (can be more than one layer) and out through the output layer. The MLP consists of nodes with a nonlinear sigmoid transfer function, which endows the ANN with capacity of learning nonlinear relationships between input data and desired response.
The MLP is often trained with back propagation, a supervised learning algorithm. Weights are adjusted according to gradient descent on the error function, usually the mean squared error (MSE). After the output nodes have been updated the error is back propagated to the hidden nodes which then are updated. The back propagation step requires a differentiable transfer function in order to calculate the gradient.

There are many versions of the back propagation algorithm and the most basic updates the weights in the direction in which the error function decreases most rapidly: the negative of the gradient. One iteration of the basic back propagation algorithm can be written as $x_{j+1} = x_j - g_j \alpha_j$, where $x_j$ are current weights and $g_j$ is the gradient and $\alpha_j$ is the learning rate.[28]

### 3.1.5 Issues in MLP ANN Training:

**Learning rate** Performance of back propagation is sensitive to the learning rate. If the step size is too large the algorithm may oscillate and become unstable, while a too small step makes the algorithm take too long to converge on a minimum of the error surface. Several versions of the BP-algorithm uses a variable step size to overcome this problem, for example the Levenberg-Marquardt algorithm[23].

**Stopping Criteria** The point of training an ANN is to find a general mapping from input data to target data. This map should be able to generalize to unseen data samples from the same distribution not explicitly learned by the ANN, that is to learn the structure of the data distribution. It is possible to train an ANN to extensively, at which point the performance function decreases for unseen data while still increasing for training data. A common method to avoid overtraining is cross validation, which aborts training when performance decreases for a separate validation data set that is not used for training.

**Size of Hidden Layer** In this thesis we use the ANN to estimate the function or mapping from input to desired output. How complex the mapping is allowed to be is decided by the number units in the hidden layer. An ideal size would allow the net to learn the underlying structure of the data allowing it to generalize unseen data points. To few nodes would not give enough to estimate the function well while too many leads to overfitting. When overfitting occurs the function accommodates for noise and incertitudes in training data that does not exist in the true function. There does not exist any rule how to decide optimal size except trying different sizes empirically.[28]

### 3.2 Wavelet Transform

Generally transformations are applied to signals in order to obtain information about the signal that is not easily accessible in the current representation or domain. The motivation for using frequency information when analyzing the EMG signal is biological and stems from location of muscles controlling the fingers in the forearm and also properties of tissues such as fat and muscle, which have a low pass
filtering effect[16]. As described in section?, muscles mainly involved in flexion and extension of the fingers are located in deep and intermediate muscle layers of the forearm. To capture the activity of these muscles, electrodes have to be placed on or between more superficial muscles resulting in an EMG signal containing muscle activity information from several muscles. The basic idea and motivation for using a frequency representation is that activity from more deeply located muscles are represented in lower frequencies.

The choice of using the wavelet transform is mainly because it is suitable for representing choppy signals with sharp discontinuities and it allows for multiresolution analysis of a signal[1].

### 3.2.1 The wavelet transform

The wavelet transform is used to get a time-frequency representation of a signal. The concept of time frequency representation can be understood in the context of the Fourier transform, which decomposes a signal into a sum of sines and cosines of different frequencies.

The Fourier coefficients resulting from the Fourier transform represents the contribution of different frequencies of sines and cosines the signal can be analyzed for its frequency content. As sines are periodic and have infinite support, which have the consequences that 1) all temporal information about when a frequency component occurs is lost, and 2) they are unsuitable to represent non-periodic and choppy signals with sharp discontinuities[1][26].

The wavelet transform bridges these limitations and similar to the Fourier transform the wavelet transform decomposes the signal into basis functions of different frequency, which is referred to as scale in the wavelet transform. Large scale correlates with low frequency components and small scale correlates with high frequency components. The functions are called wavelets and a significant difference from sinuosids is that they have finite support and thus are localized in time.

The functions that define an orthogonal basis for the Wavelet transform translated and dilated versions of a so called mother wavelet \( \psi(x) \) are defined as:

\[
\psi_{s,t} = \frac{1}{\sqrt{s}} \psi\left(\frac{t - \tau}{s}\right)
\]

(2)

The scaling \( \tau \) of a wavelet describes how compressed respectively dilated it is and shifting or translating \( s \) refers to where on the time axis the wavelet's support begins. The continuous wavelet transform is given by

\[
C(s, \tau) = \int x(t) \psi_{s,t}(t) dt
\]

(3)

In the continuous wavelet transform \( C(s, \tau) \) is given by continuously shifting a continuously scalable function along a signal and calculating the correlation coefficient. To make wavelets practical a discrete wavelet transform that shifts and scales the motherwavelet discretely was introduced. It is applied to discrete sequences of input and a discrete version of the continuous wavelet is used:

\[
\psi_{j,k}(t) = \frac{1}{\sqrt{s_0^j}} \psi\left(\frac{t - k\tau_0 s_0^j}{s_0^j}\right)
\]

(4)

\( j \) and \( k \) are integers and \( s_0 \) is a fixed dilation step while \( \tau_0 \) is dependent on the dilation step. The effect of discretizing the wavelet is that the time-scale space also gets a discrete tiling and with choosing \( s_0 = 2 \) and \( \tau_0 = 1 \) the resulting grid is dyadic as shown in figure(14). The gridding allows for temporal analysis of the signal at low scales with contracted wavelets and frequency analysis at high scales with dilated wavelets. When the discrete wavelet transform is performed on a signal, the result is a series of wavelet coefficients, and the procedure is denoted as wavelet series decomposition. With orthogonal wavelet bases the original signal \( f(t) \) can be reconstructed fully by summing the wavelet functions weighted by their respective wavelet coefficient \( \gamma_{j,k} \):
\[ f(t) = \sum_{j,k} \gamma(j,k)\Psi_{j,k}(t) \]

which is the inverse wavelet transform.

The same way wavelets cover different parts of the time domain depending on translation, wavelets of different scales cover different spectra of the frequency domain and each wavelet can be seen as a bandpass filter\[5\]. With dyadic sampling the bandwidth is halved for every increase in scale resulting in the need of an infinite number of differently scaled wavelets to cover the whole spectrum. This is solved by approximating the spectra of wavelets above a certain scale with a scaling function \( \phi \) which is derived from the mother wavelet.

The discrete wavelet transform can be efficiently implemented as a digital filter bank which involves lowpass and bandpass filters and down sampling. An example of a filter bank scheme is depicted in figure(15) and is denoted as Mallat's algorithm.

The lowpass filter uses the scaling function \( \phi \) as impulse response while the bandpass filter uses the wavelet function \( \psi \) as impulse response and scaling is done by down-sampling. The procedure results in a series of detail coefficients \( d_j \) corresponding to high frequency events and approximation coefficients \( a_j \) corresponding to the remaining low frequency content of the signal, where index \( j \) denotes the decomposition level which correspond to a scale of \( 2^j \).

3.2.2 Wavelets

The set of possible wavelets is infinite, but standard wavelet families are Daubechies (db), Coiflet (cif), Haar and Symmlets (sym), which all form orthogonal bases and differ in smoothness and time and frequency localization they have. Smoothness is indicated by how regular a function is, which generally is inversely related to how well the function is localized in time and frequency. Within a family wavelets are classified according to how many vanishing moments they have, which directly relates number of wavelet coefficients generated. Examples of some wavelet functions are given in figure(16)
3.3 Principal Component Analysis (PCA)

Principal component analysis is used to reduce dimensionality of data and identifying
new components describing the underlying structure of the data with respect to variance. A
vector of $n$ components can be seen as a point in a coordinate system with $n$ dimensions, and
geometrically PCA can be seen as a rotation to a new coordinate system with orthogonal
dimensions. Each axis or dimension can be ranked according to how big fraction of the
total variation in the data set it is responsible for.

PCA is based on the statistical representation of a random variable. Assume we have an
$m$-dimensional random vector $X$, where $X = (x_1, x_2, ..., x_m)$, with mean $\mu_x$, where $\mu_x = E(X)$, and the covariance matrix $C$ of the data set is $C = E((X - \mu_x)(X - \mu_x)^T)$. The element $c_{ij}$ in the $C$ is the covariance coefficient for components $x_i$ and $x_j$. $x_{ik}$ is the variance of element $x_i$ describing the spread around its mean. If 2 components are uncorrelated their covariance coefficient equals zero.

We can calculate an orthogonal basis for the symmetric covariance matrix by finding its
eigenvectors $e_i$ and corresponding eigenvalues $\lambda_i$ by solving $|C - \lambda I| = 0$. The eigenvalues and their corresponding eigenvectors can be calculated using for example Singular Value Decomposition (SVD). SVD is based on the fact that any $m \times n$ matrix $A$ where $m > n$ can be decomposed according to $A = USV^T$, where $U$ is an $m \times m$ orthogonal matrix, $S$ is an $m \times n$ diagonal matrix containing non-negative eigenvalues and $V$ is an $n \times n$ matrix. The vectors of $U$ are eigenvectors $e_i$ and the diagonal elements of $S$ contain eigenvalues $\lambda_i$ sorted in descending order. Each eigenvector define a principal component with the first principal component corresponding to the largest eigenvalue, the second principal component corresponding to the second largest eigenvalue and so on. The variance accounted for by each principal component is related to the size of the associated eigenvalue. Components corresponding to large eigenvalues account for a high share of the variance in the data and conversely components corresponding to small eigenvalues account for little variance in the data.

If $B = U^T$, $B$ can be seen as a transformation matrix that transforms a vector $x$ from
the input space to the space spanned by the principal components:

$$y = B(x - \mu_x)$$

where $y$ is a point in the orthogonal space spanned by the eigenvectors. Using the orthogonal matrix property $B^T = B^{-1}$ data vector $x$ can be reconstructed according to

$$x = B^Ty + \mu_x$$

As a vector $x$ can be projected onto a subspace spanned by a subset of principal components,
a reduction of dimensionality can be achieved. If $B_k$ consist of only the $k$ first eigenvectors,
the transformation

$$y_k = B_k(x - \mu_x)$$
takes a vector from \( m \)-dimensional space to \( k \)-dimensional space where \( k < m \). When reconstructed according to
\[
x' = B_k^T y_k + \mu_x
\]
\( x' \) is a linear combination of the first \( k \) components in the original space.

If the information content in a signal is located in a linear subspace this provides a way of compressing data with little loss of information.

In the context of feature extraction PCA is desirable as:

- features are easily ranked according to accountability of variance in the data.
- features are mutually uncorrelated
- acts to reduce variation in data as random noise is relegated to trailing components

PCA is unsuitable if valuable information in the signal is not contained in the largest principal components or if the information is not located in a linear subspace.

4 Method

The process of estimating joint angles of fingers and the wrist, will approached by recording surface EMG signals from extrinsic muscles controlling the hand and wrist. Extrinsic muscles control flexion and extension of joints, and therefore only these degrees of freedom will be considered. The non-linear mapping from EMG to joint angles will be estimated by an artificial neural network with different representations of the EMG signal as input data and joint angles as target data. The EMG signal will be represented as either a muscle tension estimate or as wavelet coefficients. The high input dimensionality that the wavelet transform results in will be reduced with principal component analysis. The process of estimating the joint angles is done in three steps:

- Simultaneous collection of EMG and joint angle data.
- EMG feature extraction and dimensionality reduction.
- Training and testing with artificial neural network.

4.1 Collection of Data

Joint angle data and EMG signals are simultaneously collected to form pairs of input data and target data to train and test an ANN.

4.1.1 Joint Angles

Joint angles are either calculated from data acquired from an optical positioning sensing system or received directly from a glove equipped with bend sensors at joints.

4.1.2 EMG

EMG signals are collected with bipolar silver-silver chloride surface electrodes from the forearm at 2000 Hz differentially amplified with 12 bit resolution. The raw EMG signal is amplified with either NEC biotop or Debys Bagnoli.

In the case of NEC biotop, the raw EMG is filtered with an analog bandpass filter with cut off frequencies at 50 Hz and 1500 Hz respectively before recording.

With the Debys amplifier the raw EMG is band pass filtered with cut off frequencies at 20 Hz and 450 Hz.

4.1.3 Electrode Location

Procedures concerning electrode location, described in section (2.3), are taken into consideration, but as some of the muscles recorded are located in intermediate and deep layers such as the FDS and FPL they are not always possible to follow. To record deep and intermediate layer muscles we are forced to position the electrodes proximal to the tendon in-
serted and between more superficial muscles, the procedures are also neglected when trying to find functional compartments in multitendoned muscles as ED to be able to distinguish EMG signals for movement of individual fingers.

Electrode placement is verified by observing elicited EMG signal for movements associated to the muscle.

It can be difficult to record EMG that corresponds to individual motion of one finger only. This cross talk can depend on small muscle size, the muscle is located in the deep or intermediate layer or the muscle is multitendoned and acts on several joints.

4.2 EMG Feature Extraction

Features from the EMG signal are extracted in two ways after initial amplification and filtering.

Feature extraction to obtain input data from the EMG signal is done either by lowpass filtering the data with a FIR filter as an estimate of muscle tension or through wavelet decomposition generating wavelet coefficients.

4.2.1 Muscle Tension Estimate

The muscle tension estimate at time \( t \) is obtained from \( \hat{T}(t) = \sum_{j=1}^{n} (h_j \times EMG(t - j + 1)) \) where \( EMG \) is the centered, rectified and 10 point averaged signal. \( h_j \) is the digitized impulse response \( h(t) \) of the second order finite impulse response filter \( H(s) \):

\[
h(t) = a \times (e^{-bt} - e^{-ct})
\]  

I use the same filter as Koike et al. in [33] where the coefficients \( a, b \) and \( c \) in 5 are derived to \( a = 6.44, b = 10.80 \) and \( c = 16.52 \) from surface EMG signals originating in shoulder and over arm muscles. The response is maximal after 100 ms causing a lag between the filtered signal and raw EMG signal. This lag conforms to lag between EMG signals and muscle tension reported in [7].

4.2.2 Wavelet decomposition

Performing a wavelet decomposition on the EMG signal results in a time-frequency representation given by wavelet coefficients. Motivation for using the wavelet transform is given in section (3.2). For each EMG channel input to the ANN is obtained by:

1. centering and rectification of the EMG signal
2. Division of each channel of EMG data into segments of 128 ms (256 samples).
3. Decomposition of each segment into wavelet coefficients of a wavelet type.

As the wavelet decomposition transforms the signal from one dimension to two the resulting number of wavelet coefficients is large. The number of coefficients depend on wavelet type and signal length, but a full decomposition of 256 samples typically results in more than 100 coefficients. With many EMG channels the resulting high data dimensionality may affect the generalization ability of the ANN[31] and a reduction of input dimensionality is desirable. Principal Component Analysis is used to reduce dimensionality. The PCA transform matrix is obtained from the training data set and applied on the test set.

4.3 ANN

A feed forward ANN with two layer as depicted in figure (17) is used to estimate joint angles. The nodes have differentiable sigmoidal transfer functions to allow for nonlinear mappings and the use of back-propagation algorithms. The net is trained with Marquardt-Levenberg backpropagation and training is aborted when mean squared error increases for the test data set.
4.4 Equipment

4.4.1 Measuring equipment

**OptoTrak**  Northern Digital Optotrak 3020 is an optical 3-dimensional positioning system. Optotrak's main unit contains 3 infra red sensitive lenses that provide 3-d positions of infrared markers. The joint angles required as target data is calculated from measured positions in space.[11]

**CyberGlove**  CyberGlove from Immersion Corporation is a glove with 18 sensors measuring joints of the hand and fingers. Bend sensors are located over or near the joints of the hand and wrist. Each finger has bend sensors over the MCP andPIP joints. The glove measures flexion / extension, adduction / abduction and rotations in various joints, but only flexion / extension data was used in the study.[6]

**NEC Biotop**  Biotop 6R12 from NEC is a amplifier for 16 channels with maximal gain of 105dB (corresponding to amplifying 10μV to 2V). Sensitivity is adjustable from 10μV to 100mV in 13 steps. High pass filter and low pass filters are adjustable from 0.016 Hz to 100 Hz and 30 Hz to 3kHz respectively, or inactive. We use 50 Hz and 1500Hz respectively [25]. Ambu Blue Sensor SE Silver-Silver Chloride sensors with conductive gel are used in combination with NEC biotop. They are used pair-wise in differentiable a setting. NEC Biotop is advantageous due to more sensitive amplification settings and wider passband than Delsys, but has drawbacks as it uses wet electrodes that have to be placed individually to form a pair and more difficult to find suitable locations with.

**Delsys Bagnoli 16 EMG system**  Delsys Bagnoli 16 EMG System from Delsys has 16 channels, a selectable gain of 100V, 1000V or 10000V, and a frequency bandwidth of of 20Hz to 450Hz per channel. Dry DE-2.1 single differentiable electrodes also from Delsys are used in combination with the Bagnoli system.[15]. The main advantage of Delsys is its electrode units that have both electrodes integrated at a fixed distance and are dry, making it more easy both to search for electrode locations and to relocate an earlier used location exactly, thus giving a more stable EMG signal throughout different experiments.

4.4.2 Software

**Matlab**  Calculations are made in Matlab using the Neural Network and Wavelet toolboxes.

**Custom software**  Simultaneous collection of EMG data and Optotrak / CyberGlove data is done with custom software in C++.

4.5 Experiment 1

One healthy person participated in this experiment. The aim of the experiment is:

1. Estimate index finger DIP, MCP and WRIST joint angles during flexion and extension and decide if it is feasible to expand experiment to other fingers as well.
2. Decide which wavelet type to use in in future experiments.
3. Decide number of wavelet coefficients to use.

Figure 17: Feed forward ANN used to estimate joint angles from EMG features.
4. Decide neural network parameters such as size of hidden layer and rate of learning.

To achieve this EMG data and angle data was collected simultaneously for use as input data and target data to the ANN respectively.

4.5.1 Recording of Data

Joint angle data was collected with position sensing system OptoTrak at 100 Hz. Sensors were placed at each phalanx of the index finger and on the palm to calculate finger joint angles and on the forearm to calculate the wrist angle. Markers were located at the side of the hand, palm and forearm to readily record flexion/extension and joint angles for DIP, PIP, MCP and WRIST were calculated.

EMG signals were collected with bipolar silver-silver chloride surface electrodes from the forearm at 2000 Hz differentially amplified with 12 bit resolution. The raw EMG signal was recorded and amplified with NEC biotop due to more sensitive amplification settings and wider passband than Delsys. The raw EMG was filtered with an analog bandpass filter with cut off frequencies at 50 Hz and 1500 Hz respectively before recording. See figure (18) for the experimental setting of markers and electrodes and schematic placement of electrodes in experiment 1.

Which muscles were recorded and which joints they act on are given in table (2).

12 electrode pairs were used. The sites on the fore arm were located with a dry electrode pair and were confirmed visually by monitoring the resulting EMG activity of movements. The sites were marked and wet electrodes attached. A reference electrode was located on the earlobe.

The subject was seated with his forearm resting on an arm rest and data was recorded when the finger and wrist were in static postures to fulfill muscle torque equilibrium. Wrist flexion/extension was limited to 4 states between total flexion and total extension. The

Figure 18: experimental setting and schematic placement of electrodes.
Table 2: Muscles recorded and which joints they act on

<table>
<thead>
<tr>
<th>Muscles</th>
<th>Joints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flex. Pollicis Longus, PL</td>
<td>MCP1, PIP1</td>
</tr>
<tr>
<td>Flex. Digitii Superficialis, FDS</td>
<td>MCP2, PIP2</td>
</tr>
<tr>
<td>Palmaris Longus, PL</td>
<td>Wrist</td>
</tr>
<tr>
<td>Flex. Carpi Radii, ECR</td>
<td>Wrist</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Extensors</th>
<th>Joints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ext. Pollicis Brevis, EPR</td>
<td>MCP2, PIP2</td>
</tr>
<tr>
<td>Ext. Digitii Minimi, EDM</td>
<td>MCP3, PIP3</td>
</tr>
<tr>
<td>Ext. Digitii, ED</td>
<td>MCP4-5, PIP4-5</td>
</tr>
<tr>
<td>Ext. Carpi Radialis Brevis, ECRB</td>
<td>Wrist</td>
</tr>
</tbody>
</table>

MCP and PIP joint states were varied more freely and a total of 280 postures were recorded for 5 seconds each.

4.5.2 Training and Test Data for ANN

Joint Angles  Joint angles $\theta_{PIP}$, $\theta_{MCP}$, and $\theta_{Wrist}$ are calculated from OptoTrak data to be matched with corresponding EMG samples to form training and test data sets.

Low pass filtered EMG  EMG signal was processed according to() and 11200 samples was used as training samples and 2800 samples of testing.

Wavelet decomposed EMG  To determine which wavelet is best wavelet coefficients generated by Haar, Daubechies2-10, Symlet1-8 and Coiflet1-5 wavelets were calculated for EMG sequences of length 256 samples with full level decomposition. Principal Component Analysis is performed on the coefficients and two data sets are created for each wavelet type, containing PCA transformed coefficients responsible for more than 5% and 1% of the total variation of all principal components respectively.

4.5.3 ANN

Parameters  The initial step size $\mu$ in the Levenberg-Marquardt algorithm was decided by training an ANN with 10 hidden nodes using only low pass filtered EMG and varying $\mu$ from 0.1 to 0.005. $\mu$ was decided to be 0.05.

Training  For both wavelet decomposed and only low passed EMG, sets of training and test data consists of 11200 and 2800 samples respectively and an initial step size of 0.05. Training is aborted when test data mean squared error starts to rise. In the case of low pass EMG the number of hidden nodes were varied between 1 and 50. For each wavelet type and data set, ANNs are trained with hidden layer size varying from 1 to 16.

4.6 Experiment 2

4 healthy subject participated in the experiment. In this experiment the hand is divided into 3 functional groups: thumb, index finger and remaining fingers moved like one. Remaining fingers are represented by long finger joint angles.

The goal of this experiment is to extend the number of estimated joint angles to 7: PIP and MCP joints for the functional groups and the wrist.

4.6.1 Recording of data

Simultaneous recordings of joint angles belonging to several fingers with OptoTrak imposes a problem as sensors get blocked. For instance, when sensors are located on the side of each finger, the index finger block sensors on the long finger, and the long finger blocks sensors on the middle finger. Blocking can be avoided by having the sensors located on protrusions from each fingers. This was tried, but was not deemed sufficient as it was very difficult to get the protrusions stable. Therefore we used a Cyber Glove.

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Joint angles data was collected with Cyber Glove at a frequency of 50 Hz. Joint angles collected measured flexion/extension and were the wrist joint angle and MCP and PIP for thumb, index finger and long finger respectively.

The EMG was acquired as in experiment 1 with the exception of location of electrodes that are approximately the same as in experiment 1, but extra attention has been paid to have at least one site for every functional group that corresponds to activation of that group exclusively, or at least more strongly.

The subject was seated with his forearm supported by an arm rest and data was recorded. Ideally records would be taken of static postures, but to reduce recording time data was recorded as fingers and wrist continuously moved very slowly to approximate joint equilibrium condition. 80 files of each 10 seconds were recorded when different combinations of finger groups were active simultaneously. see table (3) for combinations. MCP and PIP of each group was moved freely, and the wrist was active at all times. Inactive states are recorded to distinguish neutral postures without activity.

<table>
<thead>
<tr>
<th>Channel</th>
<th>Index</th>
<th>rest</th>
<th>number</th>
<th>File length</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1-10</td>
<td>10 s</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>11-20</td>
<td>10 s</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>21-30</td>
<td>10 s</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>31-40</td>
<td>10 s</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>41-50</td>
<td>10 s</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>51-60</td>
<td>10 s</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>61-80</td>
<td>10 s</td>
</tr>
</tbody>
</table>

Table 3: Recording scheme for experiment 2. A 1 indicate movement of finger, and 0 indicates that it is inactive.

4.6.2 Training and Test Data for ANN

Joint Angles Joint angles \( \theta_{PIP} \) and \( \theta_{MCP} \) for thumb, index and long finger and \( \theta_{Wrist} \) were recorded with Data Glove and used without further processing and was and matched with corresponding EMG data samples to form training and test data sets.

Low pass filtered EMG EMG signal was processed according to (2). 32,000 samples was used as training samples and 8000 samples of testing.

Wavelet decomposed EMG The Daubechies 3 wavelet was used to acquire wavelet coefficients from 256 samples of EMG each. PCA was performed and only coefficients corresponding to more than 5% of the variation was retained, which resulted in an indata dimension of 24. Training and test data consisted of 32000 and 8000 samples respectively.

4.6.3 ANN Training

For both wavelet decomposed and only low passed EMG, sets of training and test data consists of 32000 and 8000 samples respectively and an initial step size of 0.05. Training is aborted when test data mean squared error starts to rise. The number of hidden nodes were varied between 1 and 34 for both EMG representations.

4.7 Experiment 3

One healthy subject participated in the experiment. The goal of this experiment is to extend the number of estimated joint angles to 10: PIP and MCP joints for all fingers when moving independently and with a fixed wrist.

4.7.1 Recording of data

Joint angles data was collected with Cyber Glove at a frequency of 50 Hz. Joint angles collected measures flexion/extension and were
the wrist joint angle and MCP and PIP for all digits.

The EMG was acquired as in experiment 2 with the exception of electrodes used. In order to minimize the risk of displacing the wet electrodes when attaching them to sites identified with dry DelSys electrodes, the DelSys dry electrodes are used with a Bagoloi amplifier band pass filtering the raw EMG signal with cut off frequencies of 25 Hz and 450 Hz.

The subject was seated with his forearm supported by an arm rest and data was recorded. Ideally records would be taken of static postures, but to reduce recording time data was recorded as fingers and wrist continuously moved very slowly to approximate joint equilibrium condition. 80 files of each 10 seconds were recorded. For each finger 10 files were recorded when it was solely active and 30 files were recorded when all fingers moved independently at the same time. The wrist was immobile at all times.

4.7.2 Training and Test Data for ANN

Joint Angles  Joint angles $\theta_{PIP}$ and $\theta_{MCP}$ for all fingers were recorded with Data Glove and used without further processing and was and matched with corresponding EMG data samples to form training and test data sets.

Low pass filtered EMG  Due to inferior results with wavelet coefficients in experiment 2 only EMG signal processed to tension estimate is used to train the ANN. 16000 samples was used as training samples and 4000 samples of testing.

4.7.3 ANN Training

Training and test data consists of 16000 and 4000 samples respectively and an initial step size of 0.05. Training is aborted when test data mean squared error starts to rise. The number of hidden nodes were varied between 1 and 34.

5 Results

5.1 Experiment 1

The purpose of the experiment is to establish whether it is possible to estimate joint angles of index finger PIP, MCP and wrist from EMG signals only. 3 degrees of freedom is estimated. Two representations of the EMG signal are used: as a low pass filtered signal and as wavelet coefficients. In both cases should an optimal hidden layer size be established and in the wavelet coefficient case should also wavelet type and coefficients be chosen.

5.1.1 Low Pass Filtered EMG

Establishment of hidden layer size  Mean Squared Error (MSE) and Correlation Coefficients(CC) are calculated for measured joint angles and angles estimated by an Artificial Neural Network (ANN) with varying number of nodes in the hidden layer. Neither MSE or CC reach a minimum in the tested range of hidden nodes, but both measures show a diminishing increase in performance. At hidden layer sizes above 6 nodes only the PIP joint angle estimate shows increased performance. 30 nodes gives best performance in terms of both MSE and CC as shown in figure(19).

Performance  30 hidden nodes results in correlation coefficients 0.76, 0.93 and 0.98 for $\theta_{PIP}$, $\theta_{MCP}$ and $\theta_{WRdist}$ respectively. Performance worsens as respective joint is more distal. The decrease in performance for distal joints can also be explained by its location as tendons controlling it are affected passively by the state of more proximal joints resulting in a more complex mapping from EMG to joint angle. Also are muscles controlling distal joints more deeply located, which are more difficult to observe by the means of surface EMG. Estimation results are shown in figure(20).
Figure 20: Estimation results for $\theta_{PIP}$, $\theta_{MCP}$ and $\theta_{Wrist}$ respectively when using low pass filtered EMG as input to ANN. True angles (red line) and angle estimates (dotted green line) from test data are plotted together. To the right of each subplot are mean error, std (standard deviation of error), MSE and CC shown.

5.1.2 Wavelet Transform and PCA

Choice of wavelet type From the selection of wavelets from the Coiflet (coif), Symmlet (sym) and Daubechies (db) families no one performed clearly better, as can be seen in figure(21). PCA was performed on the wavelet coefficients and those components responsible for at least 5% of the total variation in the EMG signal were retained. As the Daubechies3 wavelet perform best with respect to correlation and also has high performance in terms of MSE it is chosen.

Choice of principal components Principal components (PCs) are chosen by deciding a fraction of total variation in the signal and discarding those components that are responsible for less. Cut off fractions of 0.01 and 0.05 yield big differences in the number of PCs without affecting the variation retained in the signal proportionally, as can be seen in table(4). Performance in respect to MSE and

<table>
<thead>
<tr>
<th>cut-off fraction</th>
<th>0.01</th>
<th>0.05</th>
</tr>
</thead>
<tbody>
<tr>
<td>number of PCs</td>
<td>106</td>
<td>25</td>
</tr>
<tr>
<td>variation retained</td>
<td>75%</td>
<td>50%</td>
</tr>
</tbody>
</table>

Table 4: Number of principal components and variation retained in the signal.

Correlation is given in figure(22). A cut-off fraction of 0.05 yields better results than 0.01.
In the case with fraction 0.01, the MSE performance increases more slowly as the size of the hidden layer increases, while the correlation coefficient for the PIP joint degrades with increased size. Low information content in the extra principal components seems to reduce the ANN's ability to generalize and more training data would be required to update weights properly. As a consequence, a cut of fraction of 0.05 is chosen.

**Performance** Increasing the hidden node number to 30, with Daubechies 3 wavelet and PCA with a variation cut off at 0.05 resulted in 0.69, 0.89 and 0.98 for $\theta_{PIP}$, $\theta_{MCP}$, and $\theta_{Wrist}$ and the results are comparable to ANN performance with only lowpass filtered EMG signals. The degradation in more distal joints is more apparent in the case of wavelet coefficients and generally the estimates more fluctuating as can be seen in figure (23).

**5.2 Experiment 2**

7 degrees of freedom is estimated. The hand was divided into three functional subgroups: thumb, index finger and remaining moving as one. The size of the hidden layer was determined as in experiment 1 for each test person and was varied between 1 and 34.

**5.2.1 Performance Low Pass Filtered EMG**

Size of optimal hidden layer was between 28 and 34 nodes for each person. Correlation coefficients varied between both test persons and joint angle as can be seen in table (5). Two tendencies can be seen in the estimation results: (i) The ANN shows difficulties in estimating the joint angles in inactive fingers. As some muscles act on multiple digits they may be active when a specific digit is inactive, causing the ANN incorrectly to estimate movement. (ii) Flexion is less well estimated than extension. Flexor muscles acting on the fingers are
Figure 22: performance with principle component cut-off fractions 0.01 and 0.05 for different number of hidden nodes.

more deep and with less well estimated flexion this suggests that EMG signals capture the muscle activity of these flexors poorly.

In the estimation of the MCP joint for the long finger in subject A it can be observed that the ANN fails to estimate a flexion level which is successfully estimated during the rest of the test data. This suggest an that an alternative muscle pattern is activated through those samples. Visual inspection of estimation results show graphs similar to figure(20) and figure(23) and are therefore not shown, but distinct examples of above mentioned tendencies and observations can be seen in figure(24).

5.2.2 Performance Wavelet Coefficients and PCA

Correlation coefficients for estimated joint angles and true angles are given in table(6). Compared to only low pass filtered signal, performance is generally worse. Most apparent is
Figure 23: Estimation results for $\theta_{\text{PIP}}$, $\theta_{\text{MCP}}$ and $\theta_{\text{WRIST}}$ respectively when using PCA transformed db3 wavelet coefficients pass as input to ANN. True angles (red line) and angle estimates (dotted green line) from test data are plotted together. Notice how the estimate fluctuates more than in figure(20). To the right of each sub plot are mean error, std (standard deviation of error), MSE and CC shown.

<table>
<thead>
<tr>
<th>person / joint</th>
<th>A</th>
<th>C</th>
<th>I</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCP1</td>
<td>0.80</td>
<td>0.80</td>
<td>0.00</td>
<td>0.25</td>
</tr>
<tr>
<td>PIP1</td>
<td>0.88</td>
<td>0.80</td>
<td>0.08</td>
<td>0.71</td>
</tr>
<tr>
<td>MCP2</td>
<td>0.80</td>
<td>0.77</td>
<td>0.84</td>
<td>0.60</td>
</tr>
<tr>
<td>PIP2</td>
<td>0.75</td>
<td>0.71</td>
<td>0.81</td>
<td>0.65</td>
</tr>
<tr>
<td>MCP3</td>
<td>0.80</td>
<td>0.71</td>
<td>0.81</td>
<td>0.70</td>
</tr>
<tr>
<td>PIP3</td>
<td>0.77</td>
<td>0.63</td>
<td>0.65</td>
<td>0.29</td>
</tr>
<tr>
<td>WRIST</td>
<td>0.81</td>
<td>0.80</td>
<td>0.05</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Table 5: Correlation coefficients for true joint angles and joint angles estimated by ANN.

The decrease in joint angles that have lower correlation coefficients in the lowpass filtered signal EMG. The same general tendencies described in section(5.2.1) are observed in estimation results, and in addition the estimates show higher fluctuation and larger deviations from true angles. Optimal sizes of hidden layers varied between 13 and 28 for subjects.

<table>
<thead>
<tr>
<th>person / joint</th>
<th>A</th>
<th>C</th>
<th>I</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCP1</td>
<td>0.80</td>
<td>0.82</td>
<td>0.40</td>
<td>0.00</td>
</tr>
<tr>
<td>PIP1</td>
<td>0.87</td>
<td>0.72</td>
<td>0.60</td>
<td>0.67</td>
</tr>
<tr>
<td>MCP2</td>
<td>0.70</td>
<td>0.71</td>
<td>0.70</td>
<td>0.70</td>
</tr>
<tr>
<td>PIP2</td>
<td>0.60</td>
<td>0.60</td>
<td>0.54</td>
<td>0.11</td>
</tr>
<tr>
<td>MCP3</td>
<td>0.80</td>
<td>0.68</td>
<td>0.77</td>
<td>0.60</td>
</tr>
<tr>
<td>PIP3</td>
<td>0.77</td>
<td>0.54</td>
<td>0.59</td>
<td>0.57</td>
</tr>
<tr>
<td>WRIST</td>
<td>0.64</td>
<td>0.82</td>
<td>0.01</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Table 6: Correlation coefficients for true joint angles and joint angles estimated by ANN using PCA transformed wavelet coefficients.
(a) EMG signals originating from flexors show a tendency to be more difficult to capture. As can be seen during the whole estimation extension is well estimated while flexion is incorrectly estimated. Thumb PIP of subject S.

(b) Muscles act on multiple digits. Therefore when a digit is relaxed relevant muscles may still be active acting on a different digit, which causes the ANN to incorrectly estimate movement in the joint. This can be observed in sample numbers 1-2000 and 3000-3800 in subject I as a fluctuating estimate.

(c) As the number of muscles controlling the hand are more than degrees of freedom in the hand, several muscle activations may result in the same movement. In subject A this could be seen in samples 7000-7500, where the ANN fails to estimate a flexion level previously well estimated.

Figure 24: Observations from estimation results for low pass filtered EMG signal. Observations are from different test subjects, and are chosen as they highlight tendencies observed in other estimation results but to lesser extent.

5.3 Experiment 3

10 degrees of freedom is estimated: MCP and PIP joint angles for all fingers for one test subject.

5.3.1 Performance low pass filter

Compared to experiments with lesser degrees of freedom estimated performance is worse, which could be expected, but correlation coefficients for MCP joints still lie around 0.8 except for thumb. It is noteworthy that the thumb has
Table 7: Correlation coefficients for true joint angles and joint angles estimated by ANN using low pass filter with 34 hidden nodes. Notice how correlation coefficients for MCP-joints are higher than for PIP-joints except for the thumb.

only a correlation coefficient of 0.69 compared to 0.89 in experiment 2 for the same subject, which would suggest bad location of the electrodes measuring the relevant muscles.

6 Discussion

Correlation Coefficients and Applications

Required estimation accuracy is dependent on which application is intended. In this thesis the intention was to control a prosthetic hand or robotic device and in that perspective the results presented are not sufficient. But we have succeeded in estimating up to 10 degrees of freedom. When considering correlation coefficients it is difficult to draw intuitive conclusions, but as shown by DaSalla et al[4], correlation coefficients around 0.85-0.9 were sufficient to control three degrees of freedom continuously in a robot. Considering the correlation coefficients around 0.8 for MCP joints in the third experiments it would probably be enough to decide whether digits are flexed or extended. A possible application could for example be as an interface to a digital flute.
**Differences in Performance**  
Distal joints are not only controlled by the deep layer muscles, but also more superficial as these control more proximal joints that affect the most distal joints, which results in a more complex mapping from EMG signals to joint angles. This could offer an explanation to the worse performance when estimating distal joint angles, but the main reason is probably failure in capturing the true signal of deeply located muscles.

Degradation in performance with the use of wavelet coefficients and PCA is in some way natural as information is removed by each discarded principal component. Apparently the information discarded is valuable for the more distal joints and the information retained does not reflect the activity of deeper muscles. A wiser choice of principal components could be to choose them not according to how much variance they contribute but how they correlate with respective joint angle.

Another reasonable approach to choose features when using the wavelet transform would be to calculate the mean frequency for each passband defined by decomposition levels, or choose those wavelet coefficients correlating best to certain joint angles.

Differences in performance between subjects as well as in joint angles can be explained by both biologic factors and experimental procedures. Biologically the difference can be explained by individual musculature with different muscles more or less developed. For example may highly developed superficial muscles restrict access to deeper layers or cause more cross talk and conversely may a small muscle cause a weaker EMG signal.

As muscles controlling the hand are more numerous than available degrees of freedom does there exist many possible patterns of muscle activation resulting in the same movement. For subjects favouring activation patterns more dependent on deep muscles it may be more difficult to capture the relevant information.

**Possible Sources of Error**  
Collection of data in experiments 2 and 3 was made in 10 second intervals when subjects moved the joints of fingers and wrist independently. The movements where considered difficult and subjects described it as fatiguing. As the EMG signal changes characteristics during fatigue the recording intervals should have been shorter. Test data was selected from the 2 last seconds of each recording, when muscles are most likely to be fatigued. Therefore it is possible that the EMG test data was not fully representable for the training EMG data.

In experiment 2 and 3 equilibrium states in joints are approximated by very slow movements which usually are performed with co-contracting muscles. Different muscle patterns active during extensive and flexive motions resulting in the same joint angle, and muscle patterns also vary with the speed of the motion. These factors make for a complex mapping from EMG to joint angles, and it would be desirable to reduce the variability in the muscle patterns order by recording static postures as in experiment 1. It is a conflict between academical results and performance in a real application where external conditions are bound to change, but a simplification as a first step would be justified in this thesis.

In experiment 2, electrode locations were identified and marked by dry delsys electrodes. Afterwards wet electrodes were attached to these locations in order to benefit from more sensitive setting options in the NEC biotop amplifier. It is possible that the optimal location was missed during the attachment of the electrodes as it is difficult to locate them on the exact marking and visualization possibilities for verification of muscle activity were worse in the soft ware used with NEC biotop. When measuring small muscles or a muscle located between others a small dislocation could significantly change the recorded EMG signal. Examples of this could be the poor estimation of thumb joint angles, controlled by FLP and EPB both small, for subjects I and S, while A
and C in contrast show good performance.

In experiment 2, hidden layer sizes between 1 and 34 were tested and larger layer sizes were not tested for fear of overfitting, but as two subject obtained best results for 34 nodes it may be possible that performance would increase with even larger hidden layers.

**Further Research** The results achieved in this thesis are promising. The tension estimate works well for degrees of freedom where activations of the involved muscles are readily recordable. The main problem when estimating distal joint angles seems to be cross talk in the EMG signals where activity of deep muscles are mixed with superficial muscle activity. A suitable approach is to use Independent Component Analysis on the EMG signals to retrieve independent sources of activity that correspond to separate muscles. Another approach is to choose wavelet coefficients better, possibly by choosing coefficients according to correlation with joint angles, or using mean frequencies or energy of different frequency bands in the signal.

**7 Conclusion**

We have shown that it is possible to estimate individuated movement of digits by using a 2-layered artificial neural network with features from forearm surface EMG signals as input signals and joint angles as output. When estimating 7 degrees of freedom, flexion / extension in the wrist and metacarpal (MCP) and proximal interphalangeal (PIP) joints in thumb, index and long finger, it was found that a low pass filtered EMG signal, reflecting the firing rate of motor neurons, outperformed an EMG representation based on the wavelet transform. Correlation coefficients between estimated and true joint angles varied, with higher coefficients for joints closer to the fore arm, a result that partly is caused by difficulties measuring the muscle activity in deep muscles controlling the distal joints.

When estimating five individually moving fingers, estimation of metacarpal phalangeal joints yields correlation coefficients to true angles at around 0.8, while estimation of proximal interphalangeal joints yield correlation coefficients between 0.6 and 0.75.

A biomechanic approach to prosthetic control is desirable as it provides natural control and allows for a large variety of hand shapes. The processing steps used, allow for continuous real time control and the estimation results make it feasible to further continue the research. A possible continuation is to use independent component analysis on the EMG signal to separate muscle activity originating from different muscles.

**References**


