Modeling and Controlling a Pneumatic Robot using a Biarticular Muscle Model and Machine Learning Techniques

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Modeling and Controlling a Pneumatic Robot Using a Biarticular Muscle Model and Machine Learning Techniques

This master thesis investigates the possibilities to use machine learning techniques to control a robot that operates using pneumatic rubber actuators, rubbertuators. The robot has two legs each operated by 6 actuators connected in a biarticular fashion, i.e. in the same way the muscles are connected in the lower limbs of humans. The robot is intended to be used for rehabilitation purposes by people who are unable to perform a normal walking pattern.

Assumptions of properties of the robot were made and a system model of the robot was designed in Matlab. Machine learning techniques were deployed to analyze the system model.

A control system using machine learning techniques were designed and a plan for evaluation of the control system is proposed.

No measurement data from the actual system was available for this research but preliminary results suggest the control system topology designed in this thesis could potentially be a part of a future implementation in the actual physical robot.
Modellering och styrning av en pneumatisk robot med en biartikulär muskelmodell och maskinlärningstekniker


Antaganden om robotens systemegenskaper gjordes och en systemmodell av roboten designades i Matlab. Maskinlärningstekniker användes för att analysera systemmodellen.

Ett styrssystem togs fram mha maskinlärningstekniker och en utredningsplan för att studera systemmodellen och styrsystemet framläggs.

Ingen mätdata från det verkliga systemet fanns att tillgå men studier av kontrollsystemet tillsammans med en systemmodell antyder att styrsystemets topologi är möjlig kandidat till en framtida implementation i den verkliga, fysiska, roboten.
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Eriko.

My family. Thank you for being supportive.

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## Glossary of Terms

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
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<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
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<tr>
<td>AD/DA conversion</td>
<td>Analog-Digital/Digital-Analog Conversion</td>
</tr>
<tr>
<td>Rubbertuators</td>
<td>Rubber actuators, a type of pneumatic actuators</td>
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<tr>
<td>BP</td>
<td>Backpropagation algorithm. Algorithm used when training ANN</td>
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<tr>
<td>MSE</td>
<td>Mean Square Error</td>
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<tr>
<td>SM</td>
<td>Used in this thesis when referring to the System Model designed</td>
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<tr>
<td>BC</td>
<td>Used in this thesis when referring to a Basic Configuration,</td>
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<td></td>
<td>a configuration of ANN and SM from which modifications and their impact on performance were studied</td>
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1 Introduction

1.1 Background

For rehabilitation of disabled people unable to perform a normal walking pattern, a variety of machines exist. Most of them operate using electrical motors. While electrical drive systems are relatively easy to control they however generate heat potentially harmful to the patient, sometimes causing burn injuries. At Shibaura Institute of Technology a controlled gait orthosis for rehabilitation of disabled people is being developed. This system differs from other systems in the aspect that it operates using rubbertuators (rubber-tube actuators) instead of electrical motors. A consequence of using pneumatics is that the power source in the system can be placed on a safe distance from the patient.

From a mathematical perspective the system is nonlinear, dynamic and has due to the biarticular configuration a high redundancy - the same kinetic pattern can be obtained by an infinitely amount of different pressure input combinations [1]. Instead of extracting formal equations - a formidable task for a pneumatic two-axis system. This thesis investigates an approach using machine learning techniques.

1.2 Objectives

The aim of this master thesis project is to investigate if a control system using machine learning techniques can be used to control the gait training system.

The objectives are:

Purpose a control strategy for the gait training system and suggest a plan for evaluation and optimization of the control system topology.

1.3 Outline of the Design Process

At the time the research on the control system was being performed the pneumatic parts of the system were being replaced. Hence access to the actual system was limited and a theoretical approach was chosen. A model of the system was developed (hereafter referred to as system model or SM). The idea behind this approach is that if a machine learning approach can control the plant model perhaps the approach can be used to control the actual gait training system. The goal of the research in this paper is to investigate if and how a control strategy that enable control of the gait training system using machine learning techniques can be used and to propose a framework to be used for evaluation and implementation.

This research has been conducted in an iterative and exploratory spirit but can roughly be divided into two phases:

1. Design of system model and the proposal of a control system topology
2. Design of an evaluation plan that contain suggestions for further exploration of control system properties

1.4 Scopes and Limitations

No measurement data from the actual system was available for this investigation and the machine had already been designed. No model of the system or simulation
environment existed. Given the above the results in this research should be viewed merely as tools that may or may not be applicable to the real system rather then methods that definitely can be applied to the actual system without any modifications.

1.5 Thesis Outline

First an introduction to studies on human walk is given in Chapter 2.1, a description of the gait training system is given in Chapter 2.2. A brief introduction to artificial neural networks is given in Chapter 2.3. The System Model, SM, and the ideas behind it are explained in Chapter 3.1. Thereafter the architecture of the approach investigated in this paper is described in Chapter 3.2. A suggested evaluation method is derived in Chapter 3.3 and evaluation results of the control topology are presented in Chapter 3.4. This is followed by a discussion on the findings in Chapter 4.1 and suggestions for further investigations in Chapter 4.2.
2 Methods

This section describes the methods used in this research. First an introduction to the analysis of walking is given. This is followed by a description of the gait training system which control system this thesis is intended to suggest a design for. After this an introduction to Artificial Neural Networks is presented.

2.1 Gait Pattern Analysis

Walking is described as a form of bipedal progression in which the repetitive movements of the lower limbs include periods of double support, when both feet are in contact with the ground, followed by periods when only one foot is supporting the body (single support) while the other is being moved above the ground (swing).

Functional Human movement - Measurement and Analysis, Durward et al [1]

Normal gait pattern for a healthy human have been extensively studied by scientists in physiology. When studying gait patterns it is common practice to look at variations of hip, knee and ankle angles over time, normalized over one gait cycle. That is, the angular variations are plotted against a variable representing time, but expressed as percentage of one gait cycle. This is called a goniogram.

The upper curve in Figure 1 shows the hip which is flexed in the beginning of the stride due to contact with ground. As the leg loses contact with ground the hip extends until about 50 per cent of the stride length, and then flexes again to prepare for round contact. As for the knee it is close to neutral in the beginning of the stride (where ground contact is made). It then flexes during double support phase where - during a short period of time - both feet are in contact with ground. The knee (lower curve) then extends a little before it rapidly flexes to shorten the leg and allow for foot clearance. The angular displacement of the ankle plays no significant part in the research in this research and has been removed from the goniogram. One aspect of the controller to be used with the gait orthosis is that, at least in this research, the desired trajectory is always the same (see Figure 1). In an actual application it would be necessary to adjust the desired trajectory to individual parameters, but in this research the trajectory is considered to be one and the same periodic function for every patient.
2.2 System Description

2.2.1 Hardware

The pneumatic system uses 12 rubbertuators (6 for each leg) connected in a fashion similar to the muscles in the lower limbs of humans, that is - according to a biarticular muscle model.

Currently only 8 of the rubbertuators are in use - the biarticulary connected rubbertuators are yet to be used (see Fig. 2)

A PC with a D/A converter [2] sends signals to 8 (in the future, 12) pressure regulators. These regulators control the pressure in each corresponding rubbertuator.

Figure 1: A goniogram showing typical angular variations for hip and knee joints in a leg as a function of per cent of gait cycle. Here the ankle angle has been omitted. [1].
Figure 2: *The gait orthosos - a photo, a schematic side-view and an illustration showing the configuration of the 6 rubbertuators and their relation to the 6 major muscles in a human leg.*

Figure 3: *A schematic overview of the system hardware.*

**Control Sequence Overview**

1. Angular sensor data from 4 angular sensors, a), are A/D-converted

2. and sent, b), to a PC. The data can be registered for data analysis but is not currently used for control.

3. The PC sends, c), a pre-defined data sequence of control data to a D/A-converter.

4. The converter sends, d), analog signals to pressure regulators.

5. The pressure regulators control the air-pressure, e), in the rubbertuators.
2.2.2 Software

The software consists of a Simulink module [3] that communicates with the D/A converter. Currently the software operates as an Open-loop controller [4] sending pre-defined control signal sequences to the D/A converter. In future modifications it will read angular values from sensors placed in the hip and knee axes of rotation (see the dashed lines connecting the gait orthosis to the A/D converter in Figure 3).

2.3 Artificial Neural Networks

Artificial Neural Networks, ANN, can be a useful tool to obtain understanding of complex input-output relationships in data. It has been used to solve many different types of problems such as classification problems, system modeling in several different fields such as finance, automatic control systems, computer vision, character recognition, robotics ([5], [6] and [7]).

In this research project ANN was chosen because it is an extensively studied technique proven useful in other applications in system modeling and control.

2.3.1 The Neuron

The basic building block in the ANN is the neuron [8]. It has properties much similar to the nerve cell found in nervous systems in humans or animals. A neuron consist of a cell body, soma, with many oblong dendrites attached to it. The dendrites receive signals from other neurons and the soma process these signals and send the processed output over a long axon that stems out of the soma and transmit the output to other neurons.

![Figure 4: A schematic overview of the nerve cell.](image)

One simplified model of the information processing in a neuron can be described mathematically as a scalar multiplication, with the resulting sum inserted into a threshold function.
\[ y_{out} = f\left(\sum_{i=1}^{n} a_i \cdot x_i\right) \] (1)

All the input signals are multiplied with corresponding connection weights. In Equation (1), \( a_i \) corresponds to a weight that is multiplied with its corresponding input \( x_i \). The \( f(x,a) \) is a threshold function implying that when the sum of scalar multiplication \( \bar{a} \cdot \bar{x} \) exceeds a threshold value the neuron will and give an output rapidly converging to either 1 or -1.

Figure 5: The building block of ANNs - the neuron. The illustration shows a neuron having \( n \) number of inputs and corresponding weights. The output is a function of the inputs and the weights.

When several neurons (see Figure 5) are stacked to form a layer and two or more layers are used (see Figure 6) the net achieve powerful processing capabilities.

2.3.2 Backpropagation Training Algorithm

The Backpropagation (BP) algorithm can loosely be described as inputting training data on the input layer, calculating the net output and comparing the output with target data - the comparison resulting in an error, \( e \). Corrections to the values, \( a_n \), in the net are then made in systematic way\(^3\) in order to reduce \( e \).

2.3.3 Preprocessing

Preprocessing can be described as the process of manipulating the training data before training, with the purpose of making the data easier for the ANN to “understand”. Typical preprocessing operations include removing mean-values, decorrelation, scaling input data, etc. [9].

\(^3\)A formal description of the BP algorithm can be in most books on ANN, such as [9]
Figure 6: An ANN having 1 hidden layer, 4 neurons in the input-layer, 5 neurons in the hidden layer and 1 neuron in the output-layer.
3 Results

As already mentioned in the introduction, no data on performance of the robot were available. Therefore, the problem to solve was more open ended. A substantial amount of work was devoted into working out the design process. This part of the works is therefore described below rather than in the methods as would have been the regular section when applying a standard method.

This section presents the design process and the results of this process. First the development of a system model, SM, is described, then the process of designing a control topology is presented. This is followed by a description of a suggested evaluation method and an exploration of the suggested control topology.

3.1 System Model

This chapter describes the derivation of a System Model (SM) of the gait-orthosis system. This SM is later used when designing the control system.

3.1.1 System Model of One Leg

The first step in developing SM of the gait-orthosis system was to assume that the system is symmetric in the aspect that the two legs in the system can be studied and modeled independently of each other. It is assumed that in a later phase in developing the control system, the two instances of a one-legged SM and their control systems can be integrated. This one-legged SM has 6 inputs and 2 outputs.

\[
\text{INPUT} \\
6 \text{ signals corresponding to the voltage levels sent from the D/A converter in the hardware to the pressure regulators connected to one leg.} \\
\text{OUTPUT} \\
2 \text{ angular values (hip and knee angle) measured by angular sensors mounted on each leg on the gait system.}
\]

The one-legged SM is designed with reference to the following three concepts.

3.1.2 Assumed Physical Properties of the Gait Orthosis

DYNAMICS

The pneumatics as well as the inertia in the two-axis pendulum structure of the system possesses dynamic properties.

This is achieved by summing up pressure values for each variable respectively over a limited amount of time-steps. That is, for each pressure variable and angular variable a weighted moving average back in time was calculated for every time-step to represent the present forces acting on the orthosis limbs.

BIARTICULARITY

This property is addressed by defining a coupling matrix, \( K_1 \) that connect the two upper rubbertuators to the hip angle variable, the two lower rubbertuators to the knee angle and also, connecting the rubbertuators \( R_3 \) and \( R_4 \) to both the angles.
The idea behind the formulation of the matrix is the assumption that the \( R_1 \) and \( R_2 \) rubbertuators mainly affect the hip angle, that the \( R_5 \) and \( R_6 \) mainly influence the knee angles and that the \( R_3 \) and \( R_4 \) have an influence on both angles (see Figure 7). The values denoted \( a \) have a positive affect on the hip angle. The values denoted \( -a \) have a negative influence on the hip angle. The corresponding holds for the second column acting on the knee angle.

\[
K_1 = \begin{pmatrix}
a_1 & 0 \\
-a_2 & 0 \\
a_3 & b_1 \\
-a_4 & -b_2 \\
0 & b_3 \\
0 & -b_4
\end{pmatrix}
\]

Figure 7: The concept of how the pressure inputs to the rubbertuators are perceived to influence the angular outputs.

**NONLINEARITIES**

The system operates around two axes - the hip and knee axis. As a consequence of this configuration the length of the rubbertuators - and hence also the forces exerted by them - will vary as the system operates and the hip and knee angles vary. The general behavior of a rubbertuator itself also possess a nonlinear nature [10]. To address this aspect the six inputs are connected with a coupling matrix, \( K_2 \). This \( K_2 \) matrix is a function of the ‘current angular values’ at any point in time. This corresponds to the concept that the force exerted by the rubbertuators is not just a function of the 6 pressure inputs, but also a function of the angular configuration.
In this matrix the first column are coefficients representing the connection between
the 6 pressure inputs and the hip angle. Also, as seen in the third and fourth element
of the first column, the biarticulary connected rubbertuators affect both the hip and
knee angles. The corresponding implementation can be seen in the second column
and its third and fourth elements. This is the same principles by which matrix $K_1$
was suggested. The coefficient values were chosen on a trial-and-error basis.

3.1.3 Bringing the Assumed Properties Into a System Model

The pressure values $p_1$ through $p_6$, summed up in time, are collected in one vector $P$. The two coupling matrixes $K_1$ and $K_2$ are element-wise multiplied with each
other forming a new coupling matrix $K_3$.

The new coupling matrix and pressure vector are then multiplied forming a set
of two values that reflect the forces affecting the two-axis structure that form a leg
in the system. The computed values are inserted into a trigonometric function that
correspond to the two-axis pendulum design.

$$\theta_{\text{hip,knee}} = \sin(P \cdot K_3) \tag{4}$$

To this two values, past angular values are added to describe some pendulum dy-
namics:

$$\hat{\theta}_{\text{hip,knee}}[n] = \beta_1 \theta_{\text{hip,knee}}[n] + \beta_2 \theta_{\text{hip,knee}}[n - 1] \tag{5}$$

ANGULAR DOMAIN

In this research project the angular outputs of the SM has been defined as an angular domain covering angles

$$-90^\circ < \hat{\theta} < 90^\circ$$

and expressed in an abstract variable ranging between -1 and 1 which is just a linear scaling of the angular values. This is due to the nature of typical working
domain for ANN. The $\hat{\theta}_{\text{hip}} = 90^\circ$ and $\hat{\theta}_{\text{knee}} = 0$ is the equivalent of keeping the
leg straight forward, perpendicular to the rest of the body. For the knee angles,
the angular values for a healthy human would typically not be under 0, and in the
actual system a safety device prevent the machine from reaching that operational
sub-domain. In this thesis SM however, the machine can enter this domain. This
is made possible in order to investigate if the control system can be trained not
to access that sub-domain - i.e. to try to make the control system independent of
the safety device and thereby avoid making use of it thus reducing the mechanical
stress exerted on it.
PRESSURE DOMAIN

In the actual system the control system output signal is a voltage signal from 0 to 10V fed to the pressure regulators. In the SM the pressure is defined between -1 and 1 since this is a typical input range of ANN\(^4\).

3.2 Control Topology

This section deals with the design process of the control system and the design process results.

3.2.1 Design Process

In the beginning of this project a very simple SM was designed, a SM with two inputs and one single output. An ANN was then trained to learn input-output relationships and act as an inverse controller. That is, given the information of desired system model angle, \(\theta\), the ANN suggested an appropriate pressure, \(P'\), that was inputted in the SM, delivering a resulting angular value \(\hat{\theta}\) (see Figure 8).

![Figure 8: The principles of the Inverse Controller.](image)

The ANN was trained with data collected from the SM. When collecting the training data, random values i.e. noise was inputted to the SM, and its outputs were registered. After being trained the ANN could gave estimates of pressure values enabling the SM to follow a trajectory. Gradually the system model was made more and more complex, introducing more and more dynamical and nonlinear properties (i.e. trigonometric functions) and also increasing the number of input and output variables making the system a 6 input - 2 output system. This approach of gradually making the problem more advanced and realistic was a means to explore the problem, acquire a basic understanding of its nature and investigate if, and in that case how, an ANN could help solving the problem. The gradually more complex SM made resulted in the ANN having more and more difficulties to control the SM.

In order to try to improve the ANN performance and address the dynamical properties of the SM, the ANN was fed also with older values of pressure.

Here the old ANN outputs are fed back and used as inputs for the ANN. This helped the ANN better understand the mapping from the pressure domain to the angle domain as the SM was assigned more and more dynamical properties.

This control system is still in Open-Loop, no information about the resulting outputs from the SM are fed back to the ANN to improve performance. A Closed-Loop approach with \(\hat{\theta}\) feeding back to the ANN was tested.

\(^4\)At least for ANN with threshold functions consisting of hyperbolic tangents.
Having more and more data used for suggestion of pressure values, the question *Why not also use future values in time?* arose. When data is collected for the ANN training set, collection is made over time resulting in two datasets: Input data, $P'[n]$, and Output data, $\hat{\theta}[n]$. After data collection, the information about the $P'$ to $\hat{\theta}$ relationship available at a certain time, $n = i$, is, besides the values at that instant moment ($P'[n = i]$ and $\hat{\theta}[n = i]$) also old values back in time ($P'[n = j]$ and $\hat{\theta}[n = j], 0 \leq j < i$). At any time, $i$, $P'[i]$ could be viewed as present applied pressure or, more generally - the answer to the question: *What is being done right now?*. The $\hat{\theta}[i]$ on the other hand could be viewed as the present angular status or the answer to the question *Where are we right now?*. The $P'[j], j < i$ consist of previous applied pressures or the What have we done so far?, whereas the corresponding $\hat{\theta}[j], j < i$ are the previous angular statuses - the answer to the question *Where have we been until now?*. Also values forth in time $P'[k]$ and $\hat{\theta}[k], k > i$ are available. They represent the future pressure values, the What will we do? and the future angular statuses the Where will we go?. It should be pointed out that during the data collection phase when random data is being inputted into the SM and the resulting outputs are being collected, at any time, $i$, the data for $P'[k]$ and $\hat{\theta}[k]$ are not yet known since $i < k$, the time instance $k$ has yet to be occurred.
$P'[n+1]$ What to do in next time-step?
$P'[n]$ What is being done right now?
$P'[n-m]$ What was previously done, $m$ time-steps ago?

$\hat{\theta}[n+1]$ Where to go next time-step?
$\hat{\theta}[n]$ Where are we now?
$\hat{\theta}[n-m]$ Where were we, $m$ time-steps ago?

Based on the ideas in the discussion above the following control topology was created.

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**Figure 11:** The purposed control topology. The Ideal angles in the figure consist of the control signal, the angular values displayed in the goniogram for a normal gait pattern. Previously suggested pressure values as well as observed angular values are fed back and preprocessed.

When the angular and pressure domains are explored by inputting random pressure values no intention such as those connotations hidden in the formulation *Where will we go?* exist. But in an application can the $\hat{\theta}[n = j], j > i$ be used as a control variable expressing a desired state? Can the $P'[n = j], j > i$ be used as a variable to be predicted, given all the other data in $P'$ and $\hat{\theta}$ above?

One aspect to explore in such a topology is the robustness and the ability to adapt in a system-patient interaction situation. Since this topology would process Input-Output information in time, can it sense disturbance as deviations from a normal behavior and learn to make corrections from them? Since both the inputs and outputs of the SM are fed into the ANN, the ANN receives something that could be interpreted as a form of step-response. Can the ANN learn not just to interact with a system but also learn to detect and adapt to changes in the environment in which the SM is being deployed?
3.2.2 Difficulties in the Design Process

During this project it became clear that designing a model without access to authentic data is rather complicated. Most of the efforts spent on designing a SM resulted in a SM that was either too simple or too complex. In the case of SM being too easy, the suggested topology learned to control the SM perfectly even with very few nodes in the net and with very little training. In the case of the SM being too complex, the SM could not be controlled to cover the entire desired range of angular outputs. Attempts to find a just difficult enough SM was time-consuming and focus turned to defining topics that would be interesting to explore if data from the actual gait orthosis could be extracted.

3.3 Evaluation Method

The control system topology involves a large number of parameters that can be tweaked to improve system performance. Such parameters include number of layers in the ANN, number of hidden nodes, amount of measurement data back in time etc. It is also of great interest to investigate how modifications of for instance the preprocessing or choice of training data influence performance. In the process of evaluating such variations it is suggested that a Basic Configuration, BC, should be defined to serve as a start-off point for further evaluation. The BC would be designed using a trial-and-error approach to find a solution that works but that seemingly has the potential work even better after a systematic search for parameters. When the BC is defined the systematic search for optimal parameters should be pursued in a process were all the changes made to the BC are evaluated against a set of criterions. Four main evaluation criterions are suggested:

3.3.1 Ability to Track a Desired Trajectory

How well can the control system keep the gait training system at the trajectory defined as a normal gait pattern in healthy human subjects defined in Figure 1, Chapter 2.1. It is suggested that an attempt to track this trajectory during 10 gait cycles is made and the average MSE $^5$ is calculated.

3.3.2 Noise Robustness - Sensor/Actuator Noise

Test of the ability to track the desired trajectory is repeated with a simulated noise (white noise) added to the angle sensor inputs and to the pressure regulator outputs. That means the ANN is trained with data from a disturbed SM and is then used to control the disturbed version of the SM.

3.3.3 Repeatability

The ability to repeat the process of data collection, training the ANN and then control the SM are suggested to be tested by performing the tests in Chapter 3.3.1 and Chapter 3.3.2, 10 times each. The average MSEs for SM with and without noise are calculated as well as the variances respectively. This is to see to what extent data collection and training will result in equivalent solutions each time they

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$^5$Mean-Square Error
are performed. Here it would also be of interest the instances in time (or rather - the positions in the gait cycle) that most often has the largest error. This is suggested to be done in order to identify what part(s) of gait cycle that the topology has difficulties to learn.

### 3.3.4 Adaptness

The ability to resist patient induced noise is suggested to be investigated in 2 ways:

1) During random intervals in the gait cycle, the pressure values on one of the actuators are set to have a weaker impact on the gait movement compared to its antagonist actuator. This is made to simulate a patient with lowered ability to exert a force in one of her/his muscles.

2) During a 1-2 times per gait cycle the signals from the angular sensors are suddenly shifted to simulate a twitch - a spasm. These investigations are suggested for two reasons: Assuring patient safety as well as exploring the control system ability to work together with a patient and maintain the gait pattern of a healthy human subject throughout the exercise.

### 3.4 Results from a Basic Configuration

In this section a Basic Configuration is defined and evaluation results are presented.

#### 3.4.1 Definition of Basic Configuration

The ANN of the BC net: A 2-layer ANN using 50 hidden nodes in the hidden layer was trained with a version of the BP-algorithm (the Scaled Conjugate Gradient Backpropagation method was used). The training was performed for 5000 epochs OR until the error in training data reached 0.001 OR until performance on validation data decreased or remained stable for at least 5 consecutive epochs - whichever of these 3 criterions that was first met.

**DATA USED FOR TRAINING**

Measurements of pressure and angles up to 11 time-steps back in time. The data is obtained by inputting pressure values, 5000 data points in time, consisting of noise uniformly distributed \([-1, 1]\). The six different pressure variables are considered to be uncorrelated stochastic processes. The resulting angles as well as the inputted pressure values were registered. This means the number of inputs to the ANN are 78 and the number of outputs are the 6 pressure values.

**PREPROCESSING**

Difference vectors for each angle variable and pressure variable were calculated. E.g. for the knee angle: \(\Delta \hat{\theta}_{knee}[i] = \hat{\theta}_{knee}[i + 1] - \hat{\theta}_{knee}[i]\). This calculation was made for several same amount of steps back in time as used when designing the SM dynamics - 11 time-steps. From the set of 5000 data points 250 data points were randomly chosen. This was made in order to reduce the amount of training data and still achieve a reasonable coverage of angular and pressure domains.

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6This is the same amount of time-steps as the SM uses for dynamics
3.4.2 Results

Visual observations of plots suggest that the controller overcompensate and the SM appears to be heavily influenced by even the third or fourth derivative of the ideal angle. Most of the 10 times the condition to interrupt the training of the ANN was the max error on training set $< 0.001$, i.e. the net learned the training set within 5000 epochs. In most cases it learned within 500 epochs.

$\text{MSE(hip)} = 0.1666$
$\text{MSE(knee)} = 0.1123$
$\text{Variance(hip)} = 0.0063$
$\text{Variance(knee)} = 0.0040$

As can be observed in the plots (see Figure 12 and Figure 13) the SM is able to roughly track the desired trajectory.

![Graph](image)

Figure 12: Results from BC. Hip angle, $\hat{\theta}_{\text{hip}}[n]$, during one step-cycle (33 time-steps). The solid line shows the ideal angle, the dashed line shows the resulting trajectory of the SM.

Parameter sensitivity

When adding white noise with a 0.05 variance to all pressure values inputted in the SM and to all angular output values from the SM, the following results were observed:
A few times the net did not learn the training set within 5000 epochs, instead still after 5000 epochs an error of approximately 0.1 to 0.2 on training set was obtained. As can be observed when comparing with the SM, the MSE values grew with approximately 50 per cent and the variance grew with approximately 100 per cent.

**Ability to Adapt to a Patient**

In order to study how the control system responds to patient induced noise the SM was modified so that at every 25th time-step the angular values were displaced. Three investigations were made.

1) 30 degree displacements in both hip and knee

The displacements for hip and knee were set to be 0.33 (randomly positive or negative). This corresponds to a displacement of 30 degrees in one time-step. The resulting angular values were saturated at -1 and 1 in order to keep the angular values within the working range of the machine. From 5000 data-points, 250 points were randomly chosen. An ANN with 2 hidden layers (60 and 30 nodes respectively) were trained with the following stop-criterions: The training was performed for 10000 epochs OR until the error in training data reached 0.00001 OR until performance on validation data decreased or remained stable for at least 5 consecutive epochs - whichever of these 3 criterions that was first met.
MSE(hip) 0.3247
MSE(knee) 0.1427
Variance(hip) 0.1020
Variance(knee) 0.0089

The high variance on the hip angle (as per compared to the undisturbed configuration) indicate that sometimes the net did not learn to control the SM very well, in other cases it performed better.

2) 15 degree displacements in hip

In this test the hip angled was shifted 0.17 (randomly positive or negative). Except for the this, the test was performed in the same way as the test on both hip and knee displacements.

First the ANN was trained with data that contained displacements.

MSE(hip) 0.1934
MSE(knee) 0.1608
Variance(hip) 0.0060
Variance(knee) 0.0177

Some trained nets gave very poor performance even though the nets learned the training-sets well. With non-disturbed training data and with displacements during evaluation.

3) Then the ANN was trained with data from a SM that did not have such sudden displacements (i.e. it was the same SM as the one used in BC) and was then set to control a SM with angular displacements of 0.15 units for the hip angle.

MSE(hip) 0.2447
MSE(knee) 0.0910
Variance(hip) 0.0430
Variance(knee) 0.0030

### 3.4.3 Variation on Basic Configuration: ANN Using 2 Hidden Layers

In some ANN applications a 3-layer net (that is, an ANN with 2 hidden layers) have been proven useful. In such cases the first hidden layer often serves as a preprocessing step [9]. The drawback however is the increased time required to train such nets. It is suggested that such an approach is investigated to see if it has potential to improve system performance. Here, the BC was modified so that the ANN was given an additional layer. The two hidden layers were set to have 50 and 20 nodes respectively and the maximum number of epochs allowed during training was doubled (to 10000 epochs). In most cases, the ANN learned the data-set within 1000 epochs.
MSE(hip) 0.1586
MSE(knee) 0.1045
Variance(hip) 0.0076
Variance(knee) 0.0078

And with noise added:
MSE(hip) 0.2212
MSE(knee) 0.1371
Variance(hip) 0.0047
Variance(knee) 0.0040

The MSE for both hip and knee increased with approximately 30 to 40 per cent. Interestingly the variances for both angles were reduced by almost half. An increased MSE and decreased variance suggest that the noise forced the SM to a trajectory that deviate (at least when compared to the non-disturbed session) from the desired trajectory, and the accuracy in this deviation was significant. Perhaps the induced noise led to overcompensation around the extreme points of the desired trajectory and perhaps the error in this overcompensation is significantly higher then the “general deviation” from the desired trajectory.
4 Discussion

In this section the results are discussed and in the subsequent chapter suggestions for future investigations are presented.

4.1 Discussion on Findings

The topology developed succeeded to - with virtually no a priori knowledge about the system model - control it using an ANN that was trained with data based on random inputs into the system model. This suggests that the topology potentially have the capability to control the actual system. To ultimately determine if the topology can be used in the actual system one would need to acquire measurement data from the physical system, explore the topology to find an optimal configuration and verify the performance in experiments with human patience interacting with the system. In this chapter findings in section 3 are discussed.

When trying to control the BC disturbed by added noise performance dropped drastically compared to the BC without noise. Also overcompensation was observed when trying to control the non-disturbed SM. This lead to the hypothesis that if the over-compensation issue could be solved the control system would also handle noise better.

The overcompensation observed for the BC may be a result of the preprocessing: In the preprocessing, differential vectors for the various angles and pressures are calculated. An approach using moving average of the differentials could perhaps give the controller a smoother operation and a better performance.

The knee angle of the BC does seldom drop below zero when trying to control it to followed the desired trajectory. This indicate that if one would unlock the mechanical safety device on the physical gait training system (a device that prevent the knee joint to reach angular values that could be harmful to patients) during data collection and then lock the device when the system is used by patients, one would teach the control system not to exert stress on the safety device.

Modeling the gait orthosis without measurement data is complicated and it is possible that the SM derived in this thesis is contain imperfections that unable the SM to perfectly follow the desired trajectory. In other words, it is possible that for the SM, as it is designed here, there may be so that it does not exist a set of time-series pressure values that enable the SM to reach its goal of perfectly track the desired trajectory.

In the displacement test for both hip and knee angle the results indicate a high variance in average MSE (compared to the BC). A 30 degree displacement in both joints in only one time-step is a very rapid displacement. The 10 stride-evaluation was calculated with 33 data-points per stride. For healthy you adults the stride time is about 1 second. This means that one data-point (one time-step) equals approximately 30 milliseconds. Furthermore, this movement would not be a rapid displacement in free air but take place inside the gait orthosis and would have to defy the resistance in the rubbertuators. The test could be viewed as an extreme stress test of the control system.

The second test with a 15 degree hip-joint displacement test shows results that are similar to the evaluation results for BC with one hidden layer. The ANN that was trained with a spasming SM were better at controlling a spasming SM than
an ANN that was trained with data from a non-spasming SM. This indicates that
the topology can learn to compensate from displacement noise if it is trained with
such data. This suggests that the topology can learn to interact with a patient and (if
trained with right data) it can learn to compensate for variations in patient behavior.

4.2 Suggestions for Future Investigations

Iterating Data Collection and Training

When the data collection is made using random values a part of the training data
will contain irrelevant datapoints such as points that in angular domain are far
away from the desired trajectory and in pressure domain contains values that sug-
gest pressure values that do not help the SM reach the trajectory. Can a strategy to
reduce the irrelevant datapoints in data collection be implemented?

Assumption 1: Each time training data is collected a set of pressure values, \( P' \), are
inputted and resulting angles, \( \hat{\theta} \), are observed.

Assumption 2: Each time the sets of \( P' \) and \( \hat{\theta} \) are used to train the ANN it results in
a net that control the SM with a pressure set, \( P' \), that allow the SM to be controlled
with a smaller error than when the set \( P' \) was inputted during data collection.

Hypothesis: The data collection and training steps could be iterated and the weights
in the ANN would converge to optimal values and during this process \( P' \) would
converge towards a set of pressure values such that \( \hat{\theta} \) converges towards the de-
sired trajectory.

Thus, the following approach is suggested to be evaluated:

1. Input random pressure values into the SM
2. Register the resulting angles
3. Make an attempt to use data registered in step 2. to train the ANN
4. Attempt to control the SM to follow the desired trajectory
5. Iterate steps 2. to 4. until the SM is able to track with low deviation.

The idea is that in such an approach the training data to be used for the ANN gradu-
ally becomes more relevant and from the infinitely large amount of mappings back
and forth between pressure domain and angular domain. Step-by-step, mappings
useful for the ANN training will be extracted.

Using synthetic training data

It would be interesting to investigate if the use of synthetic training data could aid
the training of the ANN. When inputting random data into the SM the tendency
for the resulting angles to reach the most extreme values were very low. This syn-
thetic training data could consist of qualified guesses for suggested pressure inputs
coupled with data for angular values and pressure values. Some of these values
could be set to zero: If for instance the hip angle is far too low compared to the
ideal angles - no matter what values the previous angular values were - pressure
values that activate actuators that push the leg forward and increase the hip angle
are assigned.
Amount of Data Back in Time Included in Training Data

The SM dynamics in initial experiments were modeled to include 11 old values. One topic suggested to be investigated is: How can the dynamics of the real system be determined? Suggested strategy: Binary search [11]:

1. Starting off using a very large amount of data back in time for training data and test performance.
2. Reduce the amount of data back in time by half to see if the system performance or system stability start to deteriorate.

If the performance or stability deteriorate, the amount of data back in time is increased by 50 per cent and step 2 is repeated again in order to find an optimum amount of data to include in the training process.

Can slow dynamics in the system be covered by smart preprocessing? If the dynamics in the actual system turn out to include very slow components it would imply that a large amount of data would need to be included in each dataset in the training of the ANN. It is suggested that an smarter choice of training data is implemented and evaluated. One possible approach could be described as: For each angular or pressure variable, here generalized and denoted $\alpha$, calculate

$$
\alpha_1 = \alpha[n] \\
\alpha_2 = \frac{1}{2}(\alpha[n-1] + \alpha[n-2]) \\
\ldots \\
\alpha_i = \frac{1}{2^{i-2}}(\alpha[n-2^i] + \ldots + \alpha[n-2])
$$

With this concept the amount of training data grows linearly whereas the information is included from sampled data of an amount that grows exponentially.

Number of Nodes in Hidden Layer

It is suggested to investigate if and how the generalization properties of the ANN change when the numbers of hidden nodes change.

Stiffness and Actuator Competitiveness

When collecting training data, it is essential carefully choose the appropriate SM inputs/outputs to preprocess and then use to train the ANN.

Hypothesis 1: It is assumed that if the ANN is trained with training data based on high variance noise inputs to the SM, the ANN will overcompensate for deviations from the desired trajectory. And similarly - if the training data is based on low variance noise inputs to the SM, the ANN will undercompensate for deviations from the desired trajectory.

Hypothesis 2: It is assumed that an ANN trained with data based on a mix of variances will under- and over-compensate to a lower extent than an ANN trained with training data based on only a fixed variance.

Hypothesis 3: If the inputs used for data collection are considered to be 6 independent and uncorrelated stochastic processes it is likely that the ANN will learn a behavior characterized by antagonistic actuators not working together but competing and exerting stress mechanical on the orthosis. If for instance, one were to train the ANN with data collected from the SM using stochastic data where the inputs to antagonistic actuators were anti-correlated, is it less likely for such competitive behavior mentioned above to occur?
Could stiffness in the orthosis gate be defined and its impact studied? If for, each set of antagonistic set of rubbertuators, the degree of competitiveness/cooperation was defined in a variable, for instance, $S$, calculated as follows:

$$S = p'_1 - p'_2$$  \hspace{1cm} (6)

could the noise robustness be studied as a function of $S$?

**Alter Target Trajectory During Training**

One approach that would be interesting to investigate could be described as *Learn to crawl, before learning to walk*. This relates to one of the approaches suggested earlier, Iterating Data Collection and Training. By iterating data collection and training one would - hopefully - gradually receive better and better performance. Here this would be combined with an alteration of the shape of the target trajectory. By starting out with a very simple shape of the target trajectory - let’s say a low amplitude sinus wave - and gradually let the shape converge towards the desired shape (performing data collection between each change in shape), can the final results be improved?
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