Use of acceleration and gyro sensors for gait phase detection in a prosthetic knee

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Abstract

The objective of this study is to investigate the possibility of controlling a prosthetic knee by using a Xsens sensor module that consist of 3D acceleration, gyro and magnetic sensors. The prosthetic knee used for this study is the Rheo knee manufactured by Ossur Inc. Pattern recognition methods are used to classify terrain at each step, i.e. level ground, slope or stairs. A state machine is used to model gait cycle, where phases are represented as states. Events of the gait cycle are found by sensor signals, the events cause transitions between states. Features of sensor signals are used to classify terrain. Gait phases are detected using two acceleration and one gyro sensor. Neural networks calculate an output current based on the Xsens sensor module to match the Rheo output current. The results are that acceleration and gyro sensors can be used for controlling prosthetic knees and the state machine can be used as a part of a control system for lower limb computer controlled prosthetics and orthotics.

Útdráttur

Markmið þessarar rannsóknar er að kanna möguleikann á því að stjórna gervihnjálið með því að nota Xsens nemasett sem samanstendur af þrívíðar hröðunar-, hornhraða- og segulnemum. Hnéð sem notað er við þessa rannsókn er Rheo hné sem framleitt er af Össuri hf. Mynsturgreiningartól eru notuð til að flokka undirlag hvers skrefs og undirlögin eru jafnslétta, halli og stigi. Stöðuvél er notuð til að útbúa líkan af gönguferli þar sem fasar gönguferlisins eru táknaðir með ástöndum. Atburðir gönguferilsins eru fundnir út frá merkjum frá nemunum sem notaðir eru við verkefnið og orsaka þeir færslu milli ástanda. Eiginleikar merkjanna eru notaðir til að flokka undirlagið. Tveir hröðunarnemar og einn hornhraðanemi eru notaðir til að ákvarða atburði. Með því að nota merki frá Xsens nemasettinu reiknar tauganet straum sem hnéð sendir frá sér til að stjórna bremsu, netið er þjálfað með því að nota straum fenginn úr Rheo hnénu sem viðmið. Hröðunar- og hornhraðanemar henta vel til að stjórna gervihnjálið. Stöðuvélina væri hægt að nota sem hluta af stærra stjórnkerfi fyrir tölvustýrða gervilimi og spelkur.

Contents

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1 Introduction

Recent developments in prosthetics have given amputees the ability to live normal life despite serious traumas and loss of limbs. Recently microprocessor controlled prosthetic knee's have become publicly available. A microprocessor controlled prosthetic knee provides an opportunity to control the amputee's gait cycle with more precision and make the gait cycle more natural. This study's goal is to use acceleration, gyro and magnetic sensors for gait recognition and knee controlling instead of current sensors that require a mechanical connection to the knee itself of the knee structure. There are two types of microprocessor controlled knee currently available, there are passive knees i.e. the knee is only capable of exerting power through a brake. Another type is active knees i.e. the knee itself can create power through motors and therefore give a great advantage to the users gait. The Rheo knee is an example of a passive knee.

This study aims to explore sensor combinations capable of controlling a prosthetic knee. Two main factors determine if a sensor combination is suitable for knee controlling, one is terrain classification and the other is output current control. It must be possible to distinguish between terrain based on sensor signals. Output current must be controlled according to the required knee function at any time point, the required knee function is determined by actual gait phase at every time point.

Gait analysis has been researched for a long time, few different applications and methods are used. Application of gait analysis is e.g. to estimate and improve gait deviation for people suffering from Parkinson disease [21] and Cerebral Palsy [9]. It is also widely used to estimate ability of the elderly to walk on their own without risking falls and injuries [18]. As well as for performance analysis and performance improvement for athletes [16]. A widely used analysis method is video and pressure mats [13] for ground reaction force(GRF) and video for visual detection of gait phases.

Since video gait analysis systems are expensive and require a lot of equipment they are usually performed at gait labs, recently a mobile gait analysis system has been developed. A recent mobile gait analysis system "GaitShoe" can be worn with any shoe and includes three orthogonal accelerometers, three orthogonal gyroscopes, four force sensors, two bidirectional bend sensors, two dynamic pressure sensors, as well as electric field height sensors [3]. Gait analysis is also done via acceleration [29] or gyro sensors [28] only or both [19]. Pattern recognition of human gait has been used for person identification and gender classification where features are extracted from videos [15]. Terrain classification has been done for bionic leg based on GRF and processed by neural networks(NN) [30].

Muscles and joints have completely different functions during different phases of the gait cycle. For control software to be able to control a prosthetic knee with stability and reliability the gait phase must be known at all time points and the knee needs to be able to sense and recognize the external environment. For this to be possible pattern recognition is used to classify different terrains, methods used are K-nearest neighbors(KNN) and decision trees. Those two methods are selected because of non parametric functions, adaptation and training is also quick and simple. KNN is more versatile than decision tree but decision tree is computationally more effective and is easily programmed with simple IF-ELSE sentences. State machine is a way to model systems that require different functionality for different periods of runtime. Gait phases are represented by states and the state machine monitor sensor signals to determine when state changes should occur and therefore change the systems function. Finally if terrain and gait phase are known, the appropriate current supplied to the knee brake is decided based on sensor signals. The current is calculated by a neural network, the neural network can use multiple inputs and be trained based on known data, if favor of NN is that the inputs relation to the output is not required to be known, so complex system can be used for controlling without the knowing exact function of every part of the system. When the NN is used the calculation can not be visualized easily therefore a more simple way using a knee angle sensor is also used for current calculations, the knee angle sensor can be easily visualized but this method only relies on the angle sensor and does not use other sensor signals.

Short description of following chapters:

Chapter 2 presents short history of prosthetics, introduction to gait analysis difference between healthy and amputee gait and finally short description of the Rheo knee.

In Chapter 3 theories of pattern recognition, the state machine and neural networks are presented. Simple examples are shown for better description of concepts and applications.

Chapter 4 introduce sensors used for this project, and shows graphs of sensor signals during gait both for the Xsens sensor module and the Rheo knee.

Chapter 5 presents results of terrain classification, the state machine and control signal.

Chapter 6 contains discussions about conclusions and future work suggestions.

2 Background

2.1 Prosthetics

Short summary of history of prosthetics from [25]. Evidence of amputations from 43.000BC has been found, amputations were done with primitive tools such as knives, saws and axis. At that time amputations were probably done because of infections resulting from animal attacks or other kinds of wounds.
When the gunpowder was discovered the need for amputation drastically increased because of bullet wounds and injuries resulting from cannon balls. In the early 1800s, Baron Larrey, surgeon to Napoleon Bonaparte, performed 200 amputations on the battlefield in 1 day.
The First description of artificial legs can be found as early as 1500BC in Indian literature.
A prosthesis unearthed in the ruins of Pompeii that dated to 300BC is thought to be the first prosthetic. This prosthesis was made of thin pieces of bronze fixed to a central wooden core and secured to the residual limb with a leather skirt. During this time, prosthesis were made of fiber, wood, bone and metals and were often lined with rags. Designs for prosthesis were made by a number of influential figures including Ambroise Paré, a military surgeon in the 16th century, and Leonardo da Vinci. Early prosthetics were blacksmiths, armor makers and often the patients themselves.
In the early 19th century, with the advance of general anesthesia and the increasing number of industrial accidents, the limbmakers were no longer skilled blacksmith but trained prosthetists.
War continued to provide the impetus for research and development in prosthetics. Following World War I, United Kingdom and United States were the main development and supply centers for military veterans, the Limb Fitting Center at Queens Mary's Hospital and the Armed Forces in UK , the Veterans Administration in US.

(a) Rheo knee *(b)* Proprio *(c)* Power knee

Figure 1: Ossur's Bionic technology [20]

Following World War II Canada began developing a prosthetic research program at Sunnybrook Hospital in Toronto. Big improvements of prosthetics were made during these war times because of large funds that attracted universities and private research companies to this field of research.
Additional refinements are continually being made as evidenced by recently developed microprocessor-controlled knees. Icelandic company Ossur has two microprocessor-controlled knees, Rheo Knee Figure 1a which uses a microprocessor to control brake for swing and stance control the other one is the Power Knee Figure 1c which also uses a microprocessor for swing and stance control and a motor for assisting the user with e.g. stair walking and standing from seated positions as well helping user with swing and stance control.

2.2 Gait analysis

Gait analysis is study of human locomotion. Gait analysis is used to identify locomotion related problems, e.g. back, knee and hip problems. Gait analysis can also be used to suggest changes for more efficient locomotion for athletes.
Gait analysis is usually done via markers and video systems for limb tracking and pressure mats for ground reaction force(GRF) measurements, where the forces acts on the bottom of the feet [10]. Video system are expensive and needs specific setup for accurate measurements, for that reason its hard to move video systems out of gait labs. Recently more mobile gait analysis systems have been developed, these systems mostly consist of acceleration and gyro sensors [8].

Table 1: Historical timeline of amputations, prosthetics and orthotics. [25]

43.000 BC	Evidence found that amputation was done with primitive tools.
2730-2625 BC	A device to stabilize the knee joint was found.
1500 BC	Indian literature describes artificial legs.
370 BC	Hippocrates used splints on the legs.
485-425 BC	Herodotus described an individual imprisoned by Sparta who supplied himself with a wooden foot.
300 BC	A prosthesis unearthed in the ruins of Pompeii is thought to be the first prosthesis.
131-201	Galen used dynamic orthoses for scoliosis and kyphosis.
476-1453	During the Middle ages, knights wore elaborate armor to conceal prostheses.
1200	Medical school at Bologna considers orthotics as an important part of medical knowledge.
1509-1590	Ambroise Pare' established technical standards for surgical amputations and described spinal corsets and shoe modifications.
1690	Verduin constructed a transtibial prosthesis with copper socket, leather thigh corset, and a wooden foot.
1790-1847	Lisfranc, a famous surgeon, amputates a foot in less than 1 minute.
1800	Baron Larrey, surgeon to Napoleon Bonaparte performs 200 amputations on the battlefield in 1 day. He advocates wounds being operated on within the first 24 hours.
1860	Mortality rate due to sepsis in London for transtibial and transfemoral amputations were 50 and 80% respectively.
1865	Lord Lister starts surgical antisepsis to decrease high mortality rates.
1865	J.E. Hangar, sustains an amputation while serving in the Confederate Army, places rubber bumpers in solid feet, and produces the first articulated prosthetic foot.
1918	After World War I, The Limb Fitting Centre at Queen Mary's Hospital, Roehampton becomes a primary development and supply center to military veterans.
1945	The U.S. Veterans Administration supports the development of the patellar tendon bearing and the quadrilateral sockets. Canada develops a prosthetics research program at Sunnybrook Hospital in Toronto.
1970	The U.S. Veterans Administration develops the endoskeletal prosthesis.
2000	A microprocessor controlled knee with hydraulic swing and stance phase control is developed.

Joint movements during gait are an important part of gait analysis, for better understanding of most simple joint movements of the knee and ankle Figure 3 can be referred to. Part of gait analysis is also hip and back movements but they are not discussed in this thesis. Gait can be separated to many branches, Figure 2, each of those branches can be looked at a different speed or different terrain so the complexity of gait analysis is almost endless. Grey boxes represent branches used in this thesis.

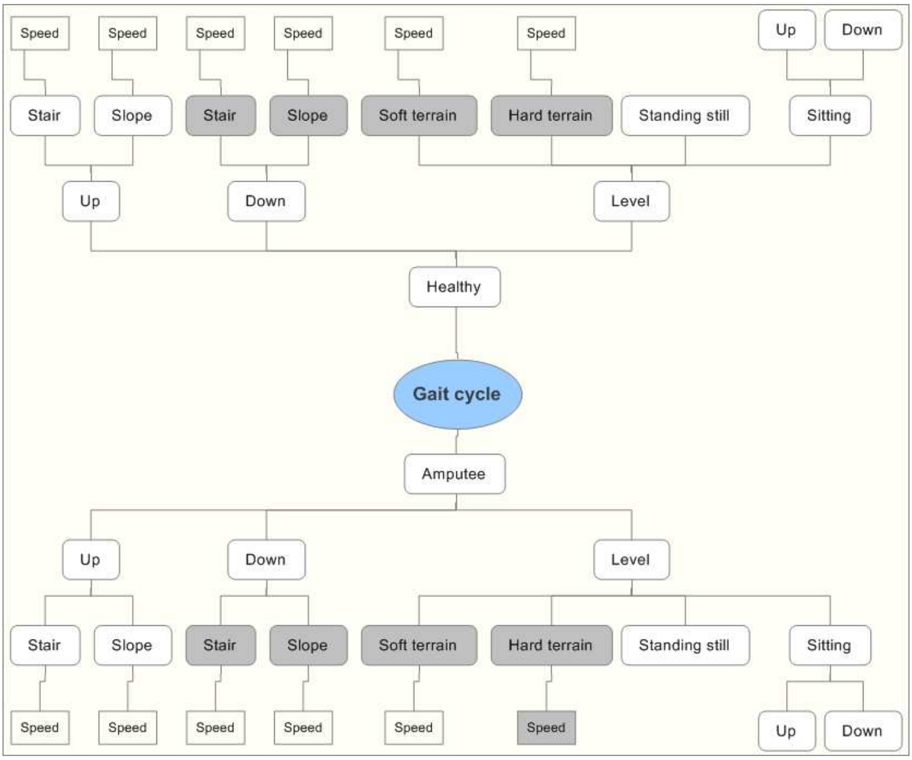
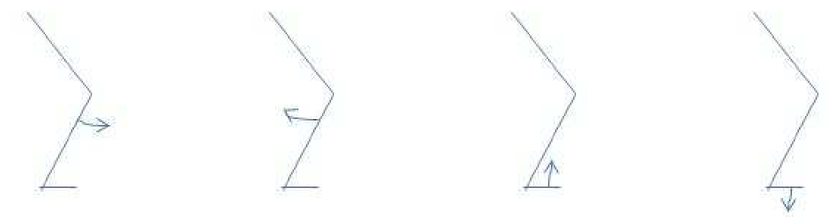


Figure 2: Complexity of human gait

2.2.1 Gait cycle

The gait cycle is a highly periodic pattern that is divided into two periods, stance and swing. The periods are then divided further into phases seen in Table 2. Gait events occur during the gait cycle, the two most familiar events are toe off(TO) and heel strike(HS), called initial contact in Figure 4 and Table 2. HS is the beginning of a step, when a person hits the ground after a swing period while the TO event is the start of a swing period, see Figure 4 for visual description of the gait cycle.



(a) Knee extension *(b)* Knee flexion *(c)* Ankle dorsiflexion *(d)* Ankle plantarflexion

Figure 3: Knee and ankle joint movements

Variables of gait cycle are e.g.

- Distance
  - Stride: Linear distance between HS of one foot until next HS of the same foot
  - Step: Linear distance between HS of one foot until next HS of the other foot
- Time
  - Stride duration: The time it takes to complete a stride
  - Step duration: The time it takes to complete a step
  - Cadence: Number of steps per minute

Periods

The stance period is the part of the gait cycle when some part of the foot is in contact with the ground. The swing period is when no part of the foot is in contact with the ground, i.e. the foot is in the air, reference Figure 4. For a regular walk the stance period makes up 60% of the gait cycle and the swing makes up the remaining 40%. In this section the gait cycle is described with the main focus on the functions of the knee.

Phases

Each period is divided into several phases, were each phase represent different function of joints and muscles.

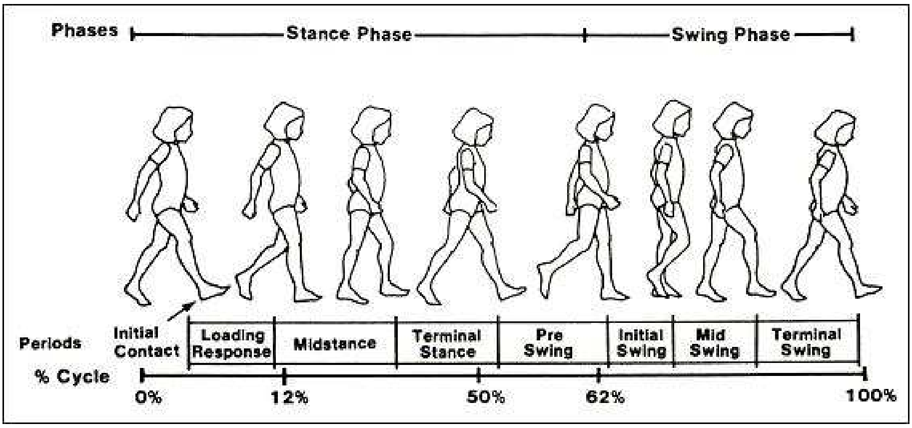


Figure 4: Normal gait cycle (Universität Wien, 2009)

Table 2: Sequence of Event in Gait Cycle [25]

Stance Period

Phase	**Description**	**Percentage of Gait Cycle**
Initial contact	When the foot hits the ground	0-2
Loading response	Until the opposite foot leaves the ground	0-10
Midstance	Until the body is over and just ahead of the support	10-30
Terminal stance	To toe-off	30-50
Preswing	Just after heel-off to toe-off	50-60

Swing Period

Phase	**Description**	**Percentage of Gait Cycle**
Initial swing	Until maximum knee flexion occurs	60-73
Midswing	Until the tibia is vertical	73-87
Terminal swing	Until initial contact	87-100

Stance period The heel strike or initial contact is the event when the foot hits the ground after the swing period. Some people do not make initial contact to the ground with the heel but rather the toes and hence this event is often called initial contact instead of heel strike, throughout this study heel strike naming will be used. The first phase is the loading response, that is when the foot hits the ground and muscles must be ready to respond to the sudden impact of initial contact, until the opposite foot leaves the ground and the foot is taking over the entire load of the body

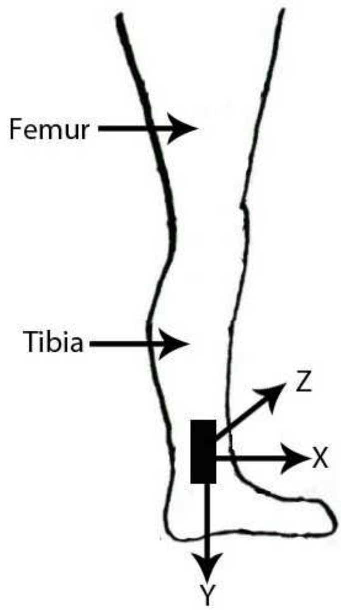


Figure 5: Human leg, the bones in this segments are called femur and tibia, sensor module location and X-, Y- and Z-axis

weight. At the loading response phase the knee is almost fully extended, but will flex slightly to lower the body center of gravity to minimize the power used for vertical movements of the body.
The second phase is midstance, midstance's critical event is to maintain knee extension by restricting the tibia from going forward.
The third phase is terminal stance, this phase also maintains knee extension but the critical event is to raise the heel until the body begins to fall toward the opposite foot.
The fourth and last phase of stance is preswing, at this phase the critical event is the knee flexion, the knee flexes and the body continue to fall toward the other limb.

Swing period The first phase of swing is initial swing, it begins when the foot is off the ground and ends when the knee has reached maximum knee flexion. This phase uses the momentum gained from preswing to create enough momentum to swing the

foot forward.
The second phase is midswing, the midswing begins at maximum knee flexion and ends when the tibia is vertical, during this phase the knee swings freely from maximum flexion to approximately 30°. During this phase the ankle dorsiflexes to make toe clearance, to avoid stumbling because of the hitting the ground with the toes when the foot is swung close to the ground.
The third and last phase of the swing is terminal swing, in this phase the critical event is that the knee has extended enough to prepare for stable landing. This phase also decrease the acceleration of the foot to prepare for accepting the body weight again, this is the last phase before the HS and start of the gait cycle.

Events Events are used to decide on transition from one phase to another, in normal gait these transition should happen in the sequence shown in Table 2.
In human gait two main events occur every cycle, i.e. HS and TO which are the start of the stance period and swing period respectively. HS is when the foot lands on the ground after the swing period. TO is when the foot leaves the ground for a swing period. Other events are harder to detect and not as obvious, they are e.g. heel off, maximum knee flexion and vertical tibia in the swing phase. Healthy people don't think about these events when walking but for people with injuries or amputees those event can help AI prosthetics and orthotics to decide on phases and periods to be able to help the user accordingly based on position in the gait cycle.

2.2.2 Gait deviations

Even though the gait cycle is similar between any two people, there is always some difference between people, e.g. walking speed, maximum knee flexion, GRF, moments created and ratio between stance and swing. A persons gait can change based on load, walking speed, injury or even shoes to name few. A different load will result in an altered gait cycle, if the person is holding a book in one hand the load the person will lean to one side and therefore alter the gait cycle observed on both legs. In the case of foot injury, a person will try to minimize the time spent on the injured leg and therefore alter the gait cycle. All these variations to the gait cycle make it difficult to have an absolute gait measuring technique.
In order to increase walking speed, the stance period time is decreased and the swing period doesn't change and therefore the stride time decreases when walking speed is increased [10].

2.2.3 Amputee gait

Leg amputees are divided into two groups

- Transfemoral(TF) or above knee amputee
- Transtibial(TT) or below knee amputee

The gait cycle of amputees is quite different from a healthy persons gait cycle. For TF amputees conventional mechanical prosthetic knee's will stay locked in extended position throughout the stance phase, then unlock in the preswing phase to gain momentum to reach maximum knee flexion. Therefore amputees need more energy during stance period because their body center of gravity has more vertical movement compared to healthy person. During the swing phase the amputee must rely more on the momentum generated during preswing because of no muscle connection to the knee joint it self. During the swing the biggest disadvantage is that when wearing conventual knee prosthetic it is fixed and does therefore not give enough toe clearance to prevent stumbling, and therefore amputees both TF and TT need to move the foot up by other parts of the body usually the hip and therefore the gait cycle is unsymmetrical, it results in a more difficult gait and it looks different from a regular gait.

2.3 Rheo knee

The RHEO KNEE® is the world's first microprocessor swing and stance knee system to utilize the power of artificial intelligence. Capable of independent thought, it learns how the user walks, recognizing and responding immediately to changes in speed, load and terrain.
The knee adapts to any situation, and not just within pre-set and limited parameters, enabling the individual to quickly regain confidence in his or her ability to walk where and how they choose [20].

2.3.1 Manufacturer

Ossur Inc (hereafter Ossur) is an Icelandic company founded in 1971 by Össur Kristinsson. Ossur is a worldwide leading company in non-invasive orthopaedics. The Rheo knee and the Power knee are a part of a three products bionic technology line Figure 1, the third product is a microprocessor controlled ankle, Proprio.

Table 3: Relation between the Rheo knee state machine and gait periods and phases

State	**Phase**	**Period**
Stance flexion	Loading response and partly midstance	Stance
Stance extension	partly midstance	Stance
Preswing	Preswing	Stance
Swing flexion	Initial swing	Swing
Swing extension	Midswing and Terminal swing	Swing

Ossur are a leading company within the fields of prosthetics, braces, supports and compression therapy. The company's phrase is "life without limitations" [20].

2.3.2 Sensors

The Rheo knee senses the environment by two load cells and an angle sensor, the sensor output is shown in Section 4.2.1. The load cells are built into the structure of the knee which makes the manufacturing of the structure complicated and expensive. Current sensors do not give enough information to estimate some gait events required for more detailed knee controlling or product combinations, e.g. the Rheo knee and the Proprio ankle. The structure is rated for specific load, currently for 100 kg users [20], if the load cell would not be required the structure could be made smaller and the whole knee unit more compact.

2.3.3 Rheo knee state machine

The Rheo knee is controlled via state machine (see Section 3.3), the Rheo knee state machine has five different states shown in Figure 6 along with available state transitions. It's possible to move to *stance flexion* state from all other states, this is a safety state and all transition except from the *swing extension* to *stance flexion* are safety transitions. Safety transitions occur if the knee control module senses an unusual sensor reading, e.g. a force during the swing period or the knee extending rather than flexing during the *preswing* state. Safety transition is triggered if the load cells sense load during states were no load should occur or unusual load reading during *preswing*.

By referring to Tables 4 and 2 and Figure 6 the most frequent paths through the state machine are described here. The regular path through the Rheo knee state machine is *Stance flexion* → *Stance Extension* → *Preswing* → *Swing flexion* → *Swing extension*.

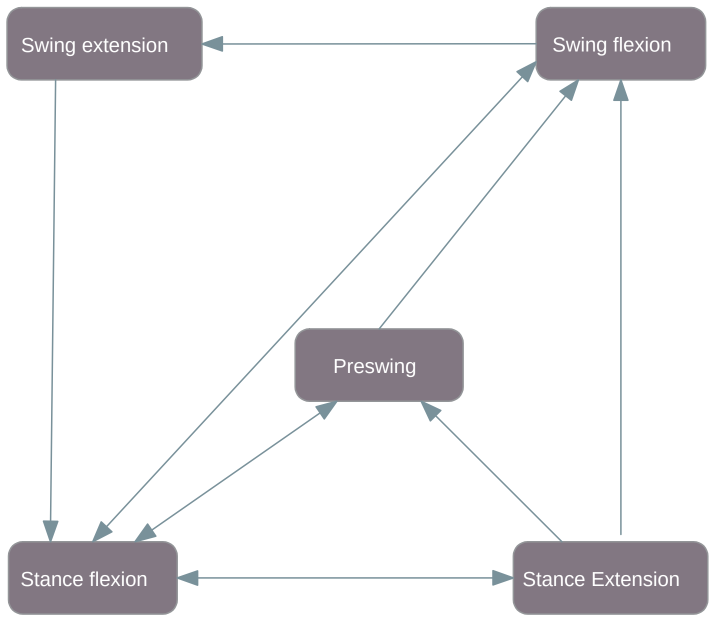


Figure 6: The Rheo knee state machine

Since few amputees are capable of performing controlled stance extension during gait the path through the state machine is usually *Stance flexion* → *Preswing* → *Swing flexion* → *Swing extension*, this is a legal path since the state machine allows other transition than just what the optimal path would suggest. In case of stair walking the path is *Stance flexion* → *Swing flexion* → *Swing extension*, the reason for this is that the amputee has all his weight on the knee when he lowering himself to the next step, so the force will remain larger during the whole stance period rather than decreasing during the end of stance period. One of the boundaries for entering the *preswing* phase is that the load is less than some specific number, if the state machine would enter the *preswing* during stair walking the control software would turn off the braking torque with potentially bad consequences.

Table 4: Description of the Rheo knee state machine and actions

State	**Description**
Stance flexion	Begins at HS, possible transitions are stance extension, preswing and swing flexion. During this phase the control software is responsive to angular velocity, i.e. if the knee starts to flex the knee output current proportional to the angular velocity of the knee joint.
Stance extension	This state is reached if the amputee is able to extent the knee during stance period, possible transitions are preswing, swing flexion and stance flexion. The control software is less responsive to angular velocity, i.e. the braking is not as harsh as in stance flexion phase.
Preswing	This state is reached if the knee senses increasing moment (see Figure 25 and Table 2) and decreasing force, possible transitions are swing flexion and stance flexion. During this state the knee's braking torque is set to zero so the knee is able to gain momentum for the swing period, since the knee does not have any motor it has to rely on power generated by the amputee during stance period.
Swing flexion	This state begins by TO, i.e. when there is no load acting on the knee, possible transitions are swing extension and stance flexion. During this state the control software damp the knee movement to achieve maximum knee angle of (usually) 60 degrees smoothly.
Swing extension	This state is reached after maximum knee angle, possible transition is stance flexion. During this state the control software damp the knee movement to end the swing as close to zero degrees without actually reaching zero degrees.

3 Theory

3.1 Pattern recognition

Humans can easily recognize faces, letters, voices, damaged food or forms by vision, hearing, smell and touch. To be able to recognize a face the brain uses parameters of the face, e.g. width, height, length between eyes, and matches them to an already familiar face. *"Pattern recognition the act of taking in raw data and making an action based on the "category" of the pattern has been crucial for our survival, and over the past tens of millions of years we have evolved highly sophisticated neural and cognitive systems for such tasks"* [7].

Computers have been designed and built to automatically recognize words, fingerprints, faces, DNA and many more applications [7]. Automatic pattern recognition systems are challenging problems because of many parameters involved in the natural world, the brain can extract various, and as many as needed, parameters of the face while the computer only has predefined number of parameters. Limited numbers of parameters can cause an overlap in the recognition system because of insufficient information and therefore cause classification errors.

3.1.1 Dimensions

Dimensions of the input data can be critical, Figure 7 shows two categories that are easily separated, but the same data in one dimension, Figure 8, is impossible to separate with decent accuracy. Too many dimensions can also cause problems, there is known a saying "curse of dimensionality" [1] which says that too many dimension will result in classification error because if data is non relevant it will act as noise and decrease accuracy of classification.

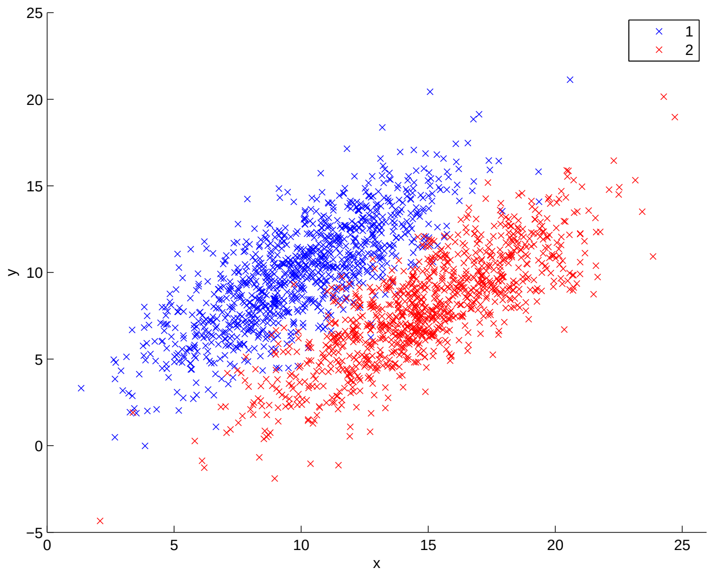


Figure 7: Two dimensional data set

3.1.2 Pattern recognition system

Pattern recognition systems can be partitioned into components, the components are shown in Figure 9 and each component's function is described in following sections.

Sensing

The inputs to a pattern recognition system are arrays of data, e.g. camera photo, microphone or sensors data. This part includes pre processing of the data, e.g. filtering, transformation and noise reduction.

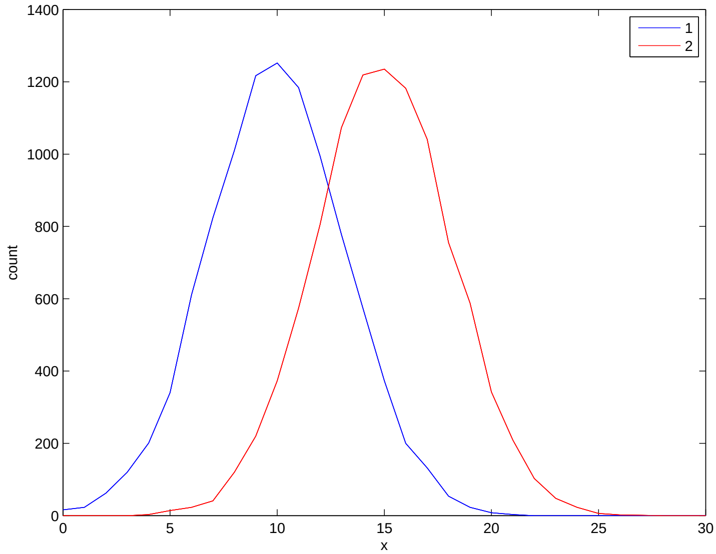


Figure 8: One dimensional data set

Segmentation

Segmentation is one of the biggest problem of pattern recognition, it decides when one sample begins and ends. In gait analysis segmentation is vital to know when step begins and when it ends for keeping track of features during each step without the data overlapping between steps. For speech recognition the problem is to detect when a word begins and ends, e.g. the word $BEATS$ could be recognized as BE or $EATS$ if the segmentation would fail to separate the speech to words correctly.

Feature extraction

Feature extraction is key to pattern recognition, it connects the input data to the classifier. The feature extractor characterizes the data in real values that can be compared by computer algorithms. Features of face detection can be width, length, face part sizes and ratio between face parts that can be measured in actual units that can be compared to a known samples.

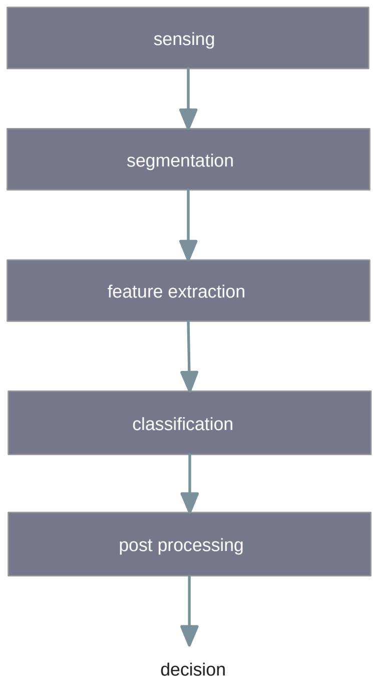


Figure 9: Pattern recognition system [7]

Classification

The task of classification is to use prior knowledge to assign a category of unknown data by using the features provided by the feature extractor, in the case of no prior knowledge similar data is classified to clusters which then require post processing for final classification. The difficulty of classification depends on the variability of the feature values. There are many variations of classifiers, e.g. decision trees, maximum likelihood estimation, regression, clustering and k-nearest neighbors(KNN) to name few.
Small two dimension example for visual explanation of decision trees and KNN can be seen in Figures 11, 13 and 14.

Univariate tree Univariate trees only check one feature at a time i.e. the split is axis-aligned. Figure 10 and Figure 11, for this example first the x feature is checked, if x is smaller than 0.5 then the sample is categorized as -1 otherwise the y feature is checked, if y is smaller than 0.5 then the sample is categorized as -1 if both node is fulfilled the sample is categorized as 1.

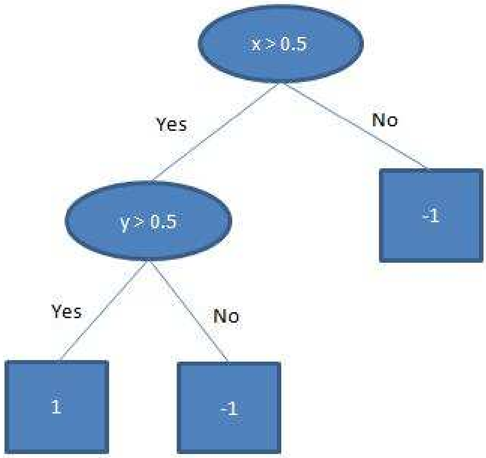


Figure 10: Univariate tree decision nodes

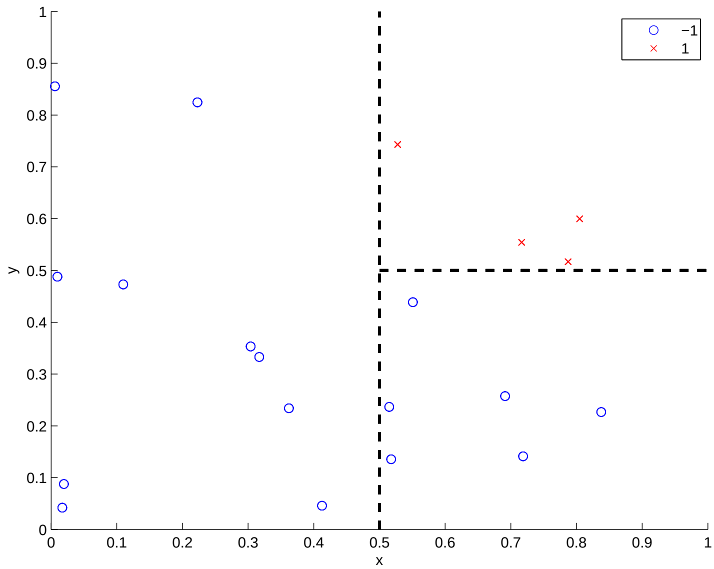


Figure 11: Univariate tree

Multivariate tree Multivariate trees use a combination of features to create hyperplane boundary instead of axis-aligned boundary and is therefore more general, multivariate trees can be used for an unlimited number of dimensions. Figure 12 and Figure 13 shows how this split works for a simple example. If $\mathbf{w_m^T x} + \mathbf{w_0} > \mathbf{0}$ then the sample is categorized as 1 otherwise it is categorized as -1.

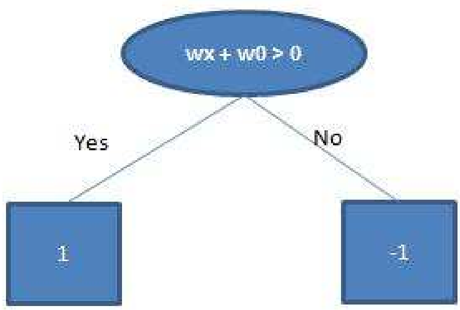


Figure 12: Multivariate tree decision nodes

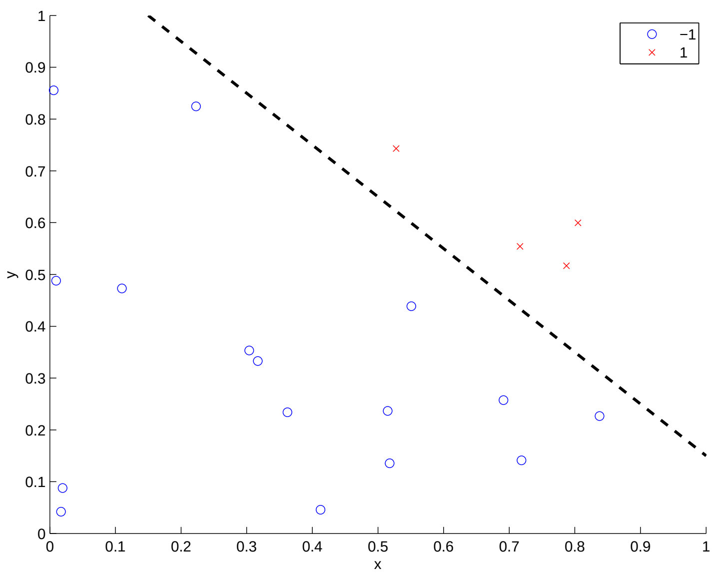


Figure 13: Multivariate tree

K-nearest neighbors K-nearest neighbors(KNN) is a nonparametric technique, i.e. it doesn't estimate probability just decides categories directly. KNN needs a database of known samples, it can be used by two methods. In the first method KNN can use a window, i.e. when a new data point is supposed to be categorized there is a predetermined window where KNN labels the new data point as the label of majority of data points from database that are within the window. The second method is to compare the new data point to the database and search for KNN, then the new data point is labeled as the label of majority of data points from the KNN, distance between samples is calculated by the euclidian distance equation [7].

$$Dist = \sqrt{\sum_{i=1}^{n} (\mathbf{x_i} - \mathbf{y_i})^{\mathbf{2}}}$$

By the second method the windows grow to the necessary size to include K neighbors. If the probability of terrain would be used for the KNN instead of final decision the post processing step would decide if the probability is enough to change or maintain terrain. Figure 14 shows the decision boundary for the small example used earlier.

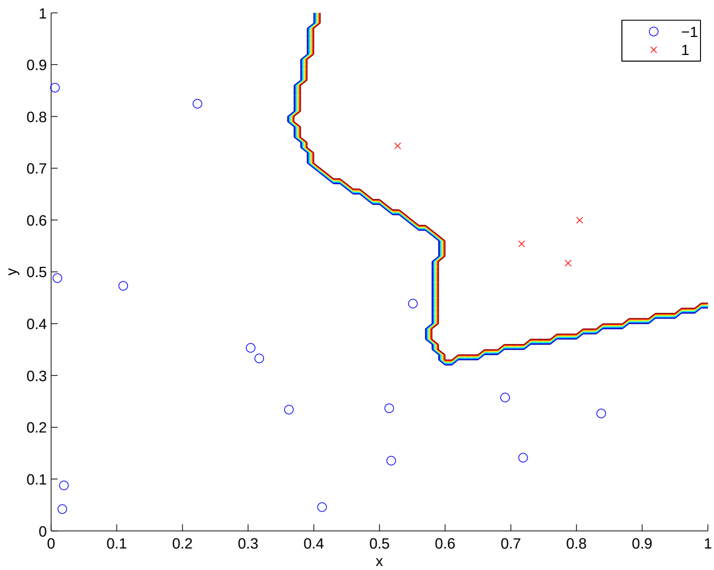


Figure 14: KNN decision boundary with $K = 3$

Higher dimensional KNN classification is also available, the way of measuring the distance must be decided since parameters don't necessary have the same significance. The parameters can be altered for various significance by multiplying them by constant.

Post processing

Classifier is rarely 100% accurate, the decision made by the classifier is more of a suggestion of category. Post processor uses the output from the classifier and other information, e.g. prior knowledge or risk of certain action, to determine the appropriate action.

3.2 Neural networks

The idea of neural networks is inspired by the brain, the brain can process great amount of data in a very short time e.g. vision, speech, recognition and learning. The neural networks are a simplified model of the brain. The human brain is quite different from a computer. Whereas a computer generally has one processor, the brain is composed of a very large (10^{11}) number of processing units, namely, neurons, operating in parallel. Though the details are not known, the processing units are believed to be much simpler and slower than a processor in a computer. What also makes the brain different, and is believed to provide its computational power, is the large connectivity: Neurons in the brain have connections called synapses, to around 10^4 other neurons, all operating in parallel. In a computer, the processor is active and the memory is separate and passive, but it is believed that in the brain, both the processing and memory are distributed together over the network, processing is done by the neurons, and the memory is in the synapses between the neurons[1].

3.2.1 Neural network

In this project 3 layer network was used, Figure 15 with activation function $tanh(x)$ [6]. First layer x_i is the input layer where $\mathbf{x}$ is taken into the network and distributed through to the next layer. Second layer of the neural network y_j is the hidden layer, there can be more than one layer but in this project only one was used because network with two layers worked as well as the one used here. The third and the last layer z_k is the output layer of the network where the estimated output of the network can be seen. Links from each neuron to all neurons in next layer are called weights w_{ji}, i.e weight from x_i to y_j, sometimes called synapses as the connections in brains.

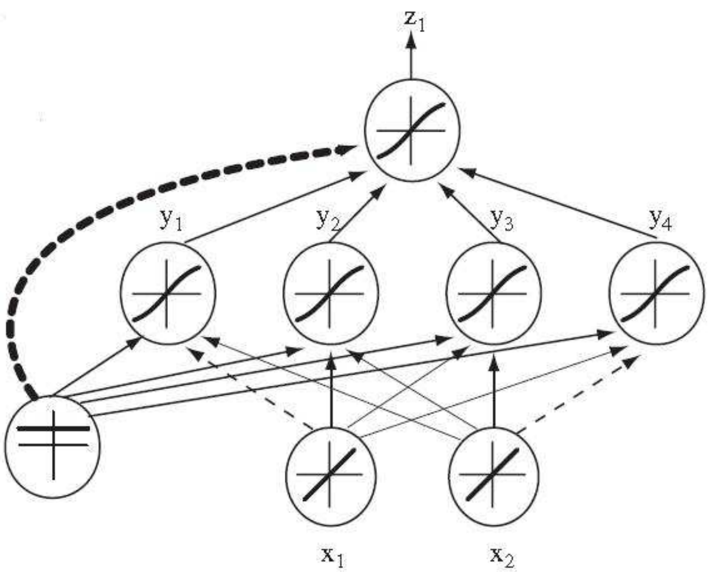


Figure 15: Three layer neural network, figure from [7]

3.2.2 Feedforward operation

From now on only three layer network will be used for demonstration. The feedforward operation is algorithm to calculate the network output for given input $\mathbf{x}$ [11]. Each hidden neuron computes the weighted sum of its inputs to form its scalar *net activation* which is denoted by net_j

$$net_j = \sum_{i=1}^{nI} x_i w_{ji} + w_{j0} = \sum_{i=0}^{nI} x_i w_{ji}$$

Then each neuron emits an output that is a nonlinear function of its activation, $f(net)$, i.e.

$$y_j = f(net_j)$$

Now each output neuron similarly computes its net activation based on the hidden neuron signals as

$$net_k = \sum_{j=1}^{nH} y_j w_{kj} + w_{k0} = \sum_{j=0}^{nH} y_j w_{kj}$$

at last the output neuron computes the nonlinear function of its net, emitting

$$z_k = f(net_k)$$

General form of the feedforward operation is

$$g_k(x) \equiv z_k = f\left(\sum^{nH} w_{kj} f\left(\sum^{nI} w_{ji} x_i + w_{j0}\right) + w_{k0}\right)$$

3.2.3 Backpropagation algorithm

Backpropagation is used for training the network, it will take one example **x** from the dataset and feed it through the network via feedforward, then calculate the error between the desired output and the actual output and update the weights depended on the error. Stochastic backpropagation was implemented for this project. The basic stochastic protocols of backpropagation is shown in the procedures below [7]

begin initialize $nH, \mathbf{w}, \theta, \eta, m \leftarrow 0$
    do $m \leftarrow m + 1$
        $\mathbf{x}^m \leftarrow$ randomly chosen pattern
        $w_{ji} \leftarrow w_{ji} + \eta \delta_j x_i$
        $w_{kj} \leftarrow w_{kj} + \eta \delta_k y_j$
    until $\|\nabla J(w)\| < \theta$
  return w
end

where η is the learning rate, $J(w)$ is the training error, nK is number of outputs and t_k is desired output

$$J(w) \equiv \frac{1}{2} \sum_{k=1}^{nK} (t_k - z_k)^2$$

δ_k is called the sensitivity of neuron z_k

$$\delta_k = (t_k - z_k) f'(net_k)$$

δ_j is called the sensitivity of neuron y_k

$$\delta_j \equiv f'(net_j) \sum_{k=1}^{nK} w_{kj} \delta_k$$

3.3 State machine

State machine, also called automata, is a software engineering tool [4]. The state machine is a tool to model a real time system that consists of a finite number of states where each state requires different actions based on various external or internal environments. The state machine does not usually have an endpoint, i.e. it is an endless loop. The system travels between states by predetermined transitions that are guarded by boundaries or flags. The whole system can change behavior based on states by different actions defined by the states.
A simple example for description of states, transitions and actions, Figure 16. This is a simple model of automatic door with motion sensors for detecting movement at the door. There are two systems, one for the door and one for the motion sensor.

States The states are $Close$, $Open$ and $Motionsensor$, the states represent closed door, open door and sensor active respectively. For each state there are at least one incoming and one outgoing transitions. Each state can have specific actions that are executed at current state.

Transitions Transitions are represented by arrows, they are triggered by events. There are two types of events in this example, timed event i.e. when time has exceeded some limit and a trigger event. There are two types of triggers, call triggers shown as $trigger!$ and respond triggers shown as $trigger?$. When a motion sensor senses movement it will transit through the loop transition, this transition set time t to zero, i.e. reset timer, and calls trigger that creates transition in door system. When $trigger!$ is called it depends on what state the door system is at currently, if the $Close$ state is active the state machine will transit to $Open$ state, if the $Open$ state is active it will loop and the timer will be reset. If the active state does not have transition called by called trigger there will be no transition. A timed event only occurs if the timer has exceeded a specific limit, in this example when the timer has exceeded 10 time units the door system will transit to $Close$ state.

Actions Actions are a set of commands executed when the state is active or when the state is entered. In the $Close$ state the action is to close the door when the state is entered, in the $Open$ state the action is to open the door when the state is entered, it will remain open if the door is already open when state is entered. The $Motionsensor$ state action is to listen and react to the motion sensor.

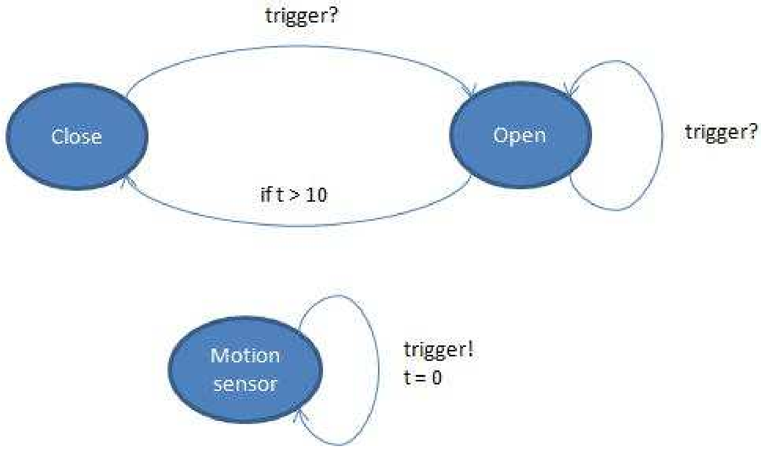


Figure 16: Simple state machine example

State machine validation Since a state machine can consist of a large number of states and transitions, the possible paths through the state machine could be more than is possible to test. For state machine validation some tools and methods have been created, one tool is Uppaal developed jointly by Aalborg University in Denmark and Uppsala University in Sweden (http://www.uppaal.com/), another interesting tool is called Rebeca (http://khorshid.ece.ut.ac.ir/∼rebeca/). Validation tools are programmed to search for illegal transitions, out of bounds states or any possible way to create an unstable state machine, by checking all possible paths through the state machine and searching for specific events or transitions that could lead to a failure of the state machine [32], [26].

4 Sensors and measurement setup

4.1 Measurements

Measurements were obtained by the Xsens sensor module and data logged by Rheo knee software. Xsens sensor module was fixed at approximately ankle height Figure 5, on an amputee walking on Rheo knee and a healthy subject. Isolated tests were performed for three terrains, level ground, stairs and slope. The amputee was asked to walk at three different walking speeds, slow, medium and fast where the amputee decided himself the appropriate speed for each of them. All data for the state machine design was obtained by a single amputee, validation performed by another amputee. Test setups were

- Level ground: Indoor, hardwood floor, 2 sets at slow speed, 8 at medium speed and 1 set at fast speed
- Stairs: Indoor, 18cm high steps, linoleum floor, 4 sets
- Slope: Outdoor, approx 10°, asphalt, 3 sets
- Soft underlay: Outdoor, level ground, wet grass, 1 set

Axis of the sensor module are shown in Figure 5, axis with reference to the tibia are

- X is perpendicular to the tibia, forward/backward
- Y is parallel to the tibia, up/down

- Z is perpendicular to the tibia and foot, sideways

Whole data series, 18 steps from stationary to stationary position, obtained at level ground and medium speed via Rheo knee software for force Figure 17, moment Figure 18 and knee angle Figure 19, only most relevant variables shown. It can be seen from the data obtain by the Rheo knee that sensor values obtained during gait are highly periodic.

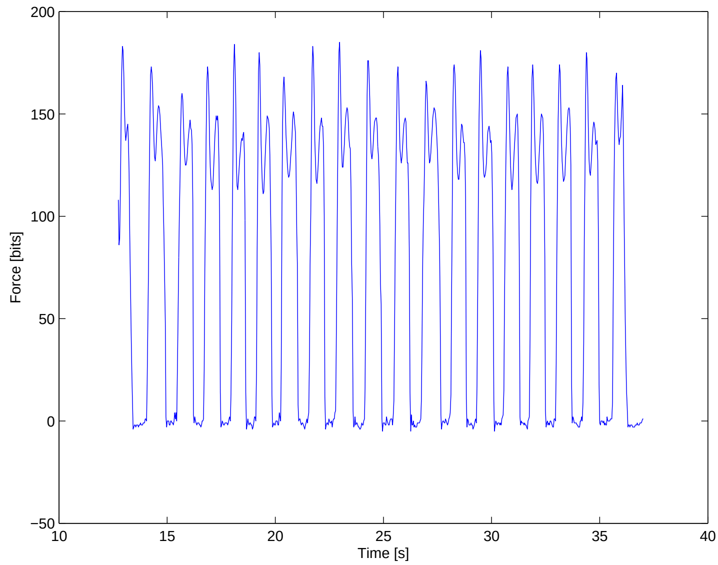


Figure 17: Rheo knee data, GRF

The whole data series, obtained at the same walk as for the Rheo knee, via Xsens sensor module for X-acceleration Figure 20, Y-acceleration Figure 21 and tibia angular rate Figure 22, only most relevant sensors shown. It can be seen from the data obtained by the Xsens sensor module that the sensor values obtained during gait are highly periodic, especially angular rate.

4.2 Sensor module

The sensor module used for data gathering during this thesis is Xsens MTi from Xsens Motion Technologies. The sensor signal processor provides calibrated signals for 3D acceleration, 3D rate of turn and 3D earth-magnetic field data. A bluetooth

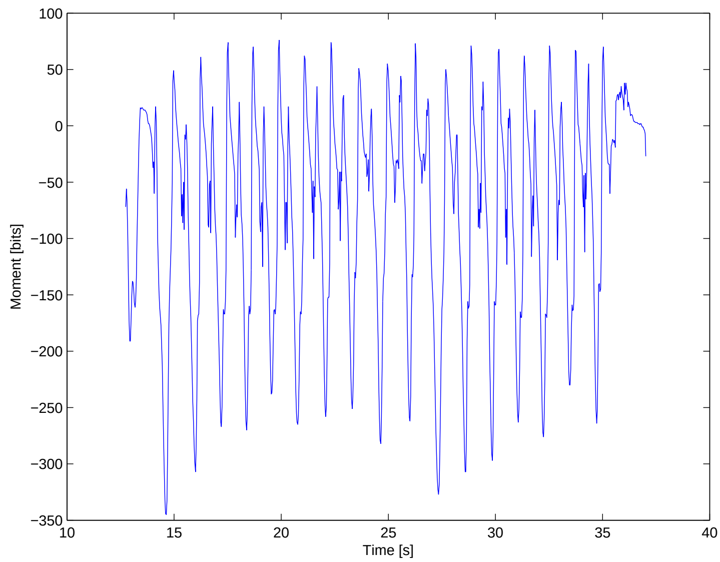


Figure 18: Rheo knee data, moment

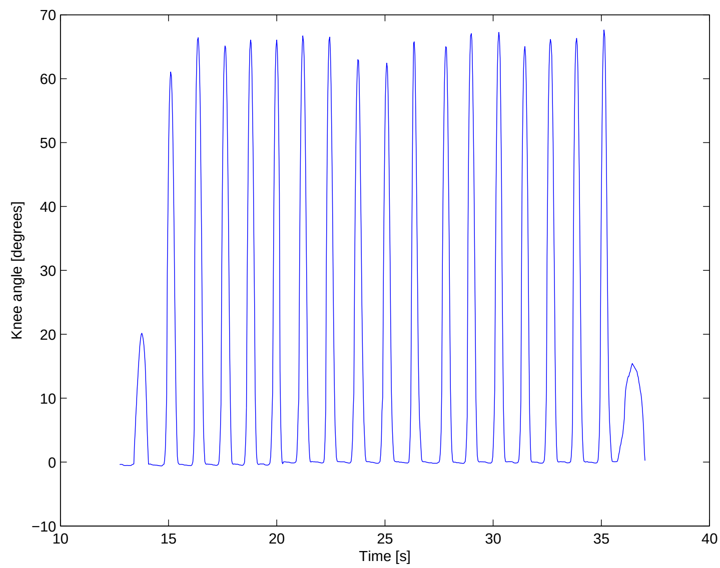


Figure 19: Rheo knee data, knee angle

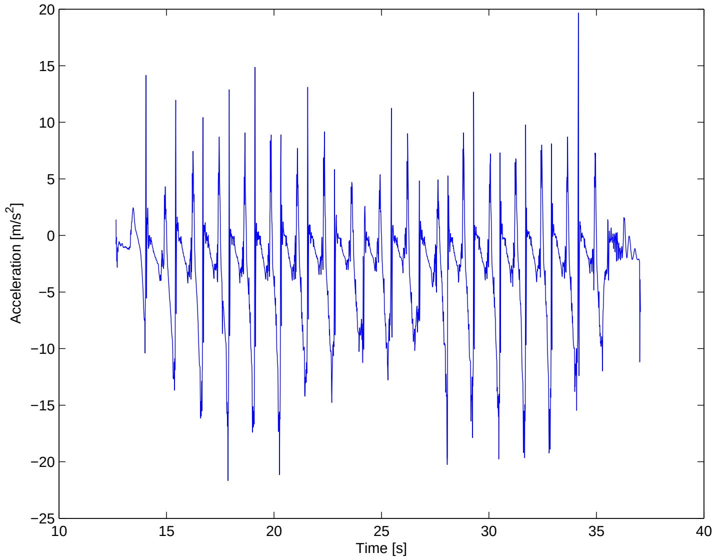


Figure 20: Xsens data, X-acceleration

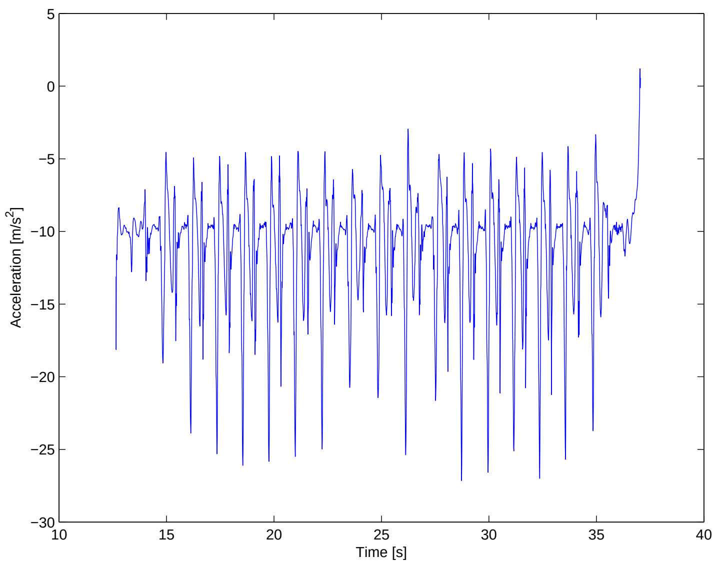


Figure 21: Xsens data, Y-acceleration

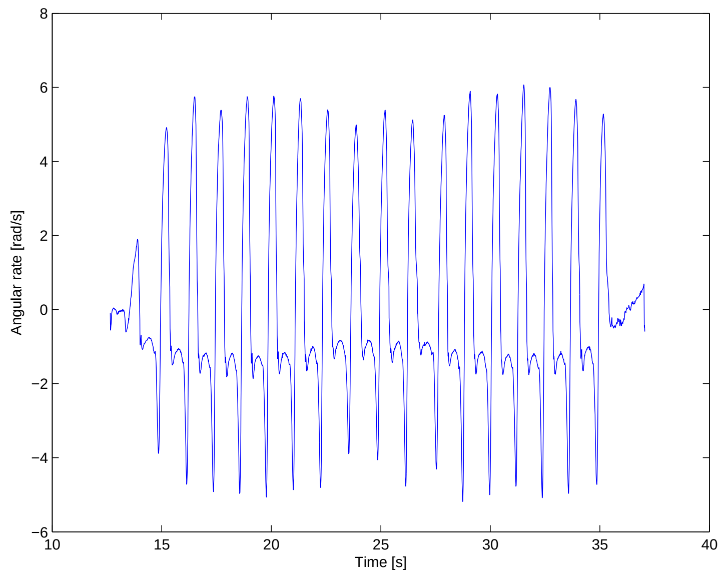


Figure 22: Xsens data, angular rate

sender was integrated to the sensor for wireless data gathering. Next section describes current sensors the Rheo knee uses for gait phase detection, then a short description of sensors used during this study.

4.2.1 Rheo knee's current sensors

The Rheo knee is equipped with three sensors, a pot sensor which measures the absolute knee angle, Figure 23, and two strain gauges also called load cells, one at the front and one at the back, which measure the load through the knee's structure. By addition and subtraction GRF and moment is calculated, Figures 24 and 25 respectively, limit for stance period is 8 bits set by the Rheo software. The Rheo knee has built in hardware differentiation for the angle sensors and in that way angular velocity of the knee joint is obtained. The GRF and moment are similar to result from a recently published article about force and moment in healthy subject's tibia [31]. The knee angle of a healthy subject will have increased to 10-15 degrees during the stance phase while amputees do not flex the knee during stance phase [10], but with the Rheo knee stance flexion is made possible with computer controlled stance control.

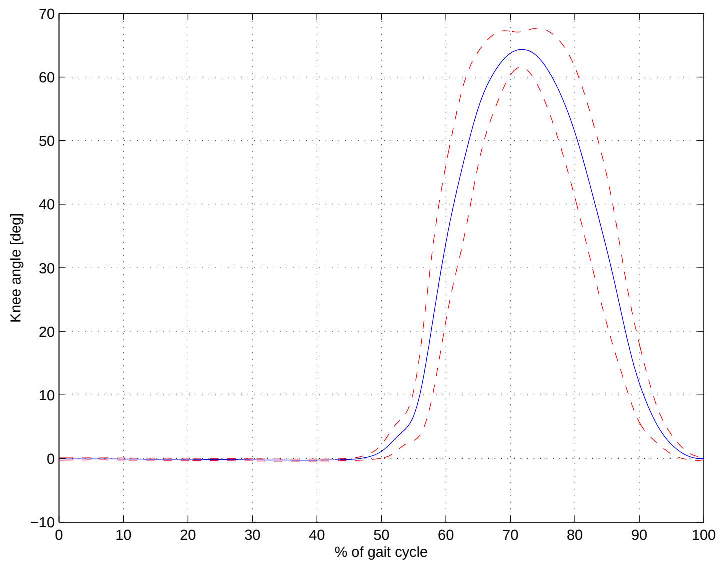


Figure 23: Rheo knee angle

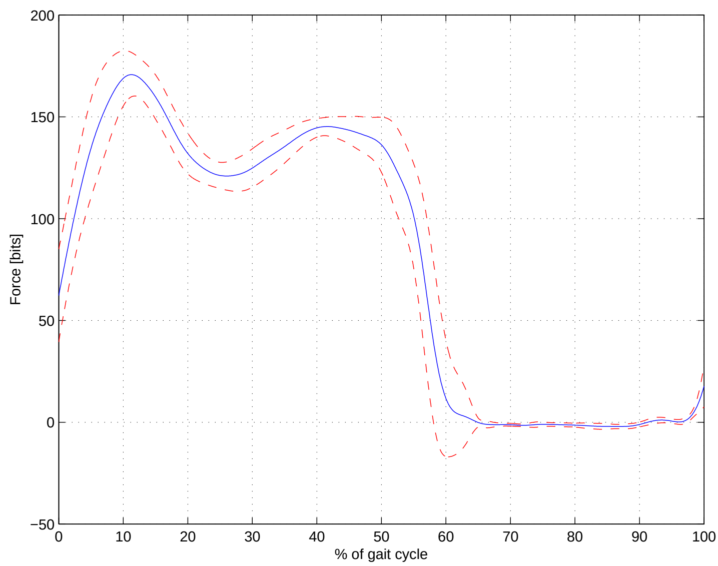


Figure 24: Rheo knee GRF

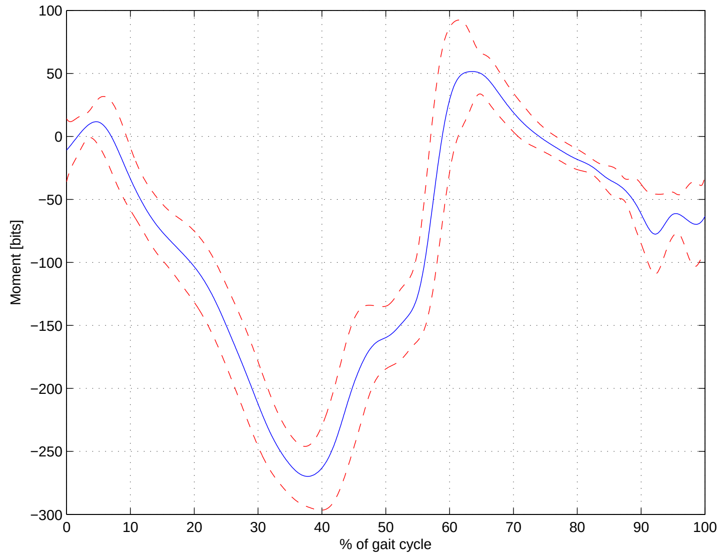


Figure 25: Rheo knee moment

4.2.2 Acceleration sensors

Acceleration sensors are used to detect motion, impacts or vibrations. A single axis acceleration sensor consists of a mass and a spring, the mass is suspended by the spring and the mass is allowed to move in one direction, which is the measured direction, the displacement of the mass is a measure of the acceleration it undergoes [17]. Acceleration sensors have fast response, are highly sensitive, require low voltage and has low current consumption. Because of low power demand they are ideal for small real time applications like prosthetic knees.
Applications where acceleration sensors are used are e.g. gait analysis [19], earthquake detection systems [27], car impact detection systems [5], gps systems [23] and game consols [24].
Figure 26 shows sensor signals for an amputee walking on level ground.

4.2.3 Gyroscope

There are few designs of an angular rate sensor (gyroscopes) e.g. spinning rotor gyroscopes, laser gyroscopes and vibrating mass gyroscopes. Spinning rotor- and laser gyroscopes are bulky and expensive. A vibrating mass gyroscope is small,

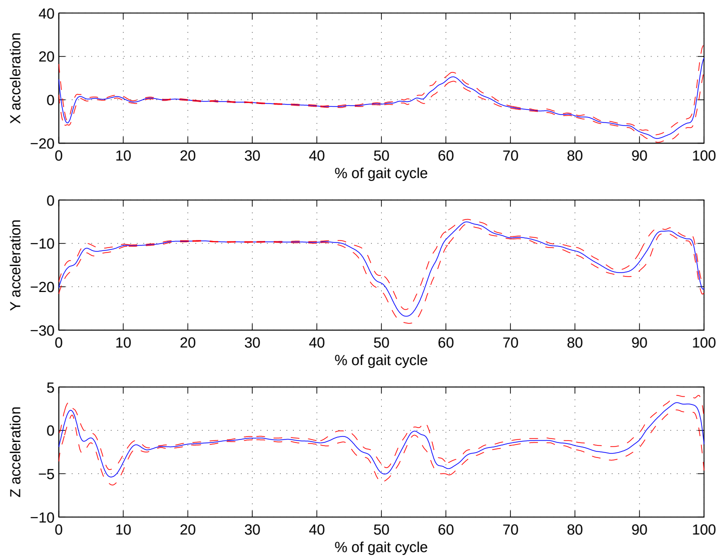


Figure 26: Xsens acceleration sensors [m/s^2]

inexpensive and has low power requirements. A vibrating mass gyroscope consists of a small mass and a distance measurement that measures displacement of the mass when the mass experience coriolis force because of angular velocity [17]. Gyro sensors are mainly used for navigational applications [14], others are e.g. gait analysis [19] and stabilization systems [12].
Figure 27 shows gyro sensor signals for an amputee walking on level ground.

4.2.4 Magnetic sensors

Magnetic sensors sense a magnetic field of the environment. A magnetic sensor is sensitive to the earth's magnetic field and can therefore estimate horizontal direction of the sensor. Magnetic materials can have an affect on the sensor, ferromagnetic materials like iron will disturb the magnetic field and the sensor won't be able to give an accurate direction [22]. Sailing maps have special magnetic symbols where the magnetic field is disturbed by a large amount of iron or other magnetic materials, which results in inaccurate heading of the ship's compass. Applications of the magnetic sensor is mainly compass related, they can be used to detect magnetic objects in e.g. sand, heading and orientation correction for gyroscopes via sensor fusion by e.g. Kalman filter [22].

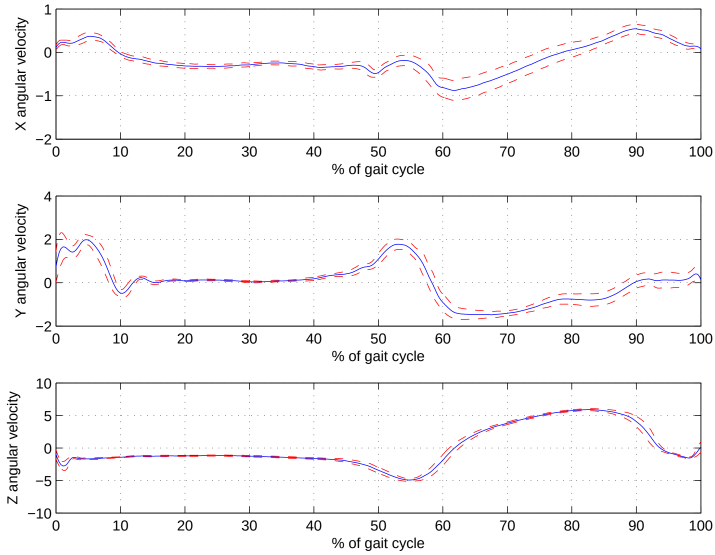


Figure 27: Xsens gyro sensors [rad/s]

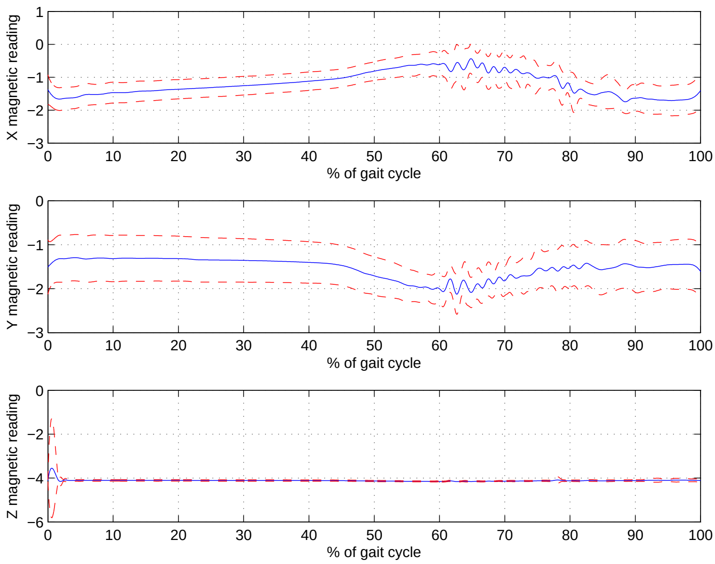


Figure 28: Xsens magnetic sensors [mGauss]

5 Results

5.1 Preprocessing

5.1.1 Principal component analysis(PCA)

Preprocessing was minimal since the sensor module has built in filters and outputs stable and usable signals. To determine which sensor should be used for this thesis the most obvious choice would be X-acceleration, Y-acceleration and angular rate since the most relevant linear movement of the foot is in X- and Y-direction and angular movement around the knee(Z-axis), refer to Figure 5. Principal component analysis was used to determine which signals represent the most variance of the signals. Table 5 shows how much variance each PCA represent, first three components explain more than 95% of the variance and therefore only first three component are looked at more thoroughly. Table 6 shows what sensors are most relevant for each component, the first component's most relevant sensor is X-acceleration, the second component's most relevant sensor is Y-acceleration and the third component's most relevant sensor is the angular rate around the knee axis. Angular rate is also the second most relevant sensor in components one and two. Based on those results the three sensors used during gait analysis are selected as X- and Y-acceleration along with the angular rate. Figures 29 and 30 are graphical representation of Table 5.

Table 5: PCA results

PCA	Percent explained	Each PCA
1	54.82	54.82
2	85.29	30.47
3	95.15	9.86
4	98.61	3.45
5	99.24	0.63
6	99.58	0.34
7	99.87	0.29
8	99.96	0.08
9	100.00	0.04

Table 6: PCA results - First three components

Sensor	Comp. 1	Comp. 2	Comp. 3
Y-acc.	-0.0670	0.9618	0.2178
X-acc.	0.9577	0.1270	-0.1683
Z-acc.	-0.1215	0.0385	0.3536
Y-gyro	0.0204	-0.1243	0.1966
X-gyro	-0.0306	-0.0209	0.0130
Z-gyro	-0.2482	0.2034	-0.8711
Y-mag.	-0.0109	0.0074	0.0263
X-mag.	0.0239	-0.0005	-0.0298
Z-mag.	-0.0009	-0.0004	0.0029

5.2 Pattern recognition

5.2.1 Terrain

The knee needs to be able to distinguish between different terrains, e.g. level ground Figure 31, stairs Figure 32 and slope Figure 33. The gait cycle varies between terrains and the knee has to be able to respond quickly and efficiently to new terrain.
Based on trials with the Rheo knee, it doesn't need to brake much during mid- and terminal stance in normal level ground walking since the knee is usually fully extended and does not flex or extend. When an amputee is walking down stairs or on declining slope all the body weight is on the knee while the user is moving from higher position to a lower by flexing the knee, therefore the knee needs more resistance to flexion than when in normal level ground walking.

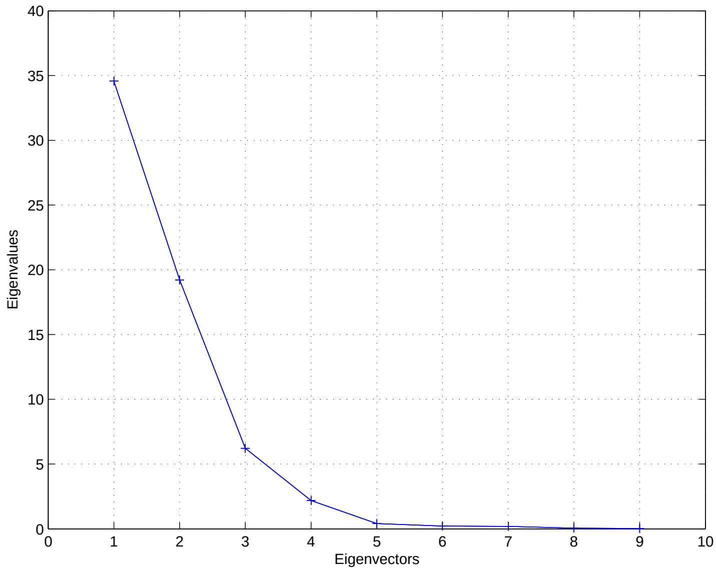


Figure 29: PCA - scree graph

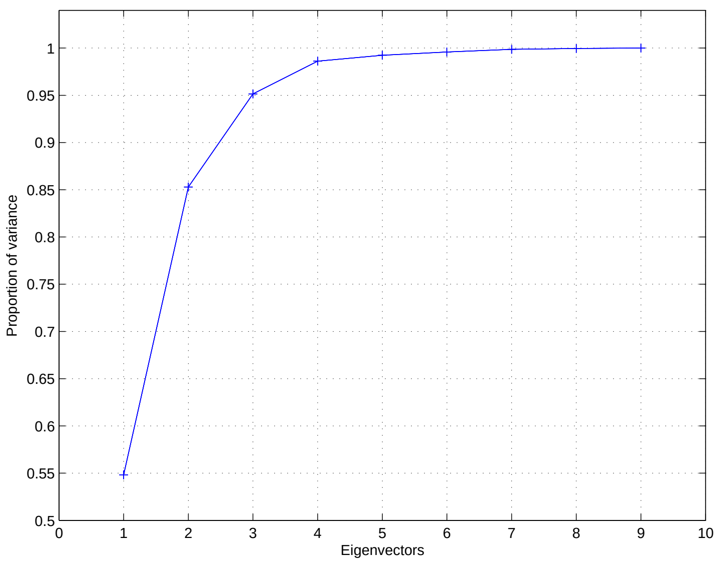


Figure 30: PCA - proportion of variance explained

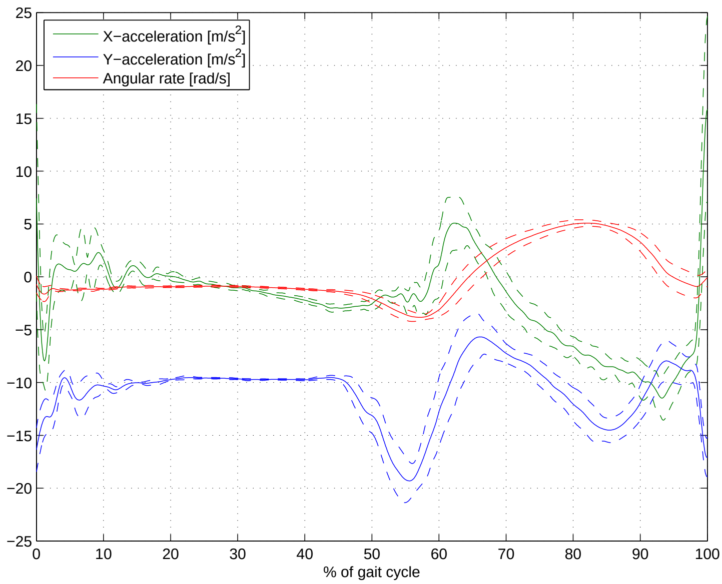


Figure 31: Mean sensor signals, level ground, medium walking speed

For comparison to sensor signals for a healthy subject, figures for level ground, stair and slope can be seen in Appendix B.

5.2.2 Features

By comparing data for the three different terrains, level ground Figure 31, stairs Figure 32 and slope Figure 33 the following features were selected for more detailed analysis.

- Peak to peak of the Z gyro signal
- Peak to peak of the X acceleration
- Maximum amplitude of the X acceleration
- Peak to peak(PtP) at toe off for X acceleration
- Maximum amplitude at toe off for Y acceleration

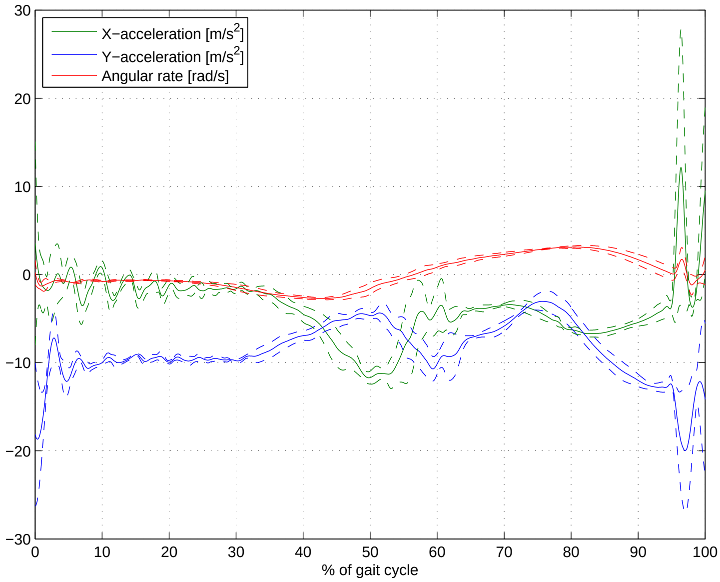


Figure 32: Mean sensor signals, stairs

- Stride duration

The Y-acceleration and X-acceleration signals at TO are prime candidates to distinguish between level ground and stairs or slope, since the peaks are reversed around the toe off. Ideally these signals could trigger different terrain settings in the control software of the knee early enough to be able to control the swing phase according to current terrain without having problem during first step because of wrong terrain estimation. The pattern recognition software could recognize the terrain in current step instead of making a decision based on data obtained during the last step.

5.2.3 Test data

Test data was obtained by isolated tests for all three terrains. All tests were performed at a self selected speed by the amputee. Level ground walking was performed at slow, medium and fast pace, Figures 34, 31, 35 respectively, those figures show that increased walking speed results in increased peaks value and decreased stance/swing ratio (refer to minimum value of angular rate signal at approximately 55-60% of gait cycle). Slope walking was performed at approximately 10° slope and performed

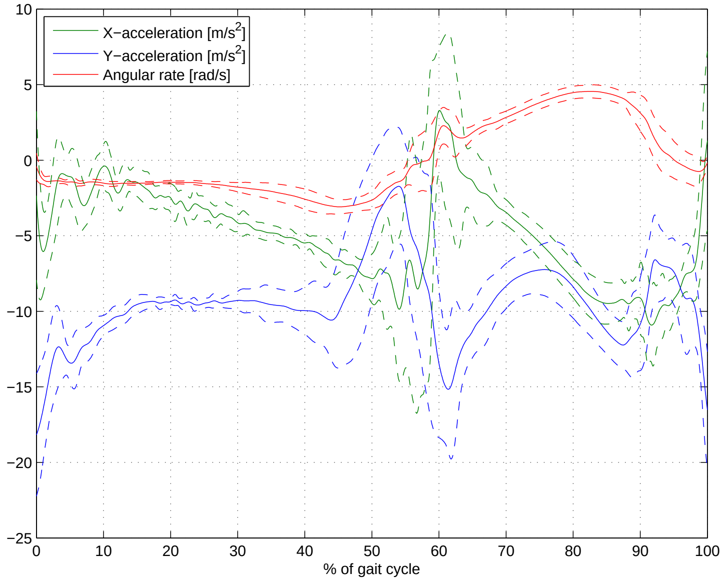


Figure 33: Mean sensor signals, slope

at slow and medium pace. Stair walking was performed at stairs with 8cm high steps.

Test data includes following number of samples, each step is regarded as one data point

- 133 data points for level ground
- 50 data points for slope
- 20 data points for stair

If Figures 31, 32 and 33 are compared, the most likely features to distinguish between the terrains would be PtP X-acceleration at toe off Figure 36 and max Y-acceleration at toe off Figure 37.
These two features on their own are not able to distinguish between level ground and stairs because of complete overlap between the two terrains at PtP X-acceleration at toe off. Max Y-acceleration at toe off is able to separate slope from level ground and stairs decently, with a small overlap at -5 to -3 (this is not a problem during higher dimension classification), two or three data points of 50 data points for slope. PtP X-acceleration at toe off has some overlap between level ground and slope, and

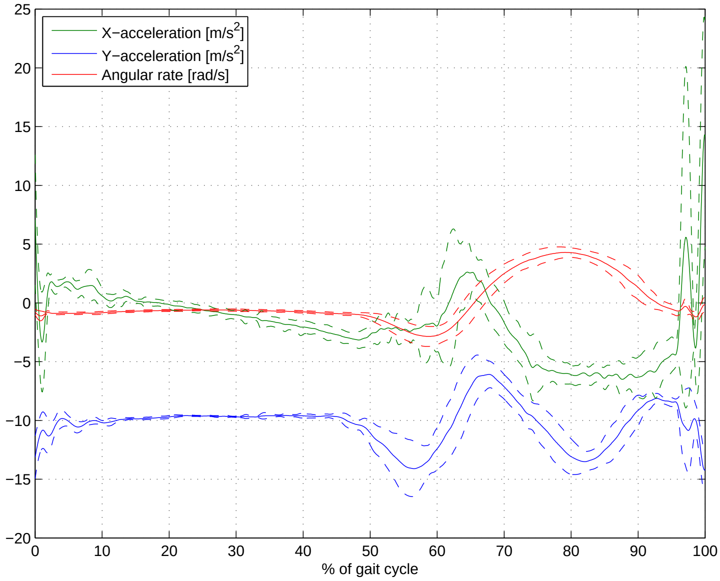


Figure 34: Level ground, slow walking speed

could not be used on its own to distinguish between any of the terrains with enough accuracy.

Features can be plotted in as many dimensions as the features are, but for graphical representation two dimensions are easiest to describe and visualize. When all features are plotted against each other two instances are the best candidates for successful classification results. All other 2D feature versus feature plots can be seen in Appendix A.

- Angular rate versus PtP X-acceleration at toe off, Figure 38
- Angular rate versus max Y-acceleration at toe off, Figure 39

Figures 38 and 39, angular rate versus PtP X-acceleration at toe off and angular rate versus max Y-acceleration at toe off respectively show that in simple manner each of the three terrains can be separated from other terrains.
Angular rate versus PtP X-acceleration at toe off data point form three well separated clusters. Angular rate versus max Y-acceleration at toe off does also form three well separated clusters but one data point from slope is at the stairs cluster and one point

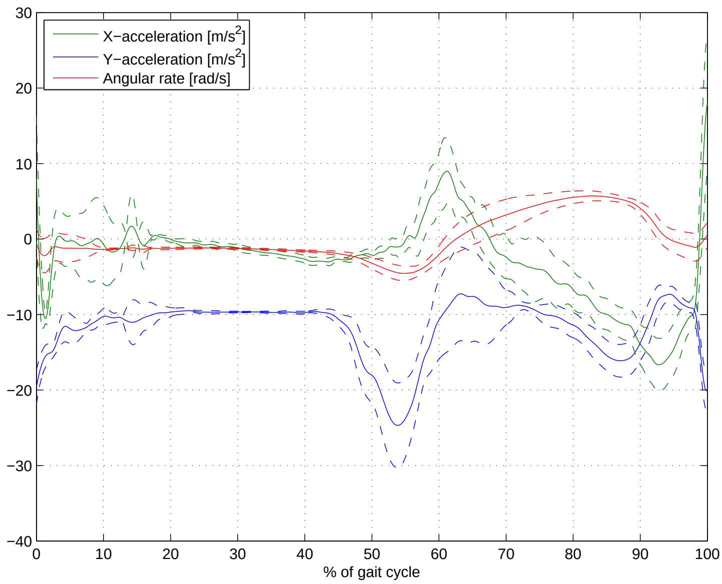


Figure 35: Level ground, fast walking speed

is between level ground and stairs, those two point could cause problems during classification if two dimensional classification would be used.

By comparing Figures 41, 42 and 43 and noticing the difference between the decision boundaries. The boundaries show that when K is lower KNN is more sensitive to noise, but as K increases the decision boundaries become more smooth and reliable. From these two dimensional data plots it can be seen that distinguishing between terrains can be done with simple classification methods.

5.2.4 Decision tree

Decision tree is efficient nonparametric method, which can be converted to a set of simple IF rules that are easily programmed in a conventional way.

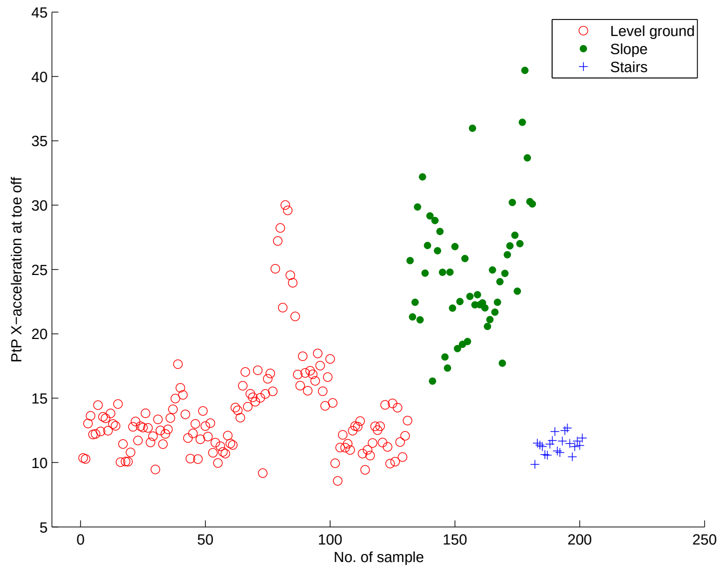


Figure 36: Scatter plot, PtP X-acceleration at toe off

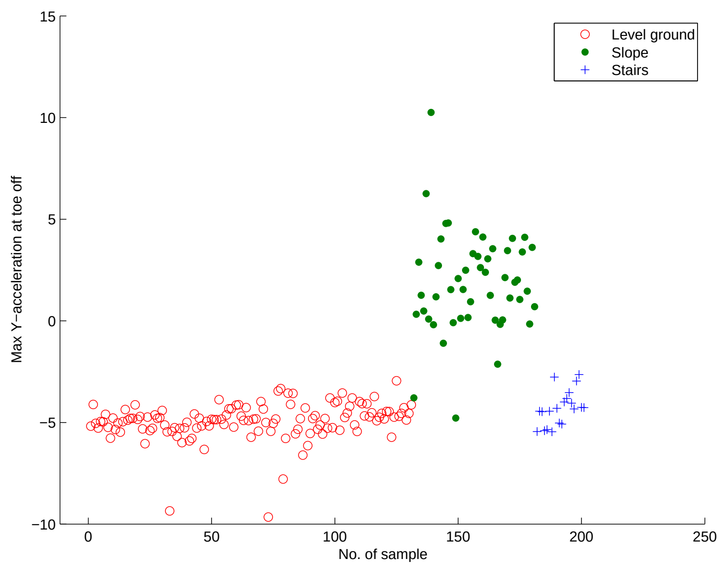


Figure 37: Scatter plot, max Y-acceleration at toe off

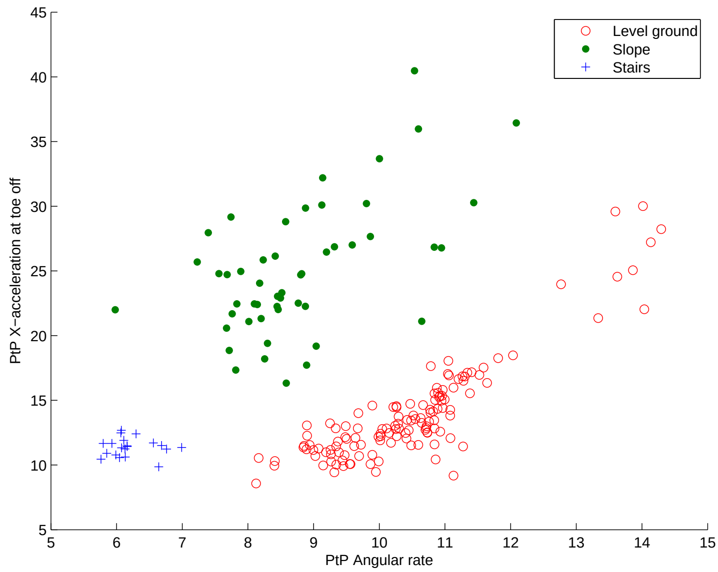


Figure 38: Scatter plot, angular rate versus PtP X-acceleration at toe off

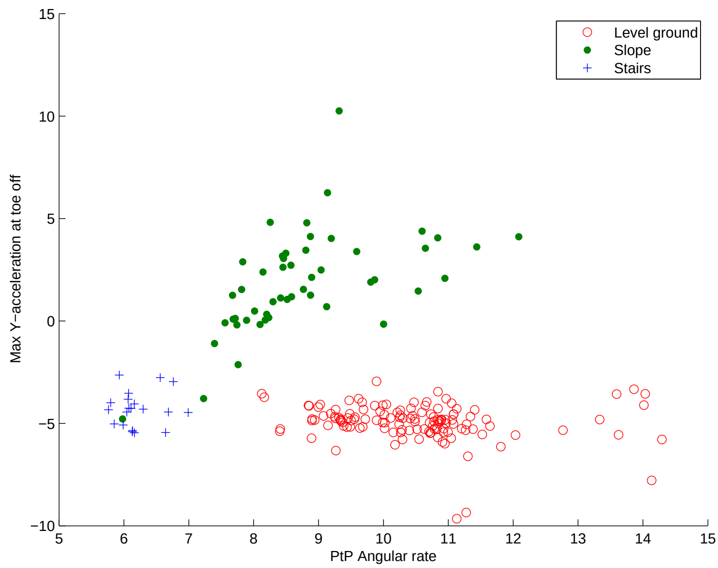


Figure 39: Scatter plot, angular rate versus max Y-acceleration at toe off

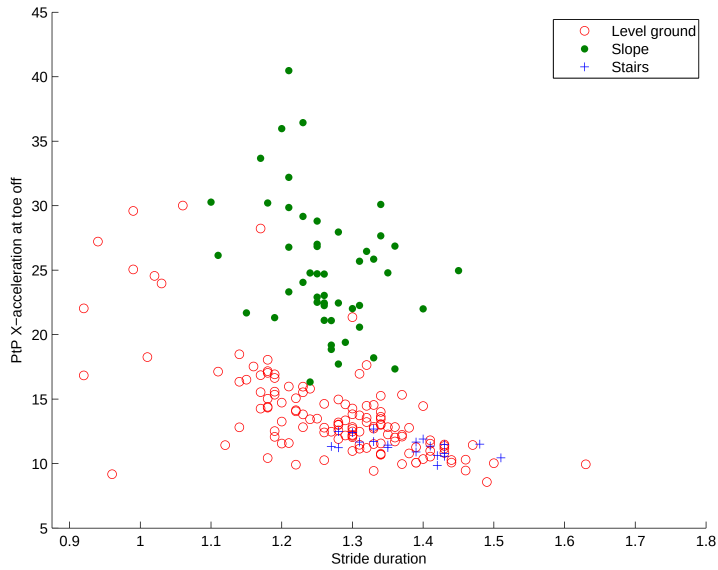


Figure 40: Scatter plot, stride duration versus PtP X-acceleration at toe off

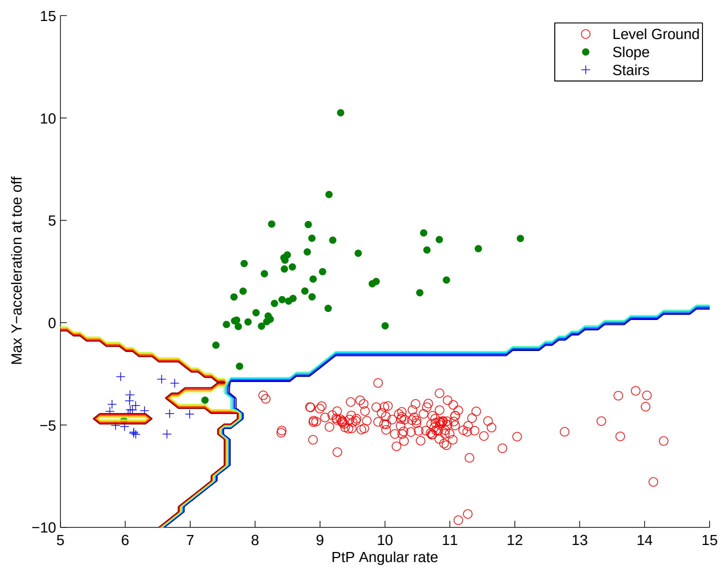


Figure 41: KNN decision boundary, $K = 1$

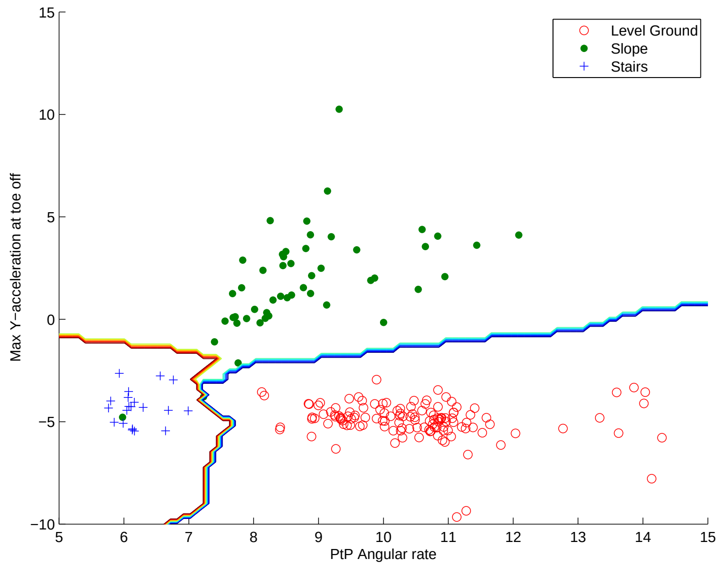


Figure 42: KNN decision boundary, $K = 5$

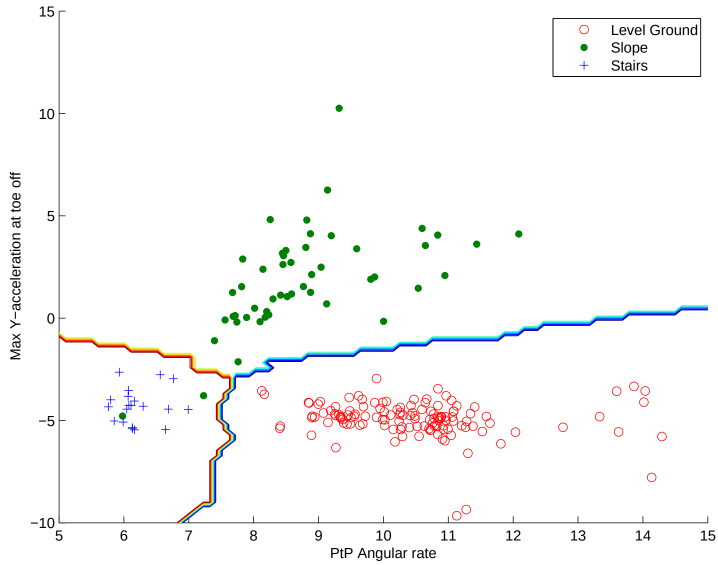


Figure 43: KNN decision boundary, $K = 7$

Univariate Trees

In univariate trees the rules use only one of the input variables for split which results in unsmooth decision boundary when the number of splits are kept at minimum see Figure 44 [1]. The benefit to this method is that it can be programmed by simple IF sentences that are easy to understand and implement. The disadvantage is that it can be really sensitive to noise and if it's to simple it can cause a problem distinguishing between groups that are close together and are not scattered perfectly for this method. Boundary shown in Figure 44 has four IF sentences, after training of the classifier the computational requirements are low.

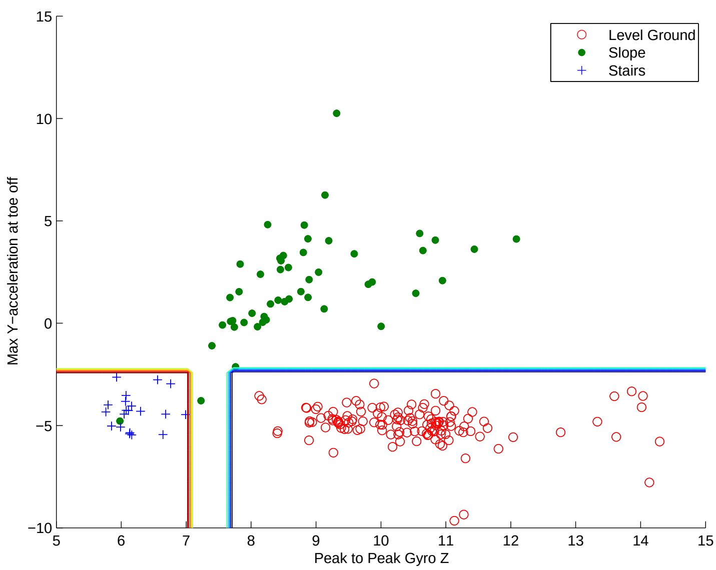


Figure 44: Univariate decision tree, boundary

Multivariate Trees

Multivariate decision tree is similar to the univariate except that the splits can be defined by more than one variable at each split, see Figure 45. These splits are achieved by three IF sentences, which shows that the multivariate decision tree has also low computational requirements but is more versatile than univariate decision tree.

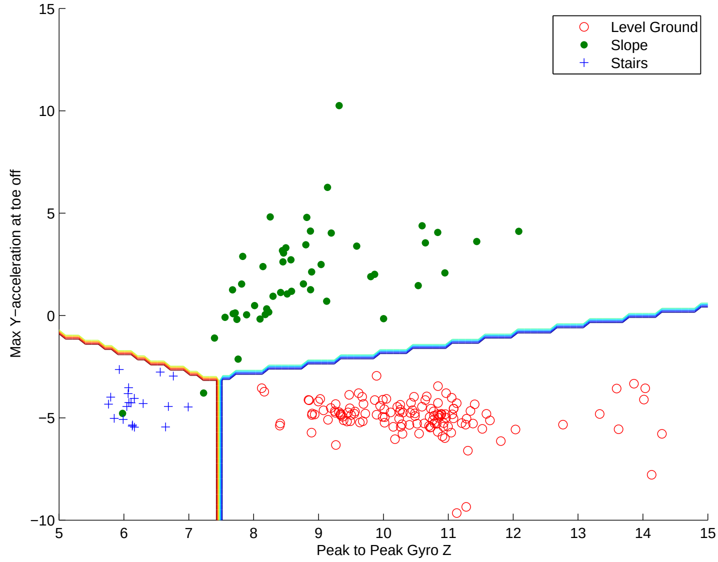


Figure 45: Multivariate decision tree, boundary

Multi dimensional classification

For three dimensional classification there is no overlap in data samples and test data shows 100% accuracy when PtP X-acceleration at toe off, angular rate and stride duration is used as parameters for the classification, Figure 46. KNN and multivariate decision tree form hyperplane that distinguish the three different terrains. Two dimensional examples were used for easier visualization of the pattern recognition methods used for this study.

5.2.5 Classification validation

Classification methods were trained by data obtained by a single amputee, validation was done by obtaining data from another amputee and letting the classifier work on that data. Two methods are shown here, the multivariate tree and KNN with $K = 5$ Figure 47 and 48 respectively, both classifiers have 100% accuracy for those few steps obtained for simple validation.

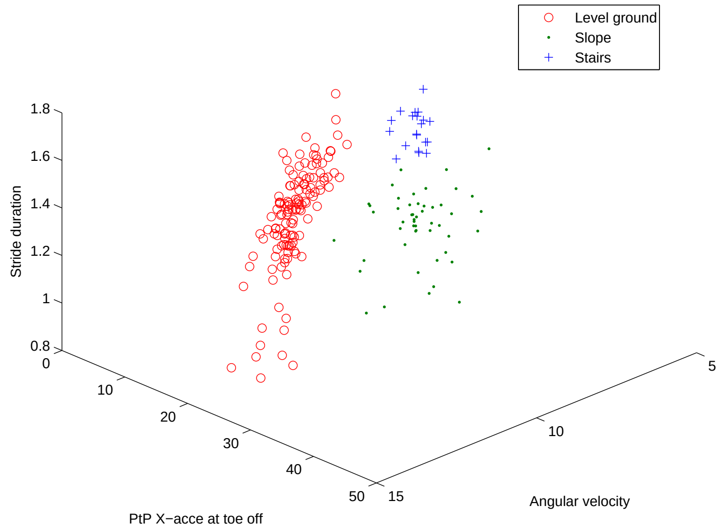


Figure 46: Three dimensional features

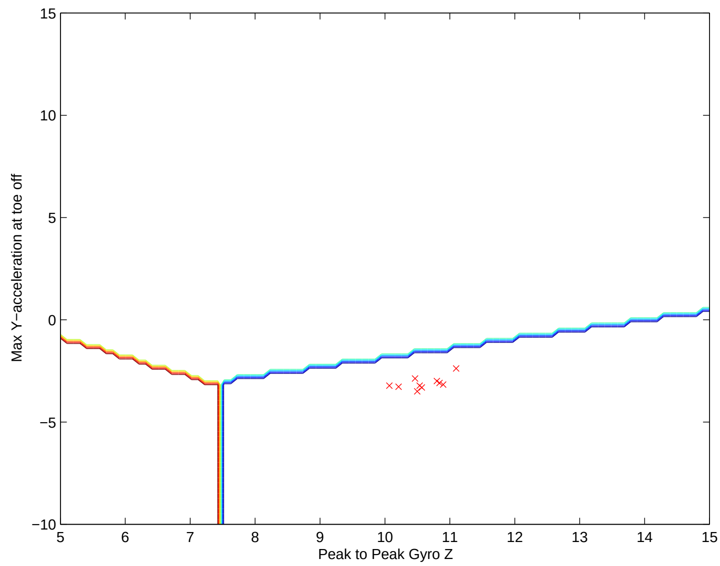


Figure 47: Classification validation, multivariate tree

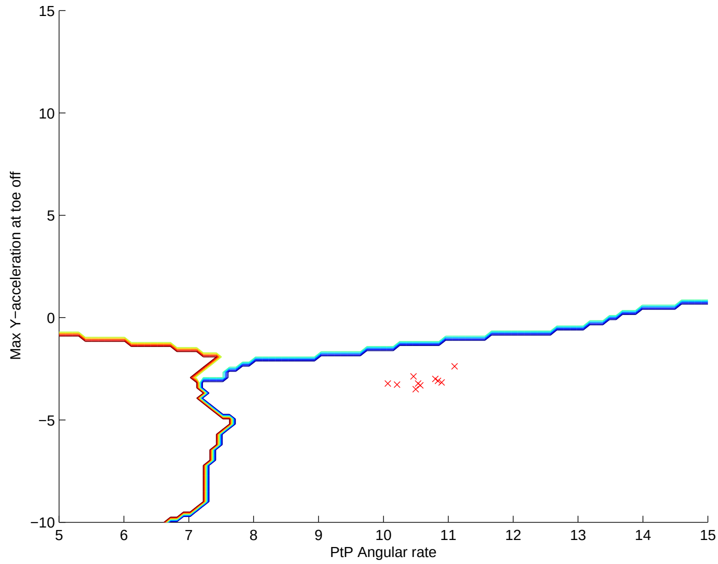


Figure 48: Classification validation, KNN $K = 5$

5.3 State machine

For the Rheo knee to function correctly the state machine must obtain correct and accurate readings from the sensors. Current sensors are sensitive to calibration, wrongly calibrated sensors can result in incorrect sensor readings and therefore incorrect state machine transitions which leads to a dysfunctional knee. Some state transitions are guarded by limits for the sensor values, those limits can be exceeded because of noise or unusual knee usage, those situations can also lead to a dysfunctional knee. Noise can lead to rapid state transitions, when signals are close to limits, which can cause the knee to function strangely for a short period of time and cause the amputee to feel insecure about using the knee.

5.3.1 Sensor module state machine

The Sensor module state machine (hereafter SM state machine) consists of sensors selected in Section 5.1. The SM state machine is used in the same manner as the Rheo knee uses a state machine see Section 3.3, but states found by sensor module represent the gait phases more closely than the Rheo knee does, relations between states and phases for SM state machine are shown in Table 7. State transitions

Table 7: SM State machine

State	**Phase**	**Period**
Loading response	Loading response	Stance
Midstance	Midstance & terminal stance	Stance
Preswing	Preswing	Stance
Initial swing	Initial swing	Swing
Terminal swing	Midswing & terminal swing	Swing

were designed to be as robust as possible by looking for peaks instead of checking limits, since no two people are the same but the state machine must work for various amputees.
Transition description in Table 9 assumes optimal level ground walking, i.e. *Loading response* → *Midstance* → *Preswing* → *Initial swing* → *Terminal swing.*
The SM state machine is closely related to the Rheo knee state machine described in Table 4, description for the SM state machine is at Table 8.
For this study a state machine was only formulated for level ground walking, data used for visualization was obtained at medium speed level ground walking. The state machine was tested on database consisting of 11 level ground walking trials at various walking speed.
For visual understanding of data, states and transitions only two steps are shown in Figures 49 to 53.

Table 8: Description of the SM state machine

State	**Description**
Loading response	Figure 49, the foot is unstable due to HS and foot not completely on ground, during this phase the control software should be responsive to sudden changes in knee angle.
Midstance	Figure 50, during this phase the foot is stable and is allowed to flex to some level to help the amputee to do stance flexion and therefore have more natural gait. There should not be any fast changes of the knee angle during this phase, only relatively slow movements.
Preswing	Figure 51, this phase is identical to the Rheo knee's preswing, this phase is used to gain momentum for the swing phase. The exact moment to move from midstance to preswing could make the difference between an easy swinging knee and uncomfortable knee where the user needs to swing the hip to generate extra energy for the swing period.
Initial swing	Figure 52, initial swing begins as TO. This phase uses momentum gained in the previous phase to swing the tibia until the knee reaches 60 degrees flexion(regular maximum knee angle for normal walking [10]).
Terminal swing	Figure 53, during this phase the knee goes from maximum angle to zero degrees. When knee is almost fully extended it's ready for next HS.

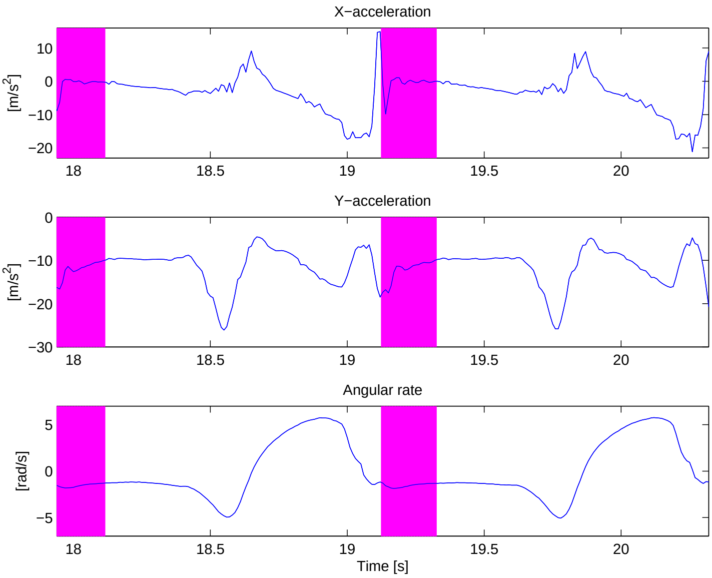


Figure 49: SM state machine, loading response

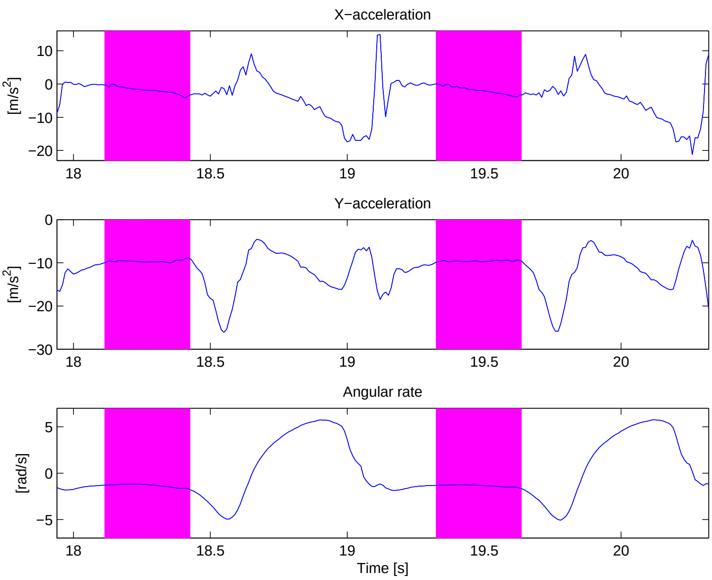


Figure 50: SM state machine, midstance

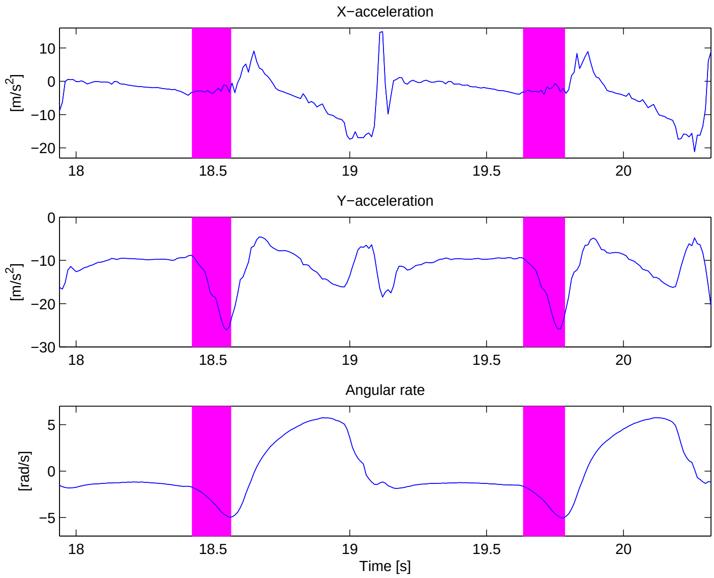


Figure 51: SM state machine, preswing

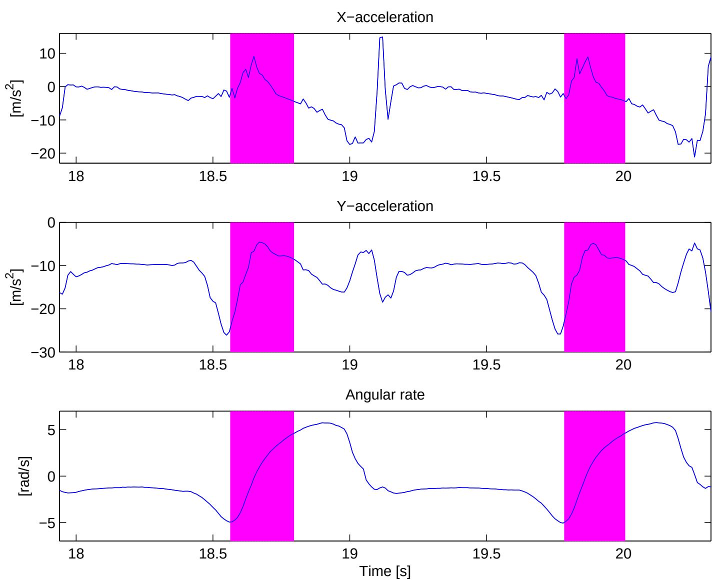


Figure 52: SM state machine, initial swing

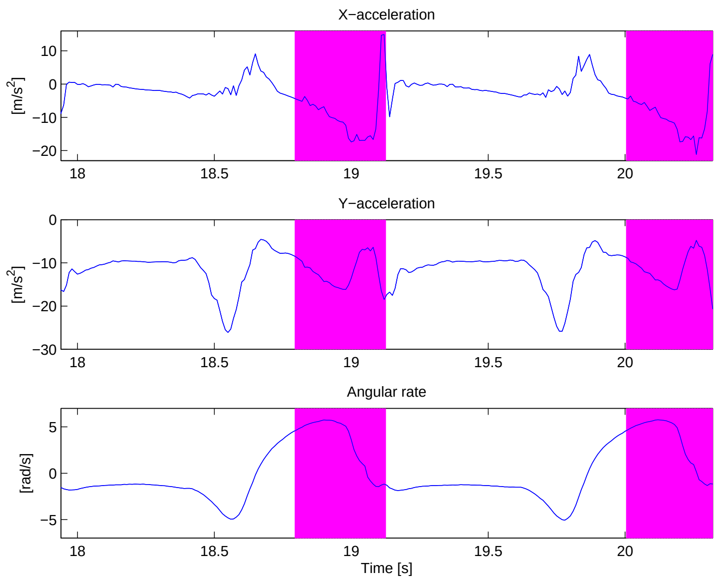


Figure 53: SM state machine, terminal swing

Table 9: Description of state transitions

Transition	**Description**
Loading response → Midstance	This is right after HS, the Y-acceleration is fluctuating because of impact caused by HS. When the acceleration has settled the foot is stable and the foot has responded successfully to the weight of users body.
Midstance → Preswing	During midstance all sensor are quite stable since the foot is in contact with the ground and therefore completely still. When both angular rate and Y-acceleration start to decrease then the user is lifting the heel off the ground and moment is created in the knee structure which creates good kick start for momentum required for swing phase.
Preswing → Initial swing	Angular rate is increasing and Y-acceleration is at local maximum. The Y-acceleration peaks when the foot leaves the ground for swing period.
Initial swing → Terminal swing	Since maximum knee angle is reached during initial swing, the knee is still at that moment before it starts extending. When the vector sum of both acceleration sensors is close to earth gravity this transition is triggered.
Terminal swing → Loading response	Due to impact the acceleration sensors spike at HS, so the transition is triggered by a spike in X-acceleration, but guarded by a flag that is set when the X-acceleration crosses zero since acceleration sensors are not very stable.

Figure 54 shows angular rate measurements for level ground walking along with state values. This figure shows that the state machine is consistent through the whole data series. Data is processed like in a real time application the state machine can not see future values only current and older. Green lines represent states, were value 1 is *Loading response*, value 2 is *Midstance* and so on. Table 10 shows the percentage of each state during gait, when this is compared to regular walk, Table 2, it can be seen that those numbers are similar. The main difference is the *Midstance* is 30% but the phases that this state represents is expected to be around 40%, the reason for this is that the preswing state is entered slightly to early to generate more momentum for the swing period. The stance period is less 60% which can be explained by the fact that the amputee who performed those tests walks faster than most people and amputee's have a slightly shorter stance period than a healthy person for same walking speed [2].

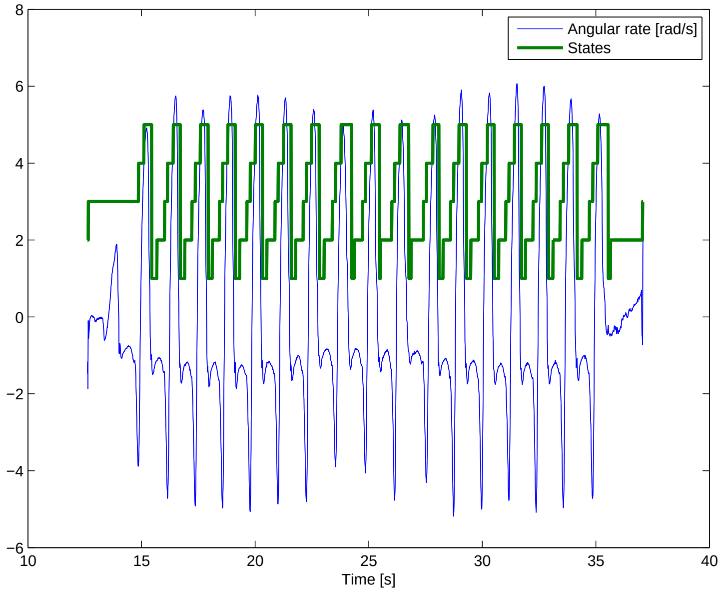


Figure 54: SM state machine and angular rate, level ground

Table 10: Phase intervals

Phase	Percentage of Gait Cycle	Total
Loading response	14.07	14.07
Midstance	28.19	42.27
Preswing	11.29	53.56
Initial swing	18.90	72.45
Terminal swing	27.55	100

5.3.2 Comparison between the Rheo knee and the SM state machine

The Rheo knee and the SM state machines use different sensors for transition and controlling the state machine.
The Rheo knee uses load cells and knee angle sensor, the difference between the stance and swing period is based on readings from the load cells, this difference is clear and reliable, but is based on limits and therefore badly calibrated load cells can result in stance and swing recognition errors. *Preswing* phase is estimated based on the load cells also, here the moment is used and when the moment is above a

specific limit the knee transits from *stance flexion* or *stance extension* to *preswing*, this limit can be exceeded because of sensor noise, this transition can require some fine tuning. During the swing period the knee only senses the knee angle, for that reason terrain estimation of current step during swing period is not ideal because of insufficient information about the movement of the foot.
SM state machine uses acceleration and gyro sensors, heel strike is easily detected by rapid changes in acceleration (calibration does not have affect since only increase in the signal value trigger the state transition), therefore the difference between stance- and swing period is reliable for all tests performed during the course of this study (additional tests are required for validation of non regular movements, e.g. side stepping). *Preswing* is estimated based on Y-acceleration and angular rate and may require some adjustments, the beginning of preswing is similar to situations when the user is falling down. Both state machines require some fine tuning to detect preswing. Acceleration sensors can detect motion during swing period and therefore have more accurate knowledge of foot positions, e.g. if the foot is moving downwards for stair and slope and adjusts swing period to changed terrain estimation.

For comparison of the Rheo knee and the SM state machines only two steps are used (same steps as before). Figure 55 shows the difference between those two state machines. Figure 55 shows that the Rheo knee state machine is using the *preswing* state for more than 50% of the stance period, this may increase the risk of user stumbling because the knee's brake is set to zero during the *preswing* state and the knee has to make a state transition to respond to unexpected situations. The transition from stance to swing happens later for the SM state machine, there are studies that agree to the timing of SM state machine, which is based on local minimum of the angular rate measurements [28] see Figures 51 and 52.

5.3.3 Midswing event

If the knee would be used along with an controlled ankle, capable of plantar- and dorsiflexion an midswing event is required to estimate when to plantarflex to be ready for initial contact. Instead of having the midswing phase as a separate state it is recognized as an event, i.e. just a time point in the swing period. Figure 53 shows that Y-acceleration has a local minimum at the mid time of terminal swing, also the angular rate has an global maximum at a similar time point, those signal can be used to estimate the midswing event.

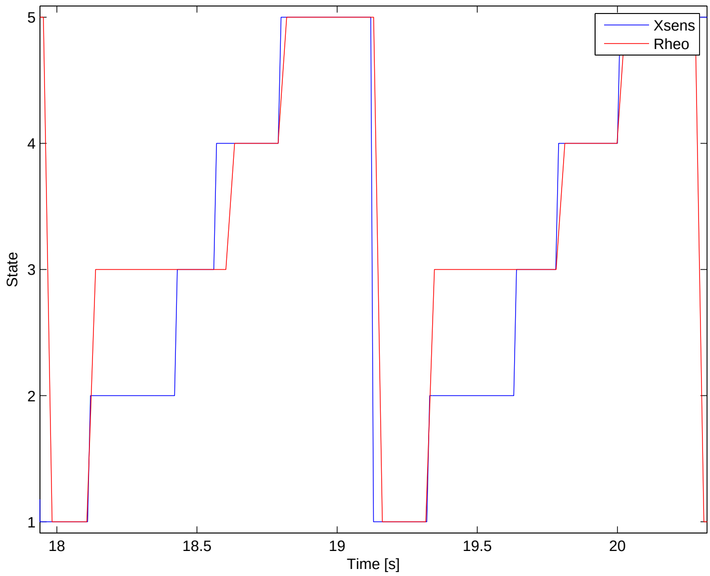


Figure 55: Comparison between the Rheo knee and the SM state machine

5.3.4 Sensor position

All test were performed with the sensor module fixed to the ankle see Figure 5. This may not be the optimal position if the knee is not used with a specific ankle that has the sensor module built in. Therefore one test was performed by the sensor fixed approximately 10cm below the knee joint. Figures 56 and 31 show that there are some differences in the signal based on the sensor position. The angular rate signal is identical as expected. X-acceleration has quite a difference but still has good spikes that could be used for gait recognition but would not work with the state machine that was built around a sensor located at the ankle since the peak at toe off seams to have shifted to before the actual TO. Y-acceleration is also quite different depending on the sensor position, but has important spikes at the same time points and could therefore be used with current state machine without any big changes. More variance for these signals is most likely caused by sensor movement during gait, it was not as easy to fix the sensor to the prosthetic knee structure as it was at the ankle position.

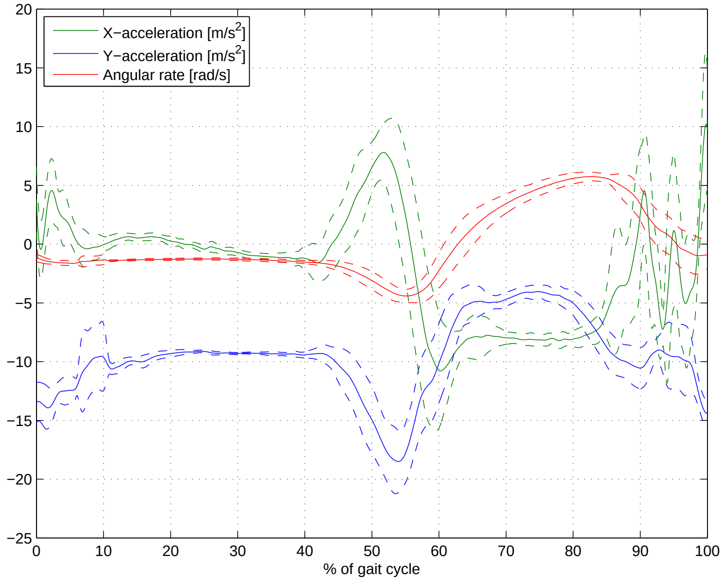


Figure 56: Sensor located approx. 10cm below knee

5.3.5 Soft underlay

A test was performed to determine the effect of soft underlay, the test was performed on level ground, at medium speed and on soaking wet grass. As before all peaks are available for gait recognition and the state machine works as well as for hard underlay. Figures 57 and 58 show mean sensor values for this test and state machine functions during the test respectively.

5.3.6 State machine validation

State machine validation was done by having an amputee who had not performed any tests that were used to formulate the state machine. The sensor was fixed to amputee's ankle and a test performed as before. Mean sensor values are shown in Figure 59 by comparing them to Figure 31 the signals are obviously different but all important peaks and sensor signals forms are present. Since all state transitions except for *midstance* $\rightarrow$ *preswing* are decided by peaks, all those transitions work as expected, the *midstance* $\rightarrow$ *preswing* transition also worked and happened at TO. State machine results are shown in Figure 60 and Table 11 shows the percentage of

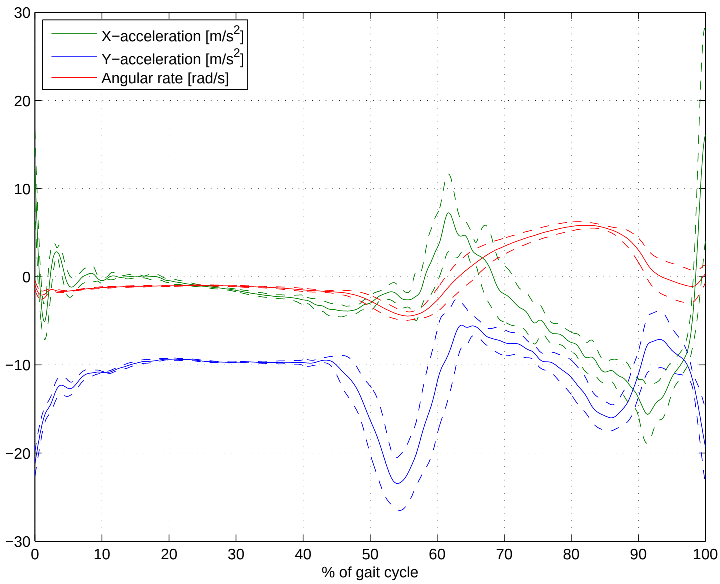


Figure 57: Mean sensor signals. Soft underlay

Table 11: Phase intervals. SM state machine validation

Phase	**Percentage of Gait Cycle**	**Total**
Loading response	12.36	12.36
Midstance	31.16	43.51
Preswing	12.97	56.49
Initial swing	17.80	74.29
Terminal swing	25.71	100

each state during gait.

5.4 Control signal

The control signal that the Rheo knee uses currently is the only reference for a control signal. Figure 61 shows the output current and the SM states along with the knee angle. The current is mainly used to make smooth knee stops, both at the end of the *initial swing* and the end of the *terminal swing*. The current increases right after HS when the foot is gaining stability for the stance period.

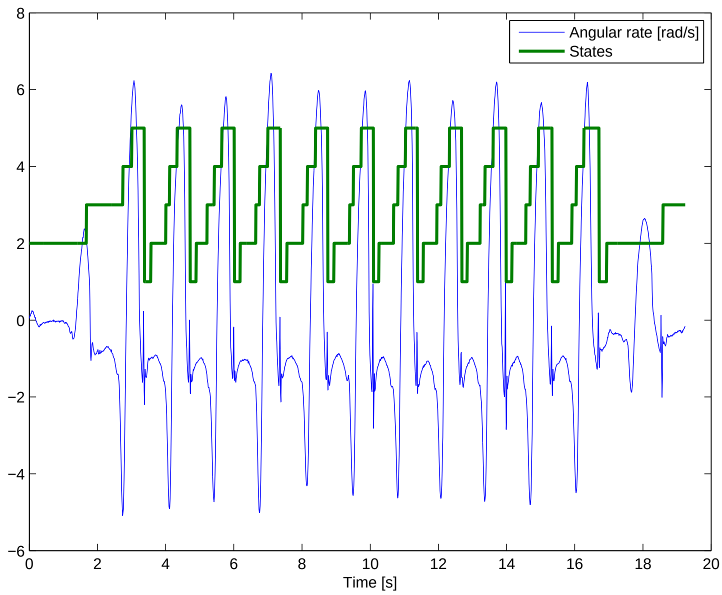


Figure 58: State machine and angular rate. State machine validation for soft underlay

5.4.1 Neural network

Neural networks were used to estimate the output current of the knee, settings used were one hidden layer and 15 hidden neurons. All possible variations the nine sensors of the Xsens sensor module and the knee ankle obtained from the Rheo knee. Training of the network used the sensors as input and output current obtained from the Rheo knee as output. Table 12 shows the top five sensor combinations when measured by correlation between untested test data output and actual output. It can also be seen that the knee angle and X-acceleration is the most vital in output calculations If the knee angle is not a part of the sensor combinations X-acceleration and X-angular rate has the most correlation the correlation is 0.75.

5.4.2 Knee angle sensor

Without a knee angle sensor the absolute knee angle is not known, that makes control signal generation hard, no simple stable and reliable control signal were found during the course of this project using only acceleration, angular rate and magnetic sensors. By combining the state machine and the knee angle a control signal can be generated

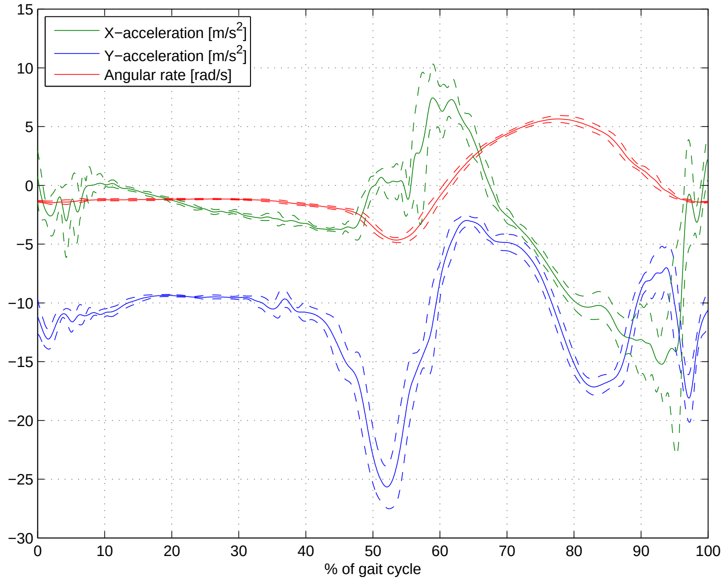


Figure 59: Mean sensor signals. State machine validation

Table 12: Neural networks results, a-Acceleration, g-Angular rate, m-Magnetic, KA-Knee angle

Y-a	X-a	Z-a	Y-g	X-g	Z-g	Y-m	X-m	Z-m	KA	Corr
0	1	0	0	1	0	0	0	0	1	0.85
1	1	0	0	0	0	0	0	0	1	0.83
0	1	0	0	0	0	0	0	0	1	0.83
0	1	0	0	1	1	0	0	0	1	0.83
0	1	1	0	1	0	0	0	0	1	0.83

by using the following equation for initial swing

$$Current = \frac{CurrentAngle - StartAngle}{EndAngle} \cdot Const_i$$

this equation gives linear gain until $EndAngle$ is reached. For making smooth terminal swing the following equation is used

$$Current = (StartAngle - CurrentAngle) \cdot Const_t$$

this equation gives linear gain until the $CurrentAngle$ reaches zero degrees. The constants must be tweaked so the $CurrentAngle$ will come as close to zero without getting there.

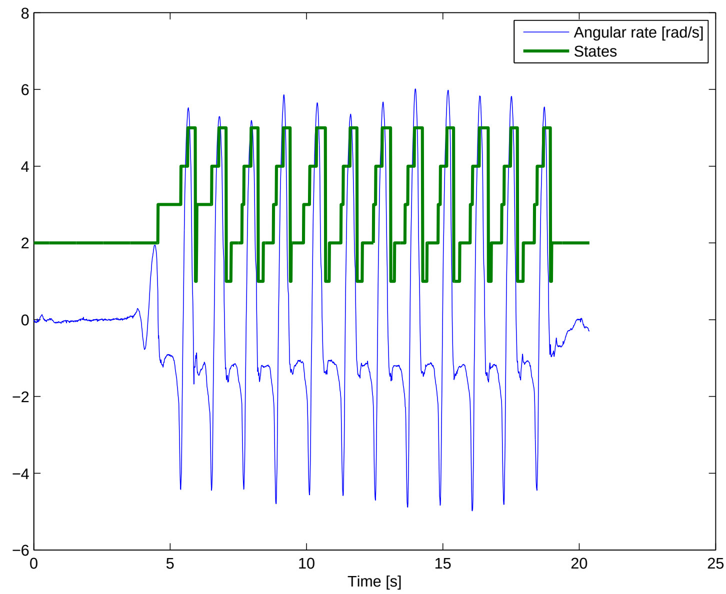


Figure 60: SM state machine and angular rate. State machine validation

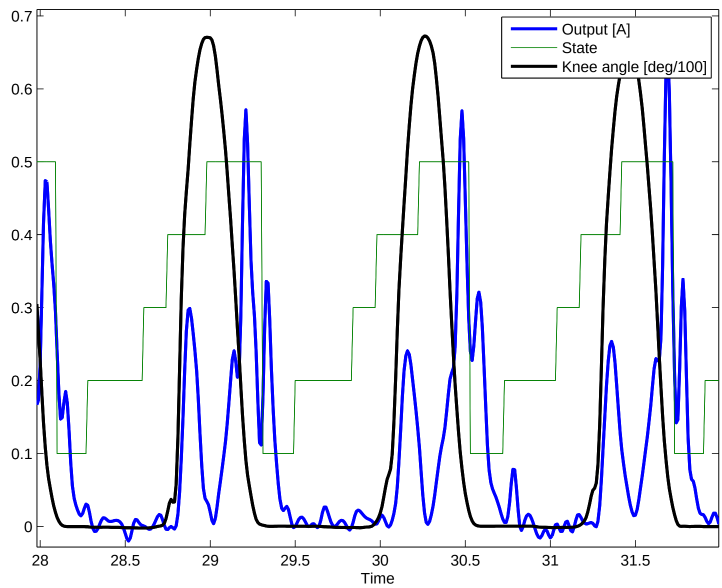


Figure 61: State machine and Rheo knee output current

6 Conclusions and future work

Combination of two acceleration sensors, angular rate and knee angle sensor is able to achieve the three main goals that the control system requires to control a prosthetic knee. The acceleration and angular rate sensor can estimate the terrain and gait phases while the knee angle sensor gives exact knee angle position and controls the control signal.
Even though this study only involved basic controlling of a prosthetic knee, it shows that it is possible to control the Rheo knee with acceleration and gyro sensors during level ground walking. Since the load cells are built into the knee's structure it is complex and expensive to manufacture them, if the load cells could be removed the structure could be made smaller with same weight rating and at lower cost. Classification of terrains is simple and effective using multivariate tree and KNN, the multivariate tree is a better choice because of low computational demand and simple implementation. Acceleration sensors detect motion during swing period and can estimate terrain changes at first step on changed terrain instead of relaying on data gathered during the last step. Knee control is achieved by two different methods

- Neural network
- Combination of state machine and knee angle sensor

When the NN is trained it requires similar inputs as the training data inputs otherwise unforeseen problems can occur, for the NN to be able to cope with user falling or unexpected situations it also requires training data for those situations. Obtaining data for unexpected situations is not possible unless the amputee is willing to simulate falls to prevent later falls. Also the NN would require constant re-training in case of user changing shoes, injuries, extra load (e.g. backpack or books) or gaining weight, training a NN is computationally expensive and time consuming and therefore not

practical in a microprocessor applications that require fast response times. There could be a separate training processor that would feed new parameters to the control processor, but still there are problems deciding on "good" steps for training the NN, i.e. what is a good step, how can the knee distinguish between "good" and "bad" step. If a knee is not behaving as expected the only possible solution is to train the NN again, it is not feasible to trace sensor values backwards, because of the complexity of the connections between inputs and outputs, to locate the cause of the problem. A prosthetic knee requires good reliability and anything that creates difficulties to find a cause of a problem is probably not the right path to go with prosthetics.
The state machine is stable and reliable and similar states between the SM state machine and the Rheo knee state machine do have state transitions at a similar time point during gait. Having stable and reliable state estimate is vital for knee controlling since all the phases require different functionality of the knee. A stable and reliable state machine opens the opportunity to use the state machine as part of controlling software for other products, e.g. computer controlled ankles, knee and ankle combination and computer controlled lower limb braces. When reliability of the state machine and simplicity of the knee angle current calculations a good control signal is created for the Rheo knee. Other possibilities are to use those sensors for gait analysis for healthy people, mobile gait analysis system, Appendix B shows sensors signals for one healthy subject.
The aim of this project has been achieved, but this project only included the most basic parts of human motions. There are many obstacles to overcome before those sensors can replace the load cell. During the course of this project, it became clear how complex a microprocessor controlled prosthetic knee is, it needs to work flawlessly for various types of people, e.g. strong users were the knee needs to damp all movements and weak users were the knee needs to swing freely throughout the swing period without any damping.

Suggestions for future work are following

- Obtain data from a larger variety of amputee for validation and estimation of events that control the state machine
- Create a prototype to run state machine and classification in real time.
- Fine tune the state machine, in particular the preswing state.
- Adaptation, adaptation is one of the advancements of the Rheo knee over other prosthetic knees, which parameters require adaptation.
- Adapt the state machine to other terrains, which parameters needs to be changed for different terrain.
- Research the sensor signals during common movements, e.g. sitting up/down, side stepping and other movements that are not as periodic as the regular gait cycle.

- Combine state machine and current calculations, this would most likely be a highly iterative process since changed current calculations would affect the state machine and vice versa.

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List of Tables

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A Features

This appendix shows scatter plots of features discussed in Section 5.2 but were not processed any further.

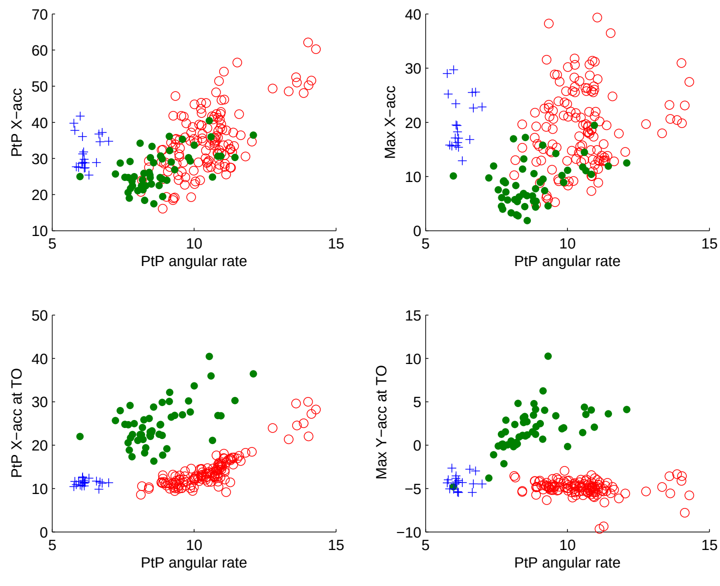

Figure A.1: Scatter plots of all features

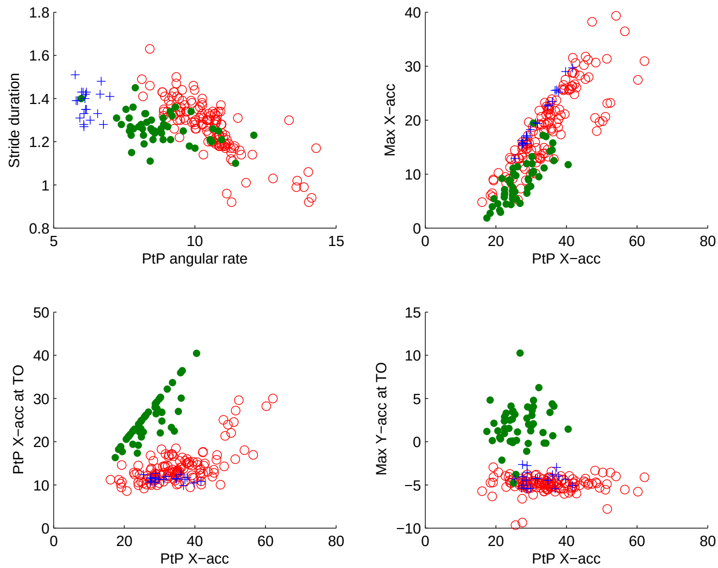

Figure A.2: Scatter plots of all features

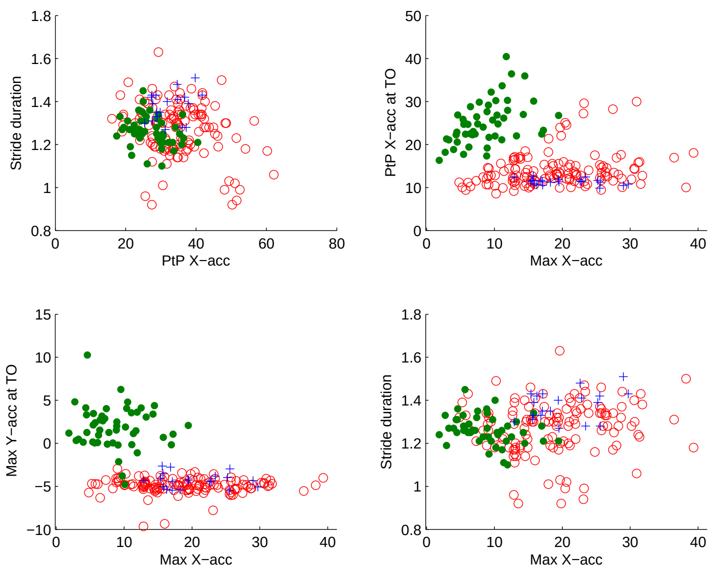

Figure A.3: Scatter plots of all features

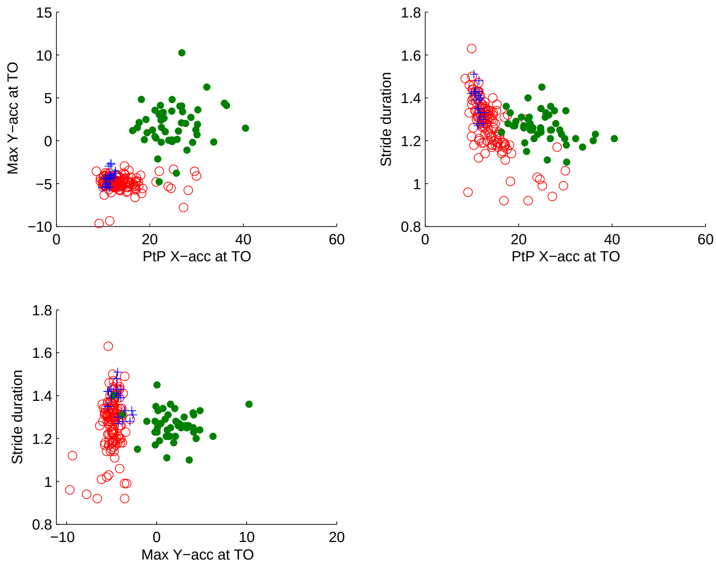

Figure A.4: Scatter plots of all features

B Terrains - Healthy subject

This appendix shows sensor signals obtained from a healthy subject on level ground at medium speed. To begin with the methods were developed by using data gathered by healthy subject and further work could involve gait analysis for healthy people.

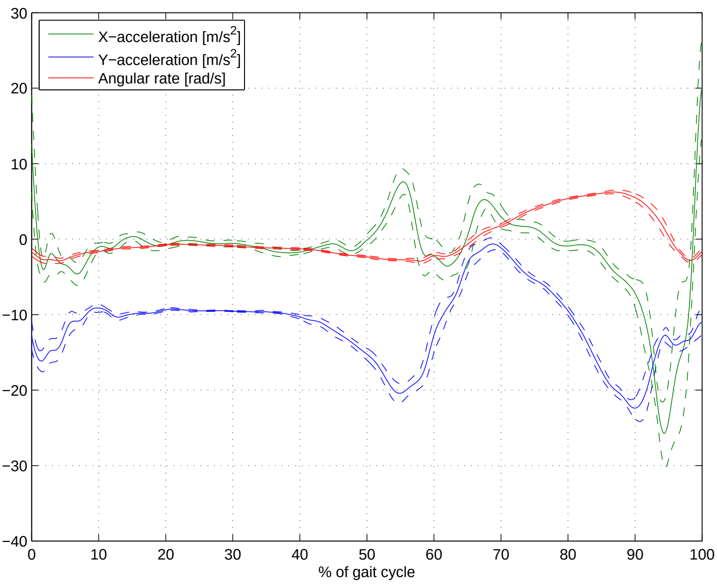

Figure A.5: Mean sensor signals, level ground

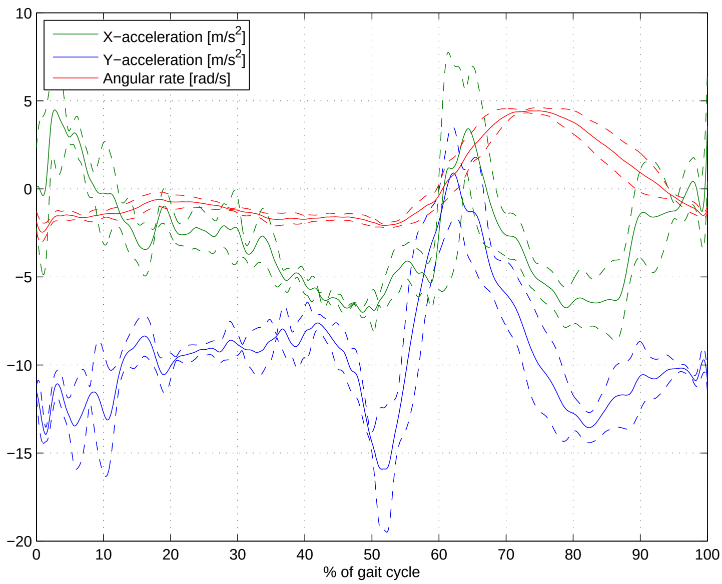

Figure A.6: Mean sensor signals, stairs

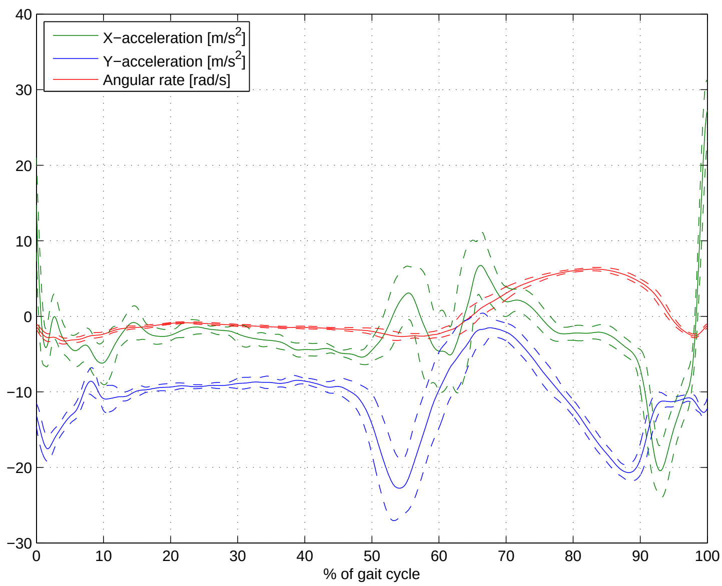

Figure A.7: Mean sensor signals, slope