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PP	Restricted to other programme participants (including the Commission Services)
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Project Abstract

The goal of the EVRYON project is to develop a novel approach for the design of Wearable Robots (WRs), e.g. exoskeletons, prostheses and other wearable mechatronic devices that can be used for a variety of applications, such as rehabilitation, personal assistance, human augmentation and more. Ideal solutions for such systems should aim at the optimal trade-off between performance, i.e. the level of assistance to be provided to the end-user, and some critical requirements, such as minimal weight and dimensions, low energy consumption and several other factors that can significantly affect the effectiveness and efficiency of WRs.

The basic idea behind the EVRYON project is that better WRs can be developed if the potentialities of 'embodied intelligence', and particularly of 'structural intelligence', are properly harvested and exploited.

EVRYON will develop an open-ended design process where both robot morphology and control are co-evolved and optimized in a simulation environment, where also the dynamical properties of the human body are taken into account. This approach is related to previous findings in the study of the emergence of structural intelligence in animals and artificial systems without any feedback control, such as preflexes in insects and emerging dynamic behaviours in passive walkers.

The EVRYON design methodology will originate a set of advanced tools for assisted mechatronic design, that will be validated by developing a novel prototype of a WR, i.e. an active orthosis for the lower limbs.

The EVRYON WR will integrate the kinematic, dynamic and control optimal solutions produced by the co-evolution process with additional variable impedance modules, which will allow the system to properly respond and adapt to the impedance patterns of human walking.

The WR prototype will be tested on a group of elderly subjects with age-related locomotion disabilities so to assess its acceptability and its ability to restore proper walking and increase personal autonomy.

Table of Contents

List of acronyms

The following abbreviations are used in this report:

ANN	**Artificial neural network**
EMG	**Electromyography**
FF	**Feed forward (open loop)**
PD	**position derivative**
WR	**Wearable robot**

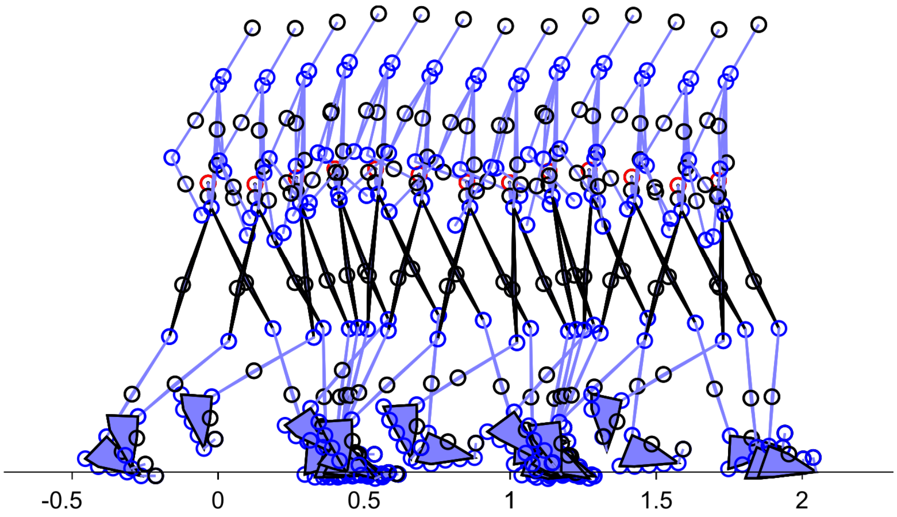
Executive Summary

Task 2.4 requires the modelling and simulation of the robot joint to an active human body. The active human body is driven by EMG signals. The EMG signals are mapped to joint torques that are used in open loop. This joint torque can then be used in the simulation environment of task 2.2 and 2.3.

The approach chosen to drive the model is to make use of an artificial neural network. This network receives input from the EMG signals and outputs the joint torques. The network was trained and tested for three different datasets: data from one subject one condition (walking), data from one subject multiple conditions (walking, starting, stopping), and data from multiple subjects and a single condition (walking). The data gave accurate predictions on torque level (correlation coefficients between measured and predicted data were respectively .97, .93, and .88). The mapping was also accessed on muscle level. On muscle level, some discrepancies existed between the physiological function of the muscle and the function of the EMG signal in the network.

The mapped toques were evaluated in open loop (feedforward-control). Two feedforward-controllers were tested. One with the measured signals (direct torque FF), one with the torques obtained from the neural network (EMG driven FF, figure). Both controllers were not stable in open loop. An additional feedback controller was used to guaranty stable gait. With this feedback added both feedforward controllers performed equally well.

To link the human to the wearable robot (WR) and to use the simulator to control the Lopes rehabilitation robot, addition import and export modules have been made. The WR's that are optimized in the Webots environment can be imported to the simulator. From the simulator Lopes controller can be created that simulates the WR on the Lopes.



One and a half gait cycle with the EMG driven FF and additional feedback captured from the simulation environment

1 Introduction

Task 2.4 requires the modeling and simulation of the robot joint to an active human body. The active human body is driven by EMG signals. The EMG signals are mapped to joint torques that are used in open loop. This joint torque can then be used in the simulation environment of task 2.2 and 2.3.

2 Methods

In general, there are two methods to map electromyography EMG signals to joint torques. One method is to use an anatomical muscle tendon model as for example proposed by (Lloyd & Besier, 2003). The other method is not to explicitly define a muscle tendon, and use a direct mapping. This mapping could be a simple matrix multiplication, but also mappings that are more complex are possible. One of the most promising techniques is the use of an artificial neural network (ANN) as for example used by (Liu, Herzog, & Savelberg, 1999).

The chosen approach for mapping the EMG signal to the joint torques was to use an artificial neural network. This type of mapping is attractive since after the mapping is performed it is less computationally demanding that the calculation of torques with a complex muscle tendon model. The quality of the mapping improves with the amount of learning data that can be used to train the network. A large amount of gait data was available from the earlier deliverable (d2.2/2.3), what made the choice for an artificial neural network approach even more attractive.

Figure 1 shows a schematic overview of the proposed neural network. The neural network has three layers. The first layer is the input layer. In this case the EMG signals form the input of the neural network. The second layer is the hidden layer with an arbitrary number of nodes. This layer takes input from the input layer and performs mathematical operation on the input and outputs the result from this operation (adding, multiplying). The last layer is the output layer that takes its input from the hidden layer.

All nodes from two neighboring layers are interconnected. To train the network a dataset is used with matching inputs and outputs. When the network is trained the gains and offsets for the mathematical operations on the hidden layer are determined. The training of the network is done by an optimization algorithm.

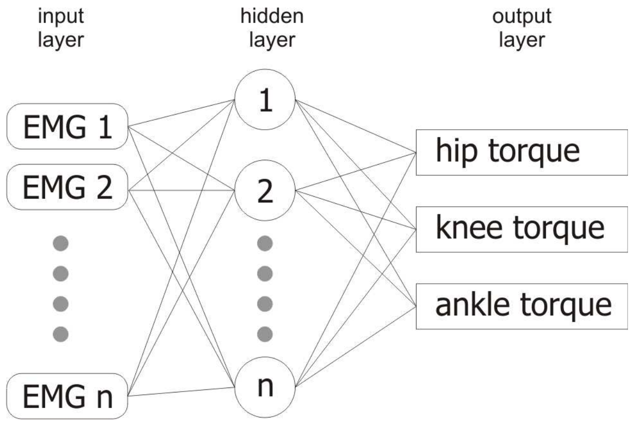


Figure 1: schematic picture of an artificial neural network

This section discusses the used data (2.1), the processing of the data (2.2), the used neural network (2.3) and the inverse-forward modeling (2.4).

2.1 Gait data

The gait data from the database as described in deliverable 2.2-2.3 is used. This database contains data for 8 healthy subjects (4 male, 4 female, age 24±1, weight 68.8±12.1, and height 180±0.1) recruited from the Dutch student population. The database contains 3d kinematic and kinetic data, EMG data recorded from eight muscle groups (*gluteus maximus, gluteus medius, biceps femoris, gastrocnemius medialis, rectus femoris, adductor longus, vastus lateralis, and tibialis anterior*). Additionally the ground reaction forces were measured.

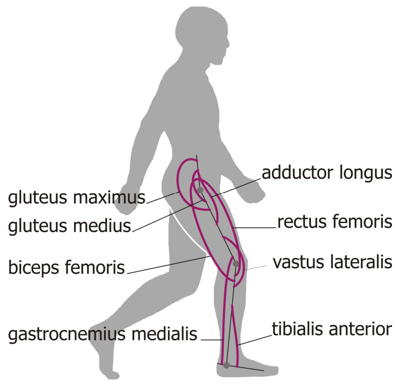


Figure 2: Leg muscles of witch EMG is recorded

2.2 Data processing

The data is filtered and normalized to for a suitable input for the neural network.

2.2.1 EMG – filtering and rectifying

The EMG signal is filtered. First notch filters are applied to remove grid noise (50, 150, 250, 350Hz). Subsequently, the signal is band pass filtered with a second order Butterworth filter between 10 and 400Hz to remove movement artifacts. After that the signal is rectified and low pass filtered (zero phase) at 4Hz. From the last 30 seconds of each condition for each subject an average step is calculated.

2.2.2 EMG – normalizing

To make the EMG data suitable for input to the neural network the EMG data needs to be normalized. The used ANN requires input signals between zero and one, and performance is enhanced if the signals are in between 0.1 and 0.9. Additionally the data need to be normalized to remove inter subject differences. For every subject a normalization trial is defined. In this trial the 2nd (p2) and 98th (p98) percentile is calculated. These values are scaled to the [0 - 1] interval.

$$V_{out} = \frac{V_{in} - p_2}{p_{98} - p_2}$$

And a hyperbolic function is used to keep values within the [0.1 - 0.9] interval:

$$V_{out} = 0.1 + 0.8 \tanh\left(V_{in}\right)$$

The normalized EMG values are shown in Figure 3.

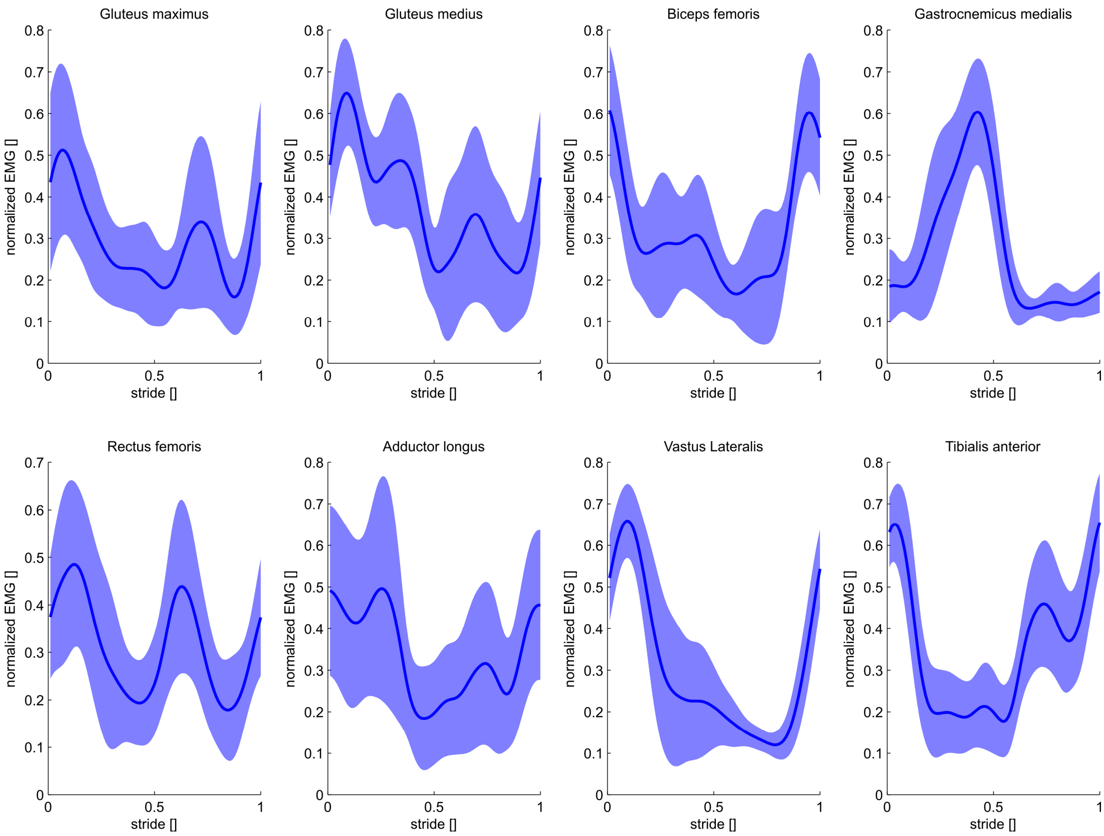


Figure 3: Normalized EMG profiles for 60 trials (8 subjects). The plots show the average value along with the standard deviation. The time is normalized to 1 stride.

2.2.3 Torque – normalizing

Similar to the EMG signal the torque signal needs to be normalized. For the output signal, a range between minus one and one is acceptable. Torque data is usually normalized to the subjects weight (Winter, 1983). To fit the required interval the torques are arbitrarily divided by ten times the subject weight instead (Figure 4).

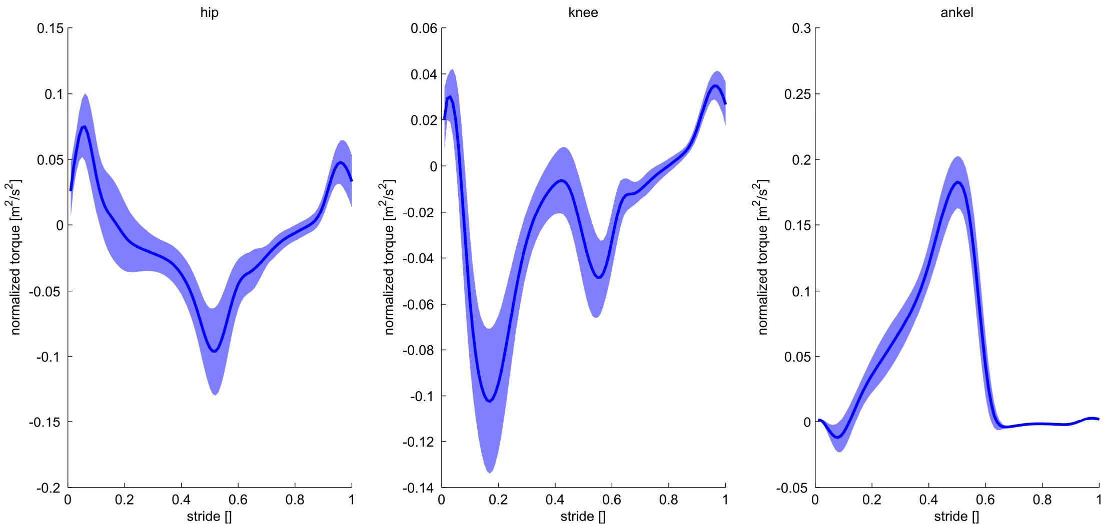


Figure 4 Normalized Torque profiles for 60 trials (8 subjects). The plots show the average value along with the standard deviation. Weight is normalized to ten times the subject weight. The time is normalized to 1 stride.

2.3 Neural network

The used ANN is the Nonlinear Input-Output network from the MATLAB (2010b) Neural Network Time Series Tool. The used network has two time delays and five nodes on the hidden layer.

The quality and applicability of the neural network is strongly dependent on its generality. The neural network becomes more useful if the network can be applied to multiple datasets. The accuracy however is often lower when different datasets need to be mapped. Therefore, different tests have been performed (Table 1).

Test	**Case**
Single subject – single condition	Walking at a self-selected speed, 10 trials: 9 trials used for training of the algorithm. 1 trial is used to evaluate the algorithm
Single subject – multiple condition	Walking at a self-selected speed, walking at 1.2m/s, walking at 0.8m/s, gait initiation left and right, gait termination left and right. Gait initiation with the left leg used for testing
Multiple subject – single condition	Walking at a self-selected speed, 10 subjects, 61 trials: 9 subjects used for training of the algorithm. 1 subject is used to evaluate the algorithm.

Table 1: Different optimization scenario's for the neural network

2.3.1 Quality of the fit

The quality of the fit is accessed on two levels. First, the quality is accessed on torque level. Secondly, the quality is accessed on muscle level.

2.3.1.1 Torque level

The quality of the fit on torque level is given by how well the predicted (mapped) values match the original recorded values. As a quantative measure, the correlation coefficient between the two signals is used. The neural network is compared to a linear mapping method. Objective was to find a matrix [A] that maps the input to the output.

$$X_{EMG} \cdot A = Y_{torque}$$

The least square error between the mapped torque and the original torque was minimized.

2.3.1.2 Muscle level

Secondly, the quality of the fit is calculated on muscle level. For each of the eight muscles a new EMG input signal for the network is constructed. This signal is the original input signal where the signal for the muscle to be tested is set to 0.1 (the minimal value). The output of the network with the new input is compared to the output of the system with the old input. The difference between the two signals is the contribution of the muscle of witch the input was set to zero. This test can tell if the mapping was physiologically feasible. The mapping is physiologically feasible if the neural network maps a EMG signal to the same joints as that are spanned by the corresponding muscle.

2.4 Modelling and control

2.4.1 Simulator

For all simulations, the newer version of the simulation environment as presented in deliverable 2.2/2.3 is used. The new simulation environment contains a graphical user interface as shown in Figure 5. Additionally a new contact model is used, the contact model is derived from the contact model as described in (Ackermann & Van den Bogert).

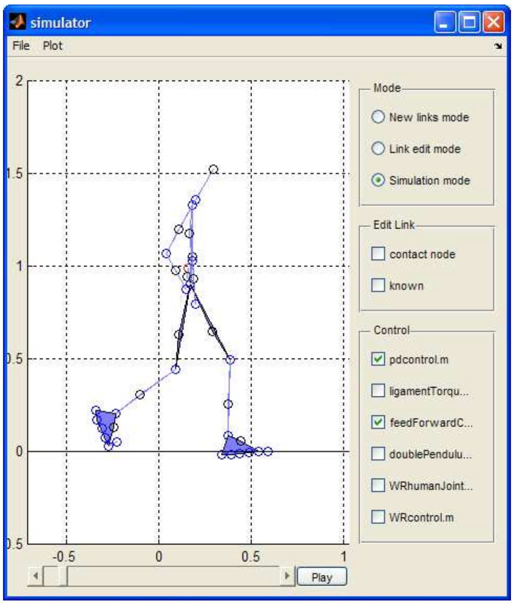


Figure 5: graphical user interface of the simulation environment

2.4.2 Human model

The human model is slightly adapted from the model as presented in deliverable 2.2/2.3. The foot model is changed to a two-segment model, a foot and a toe. The foot and toe are linked with a passive spring damper system. The separate toe contributed to a more human like toe roll-off.

2.4.3 Inverse-forward modelling

The torque data that was used to do the EMG mapping came forward from inverse dynamic analysis. This means that the motions were recorded and the torques were calculated. For the simulation of the walking human joint to a WR, forward dynamics is used, the torques are known and the motions are calculated. Ideally doing an inverse dynamics step and a forward dynamics step would result in the same motions again. For more complex model this is almost never the case due to modelling errors (e.g. contact dynamics, geometry errors), or numerical errors (integration errors).

In this particular case, only open loop (feed-forward) control with the pre-recorded torques will not guaranty stable walking. This problem is solved by using a governing controller that guaranties model stability. This controller is a standard pd-controller where the gains are tuned to stabilize the model. The quality of the feed forward control can be measured by the amount of feedback effort, since in the ideal case the feedback effort should be zero. The total control structure is shown in Figure 6.

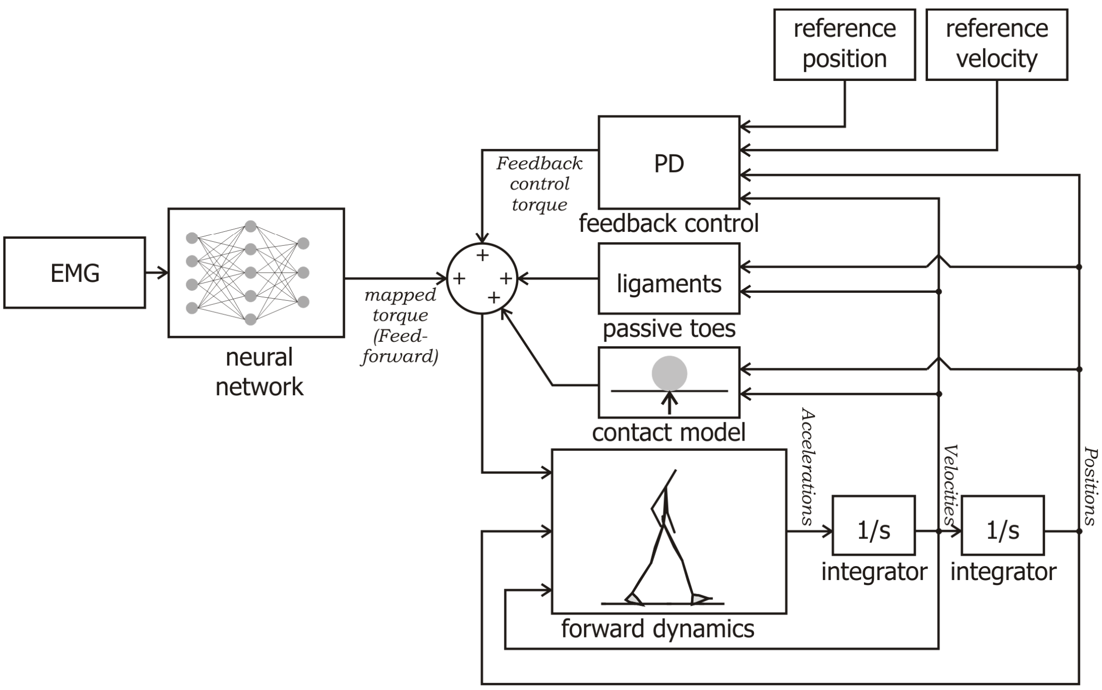


Figure 6: Schematic overview of the model control. Forces are applied to the model by the contact model, passive toes and the control (EMG feedforward-control, PD feedback-control)

2.4.4 Feedforward-control

Throughout this report, two types of feedforward (FF) control are used. First there is feedforward control with torques obtained directly from the gait database (Direct torque FF). Secondly, there is feedforward control with the torques obtained from the EMG driven neural network (EMG driven FF).

2.4.5 Linking the simulation environments

For this project, different simulation environments are used. The structural optimization (deliverables D4.2-D4.3) is done in Webots, the human modelling (deliverables D2.2-D2-3) are done with the simulator described in this report, and the experimental testing (deliverable D3.4) is done with Lopes running MATLAB/Simulink. The simulator has the build in functionality to link the different simulation environments with several import and export features.

2.4.5.1 Webots / simulator

The different optimized WR structures can be imported to the simulation environment. As an example, Figure 7 and Figure 8 show the same structure in both environments.

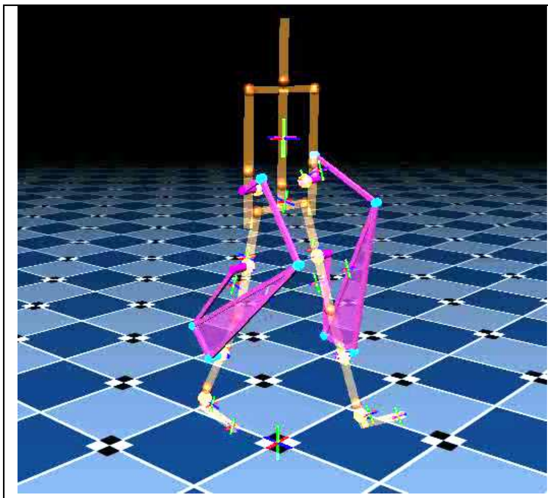


Figure 7: Human joint to a wearable robot in Webots.

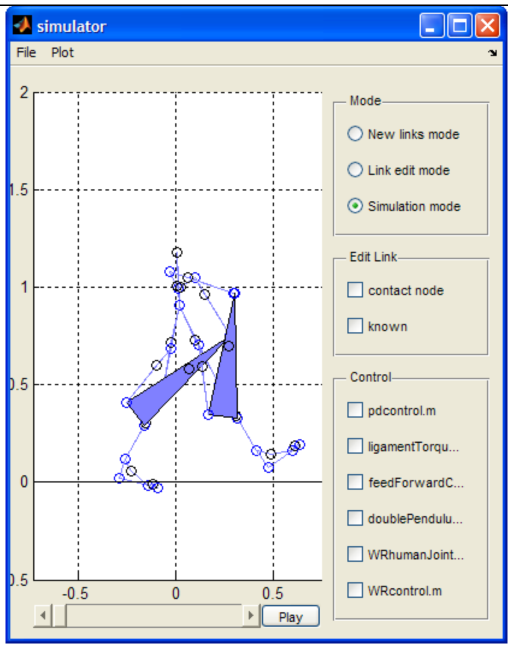


Figure 8: Human joint to the same wearable robot in the simulation environment.

2.4.5.2 Simulator / Lopes

The simulator has built in functionality to write a Simulink Lopes controller. This controller has the following functions:

- Transparent Lopes (The controller cancels out the dynamics of Lopes)
- Kinematic modeling (It maps the Lopes kinematics to the WR kinematics)

- Inverse modeling (It simulates the mass and inertia of the WR)
- WR Control (It simulates the passive (springs, dampers), and active (Series Elastic Actuators) elements of the WR)

The link between the simulation environment and Lopes is more extensively described in deliverable 3.4

3 Results

3.1 Single subject – single condition

This section shows the result for a single subject and a single condition. The result of the toque mapping is shown in Figure 9. The correlation coefficient between the mapped torques and the predicted torques is 0.9751. As a comparison also a least square fit of the test trial performed. This resulted in a correlation coefficient of 0.8723. The fit is shown in Figure 10.

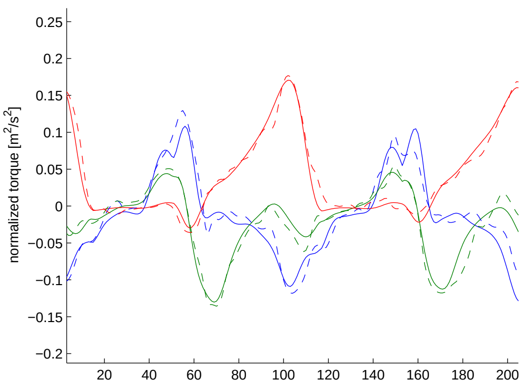


Figure 9: ANN fit. Single subject - single condition. Solid lines represent the measured data; dashed lines represent the estimated data. (--hip, --knee, --ankle). Correlation coefficient r = 0.9751

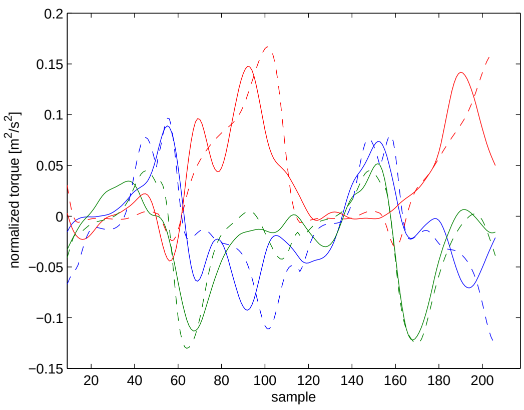


Figure 10: Least square fit. Single subject - single condition. Solid lines represent the measured data; dashed lines represent the estimated data. (--hip, --knee, --ankle). Correlation coefficient r = 0.8723

The effect of the individual muscles is shown in Figure 11. The data is reviewed qualitatively. The muscle function in the network and the physiological muscle function are given in Table 2.

3.1.1 Effect of individual muscles

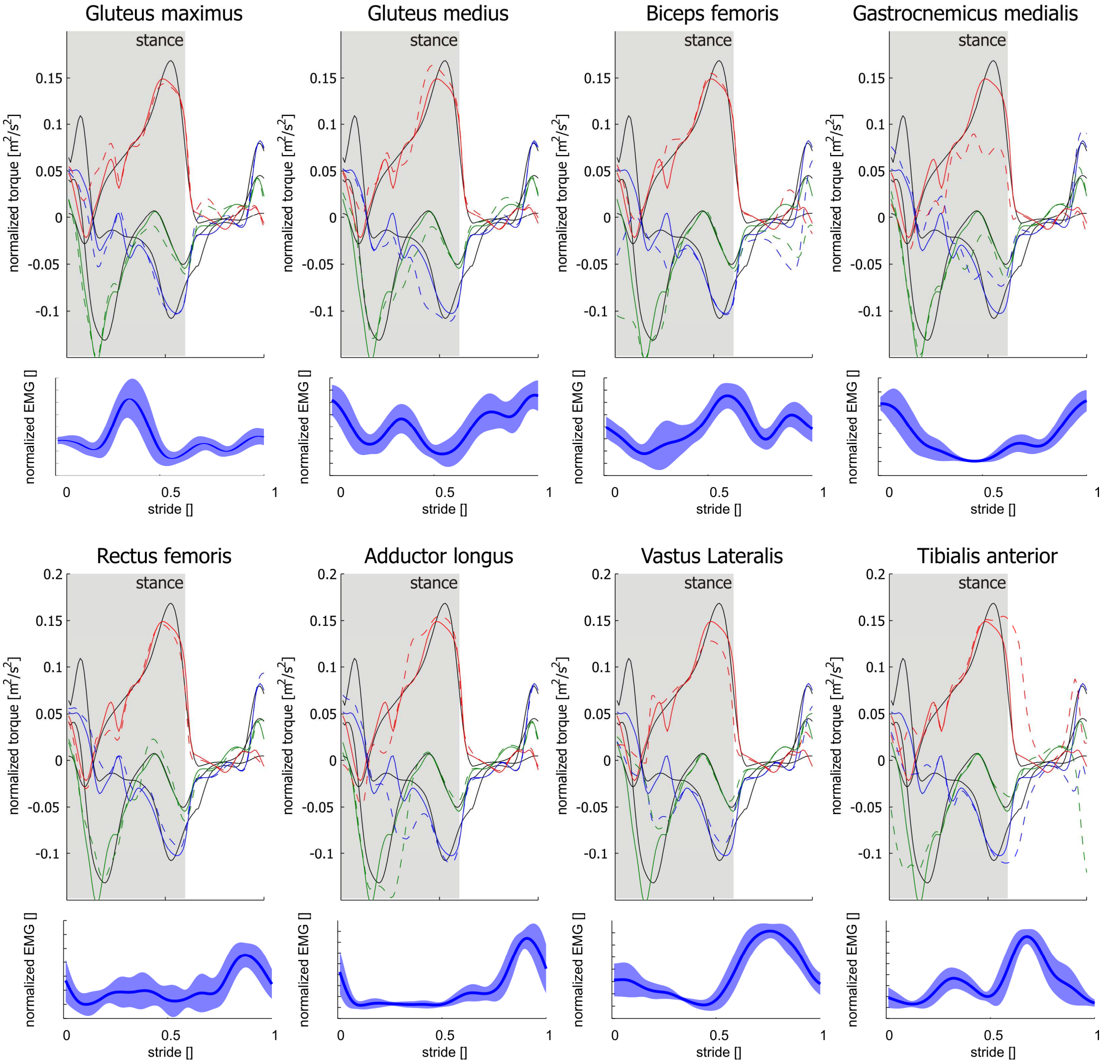


Figure 11: Effect of the individual muscles, EMG of each channel is set to 0.1 (minimum values). The panels below the torque plot show the original EMG signal. Black solid lines represent the measured data, solid lines represent the estimated data, dashed lines represent the data where the EMG signal of one muscle was excluded. (--hip, --knee, --ankle).

Muscle	Joints spanned	Effect in network
Gluteus maximus	Hip	
Gluteus medius	Hip	
Biceps femoris	Hip, knee	Knee, Ankle
Gastrocnemius medialis	Knee, Ankle	Hip, Knee, Ankle
Rectus femoris	Hip, Knee	
Adductor longus	Hip	Hip
Vastus lateralis	Knee	Knee
Tibialis anterior	Ankle	Knee, Ankle

Table 2: Difference between the muscle function based on the physiological characteristics and their function in the network.

3.2 Single subject – multiple condition

Figure 12 shows a typical result for a single subject multiple condition network. The network was trained with data from: walking at a self-selected speed, walking at 1.2m/s, walking at 0.8m/s, gait initiation left and right, gait termination left and right. The test data was gait initiation with the left leg used for testing

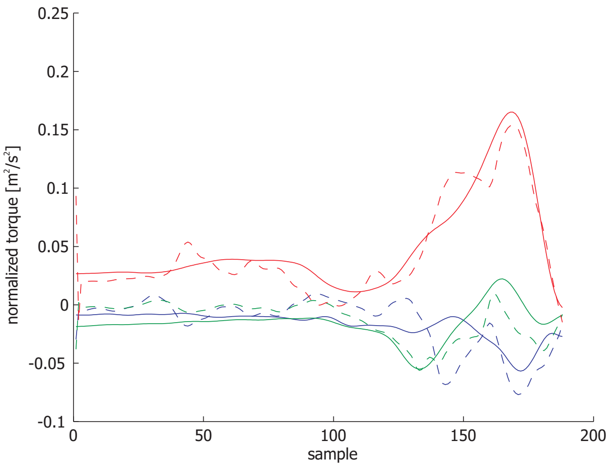


Figure 12: Single subject – multiple conditions. The network was trained with data from a single subject performing multiple movements. The test trial for this condition was a starting movement. Solid lines represent the measured data; dashed lines represent the estimated data. (--hip, --knee, --ankle). Correlation coefficient r = 0.9348

3.3 Multi subject – single condition

This section shows the result for a multi subject and a single condition. The result of the toque mapping is shown in Figure 13. The correlation coefficient between the mapped torques and the predicted torques is 0.8763. The effect of the individual muscles is shown in Figure 14.

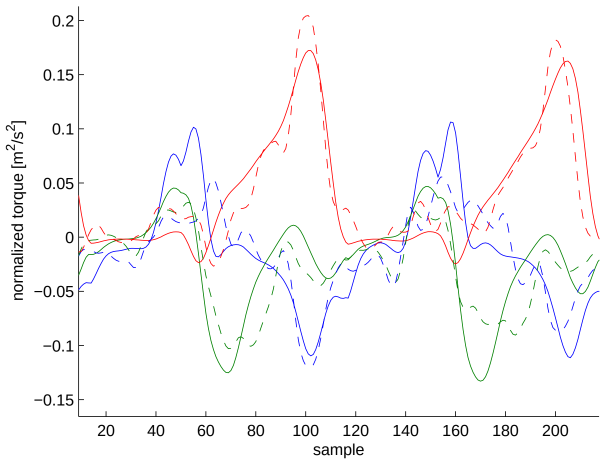


Figure 13: Multiple subject - single condition. Solid lines represent the measured data; dashed lines represent the estimated data. (--hip, --knee, --ankle). Correlation coefficient r = 0.8763

3.3.1 Effect of individual muscles

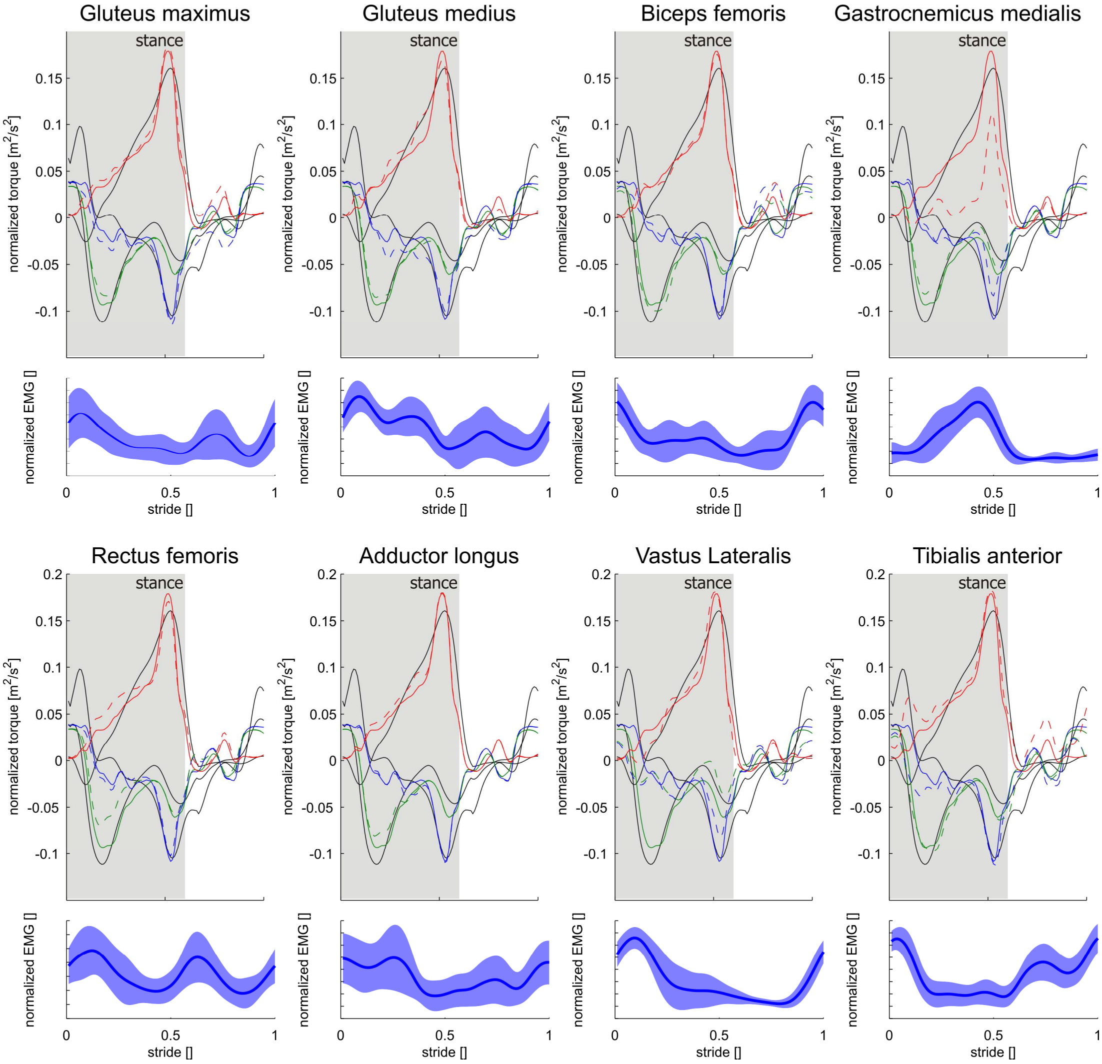


Figure 14: Effect of the individual muscles, EMG of each channel is set to 0.1 (minimum values). The panels below the torque plot show the original EMG signal. Black solid lines represent the measured data, solid lines represent the estimated data, dashed lines represent the data where the EMG signal of one muscle was excluded. (--hip, --knee, --ankle).

3.4 Control

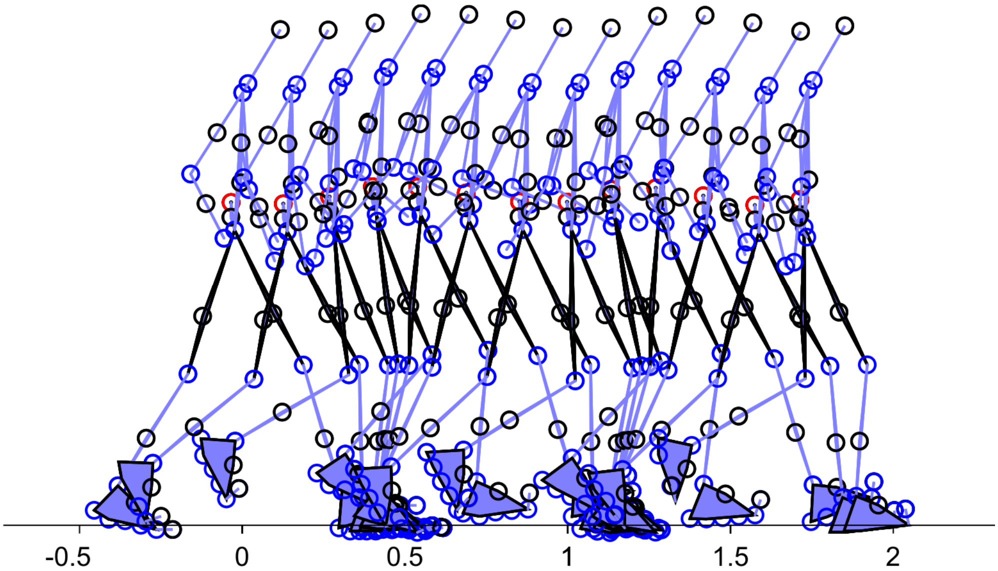


Figure 15: One gait cycle. This image is constructed out of different output images of the simulation environment

The human model is controlled with feedforward-control and pd-control. Two feedforward controllers are used direct torque control and EMG driven control. The effect of both controllers on the total control effort is shown in Figure 16. In this section, the neural network for the EMG control is trained with walking data from one subject (single subject, single condition from previous paragraphs).

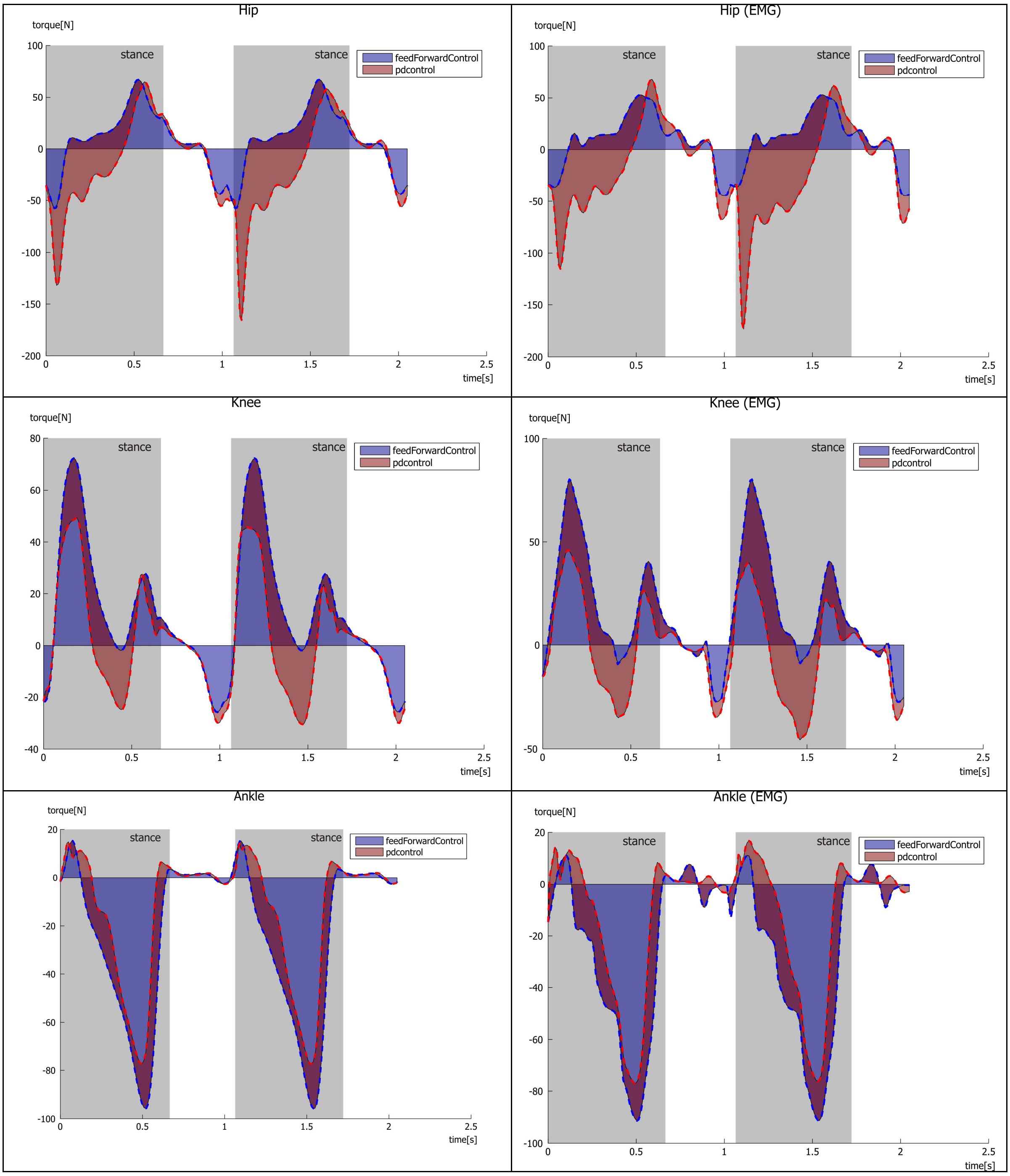


Figure 16: Feedforward and feedback control of the hip, knee and ankle joint of one leg during two gait cycles. The left pictures show feedforward control with the torques directly from the database (Direct Torque FF). The right pictures show feedforward control with torques that were obtained from the EMG driven neural network (EMG Driven FF).

4 Discussion

4.1 EGM mapping, toque prediction

The Neural network gives an accurate prediction of the joint torque. The prediction is best if trials recorded from one subject are used to train the network (correlation coefficient = 0.9751). With increasing generality of the mapping like multiple movements, or multiple subjects the torque mapping slightly loses accuracy (correlation coefficients respectively r = 0.9348 and r = 0.8763).

The neural network method outperforms simpler methods where a single correlation method maps the input to the output.

4.2 EGM mapping, muscle prediction

The plots on the effect of individual muscles on the EMG mapping give an indication of the physiological feasibility of the control. If the network maps the EMG signal to a different joint then where the muscle originally actuates the mapping is not physiologically feasible. This is observed several times in the network, for example: The EMG of the gastrocnemius maps to the knee and ankle torque, what could be expected, as well as to the hip torque, this was not expected. Some muscles have hardly any effect of the torque mapping.

A possible explanation for the difference between the effect of the individual muscles in the network and the expected effect based on the joints they span could be the difference in signal quality. The signals that have a high standard deviation (e.g. gluteus maximus) have less effect on the mapping than the signals with a low standard deviation (e.g. gastrocnemius medialis). The high standard deviation would also result in a high standard deviation in the predicted torques making them less suitable as an input signal.

The physiological feasibility is relatively low. There are however still options to increase this feasibility. One is to set constraints to the mapping. For example, a muscle could only map the torque of the joint or joints it spans.

4.3 Control

The torques are to be used in open loop (feed forward). Only feedforward control can not guaranty stable walking. To guaranty stable walking an additional pd-controller is used.

In the simulation the torque provided by the feed-forward control, and the torque provided by the pd-control are separated. For both scenarios (measured torque feedforward and mapped EMG feedforward) some general trends are observed.

For the ankle the amount of pd-control is small compared to the amount of feedforward control. This indicates good control.

For the knee the amount of pd-control compared to the amount of feedforward control is higher. The total amount of control given matches the location of the peaks in the feed forward component. This indicates that the basic characteristic of the gait pattern are found, but there is clearly an offset and gain error.

For the hip the same behavior as for the knee is observed, although the differences in gain and offset are bigger.

The differences in feed-forward torque are small if compared to the amount of pd-control. The walking model with EMG driven feed forward performs therefore just as good as the model where the measured torque is fed forward.

5 References

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