EMG-Driven Human Model for Orthosis Control

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Abstract

In this paper we present a simplified body model of the human lower extremities used for the computation of the *intended motion* of a subject wearing an exoskeleton orthosis. The *intended motion* is calculated by analyzing EMG signals emitted by selected muscles. With the calculated *intended motion* a leg orthosis is controlled in real-time performing the desired motion.

To allow motions with different velocities and accelerations, the body model contains physical properties of the body parts and is animated with data recorded from the pose sensors as a basis for the prediction. Computing the *intended* motion is achieved by converting calibrated EMG signals to joint torques and forces which are also part of the model. The extrapolation is performed for a short period of time, calculating the joint coordinates for the actuator control loop.

The algorithm was examined with the experiment of flexing and extending the knee while raising and lowering the thigh. The discussion compares the motion performed by the leg orthosis and the desired motion.

The algorithm of the model and the preliminary experimental results are both presented.

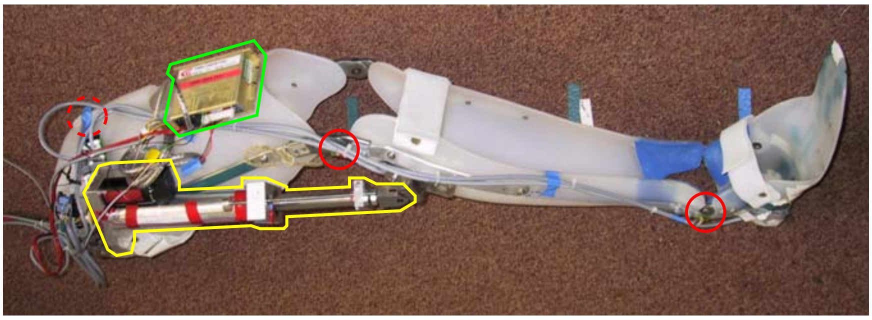

Figure 1: The orthosis for the right leg. Hall sensors are marked with solid circles (red), accelerometers with dashed circles (red), the actuator (yellow) and servo amplifier (green).

Introduction

Beside the standard application of EMG signals to analyse disabilities or to track progress in rehabilitation, more focus has been put on controling robot arms and exoskeletons with EMG signals (Lee (1984), Fukuda (1999), Mirota (2001)) in recent years. In Lloyd (2003) a promising but very complex musculoskeletal model is presented that takes into account 13 muscles crossing the knee to estimate the resulting knee torque.

The advantage of EMG signals is that they form an intuitive interface and they can be used with every patient who is not paralyzed. Even if the muscles are not strong enough or the limbs hindered while performing a motion, signals of the *intended motion* (desired motion that cannot be performed) can still be recorded. In our environment the orthosis (see Figure 1) that is attached to the leg restricts the motion in the knee if the actuator is not powered, so the intention has to be detected without the possibility of detecting any motion.

System Description

As can be seen in Figure 2, the system is divided into two parts, the kernel block with real-time data acquisition together with the PID-controller for the actuator and the motion analysis block with the biomechanical model in the user space.

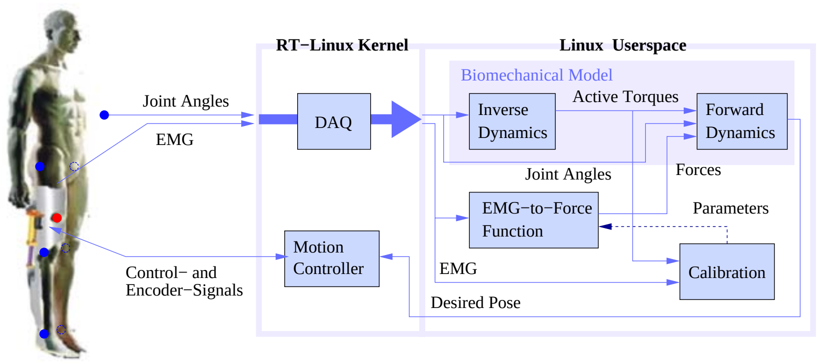

Figure 2: System overview. The data are recorded from the pose and EMG sensors attached to the orthosis and passed to the biomechanical model to predict the intended motion. The result is fed into the motion controller to move the orthosis to the desired pose.

Data Acquisition System

The measurement system used for the algorithm consists of two groups of sensors: The EMG sensors to read the muscle activity and the pose sensors to get the current state of the subject.

The EMG sensors are placed on top of two muscles responsible for flexing and extending the knee: the M. semitendinosus and M. rectus femoris. Many other muscles cooperate during this motion but we have chosen the ones with the largest contributions to the resulting torque in the knee in our setup (see Platzer 2003). The signals are sampled from DelSys 2.3 Differential Signal Conditioning Electrodes.

Ankle and knee angles are measured on both legs with Philips KMZ41 hall sensors and the thigh and trunk angles with accelerometers ADXL210 from AnalogDevices Inc. (as described in Willemsen (1991) and Fleischer (2004)), all only in the sagittal plane. All sensors are sampled with 1 KHz.

Signal Flow

As mentioned in the introduction, the intended motion of the subject should be analysed to let the *human* control the *orthosis*. To be able to compute the *desired pose*, the *current pose* of the subject is read from the *pose sensors* attached to the limbs and fed into the *biomechanical model* together with the EMG signals from the appropriate muscles. The *biomechanical model* then calculates the *desired pose* for the next timestep and passes it to the *motion controller* that is responsible for controlling the actuator towards the desired pose.

To be able to use the *EMG-to-force function*, parameters of the function have to be calibrated. This is performed in the block *calibration*: The *biomechanical model* calculates through inverse dynamics the *active forces* (forces that must have been active in the joint crossed by the modeled muscles that resulted in the latest motion). Those forces (for the knee extensor the knee torque is used) are fed into the block *calibration* together with the corresponding EMG values to optimize the parameters of the EMG-to-force function.

Human Body Model

The human body model consists of two legs with feet, shanks, thighs and the torso. All limbs and the torso are modeled as rigid bodies (rectangular parallelepipeds) connected with swivel joints. Body masses are calculated as fixed fractions of the total body weight (m_{total}=88 kg) of the subject (the figures can be found in Winter (1990)). Body dimensions are taken from our subject. Two muscles M_f and M_e have been added producing the corresponding force F_{Mf} and torque T_{Me} to allow flexion and extension of the knee (due to the anatomy of the knee extensor in the regarded range of motion it is better to use the torque here). The points of origin and insertion of M_f are fixed and have been chosen by hand in analogy to human anatomy. Furthermore, the model takes into account ground reaction forces at both feet and gravity. The generalized velocities $\mathbf{u}$ and accelerations $\dot{\mathbf{u}}$ are calculated as derivations of the generalized coordinates $\mathbf{q}$ (angles recorded from the pose-sensors).

The dynamic equations of the body model have been generated with the symbolic manipulation tool AUTOLEV. Details of the model and the calibration algorithm can be found in Fleischer (2004).

Calibration

The calibration algorithm takes pairs of post-processed EMG values and muscles forces calculated by the inverse dynamics from the same point in time and stores them in a table indexed by the EMG value: the activation level of the muscle. Older values might be overwritten. When the calibration is performed, all pairs stored in the table are taken as points on the EMG-to-Force function

$$F(x) = a_0 \cdot (1 - e^{-a_1 \cdot x}) + a_2 \,.$$

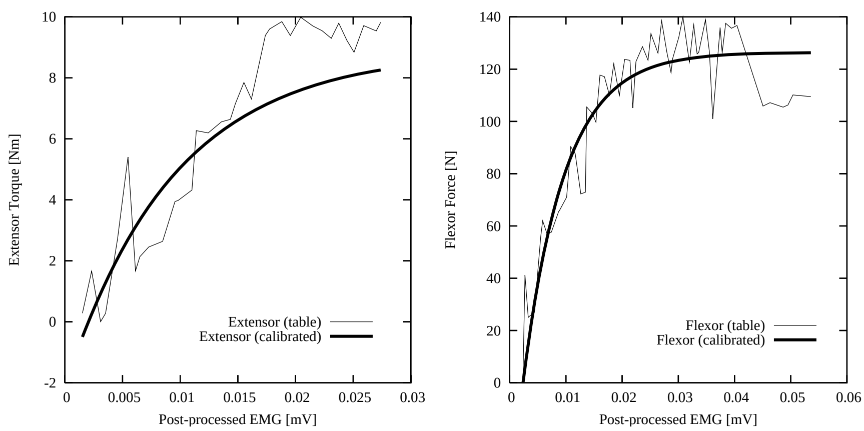

Figure 3: This diagram shows the results from the calibration of the EMG-signals for the knee flexor and extensor: The Functions $F_e(x)$ and $F_f(x)$.

The Nelder-Mead Simplex algorithm is used to optimize the parameters a_0, a_1 and a_2 by minimizing the least square error of the force from the function F(x) and the force value stored in the table.

In Figure 3 the contents of the table is plotted as a function of the EMG signal together with the calibrated functions $F_e(x)$ and $F_f(x)$ for the knee extensor and knee flexor.

Motion Prediction

During initialization of the algorithm the body model is synchronized with the current state $\mathbf{S}=(\mathbf{q}, \mathbf{u})$ of the subject. For the knee joint the dynamic equations of the model are solved for acceleration $\dot{u}_{knee}$ and computed by applying the EMG signals to muscles M_f and T_{Me}. Both M_f and T_{Me} are greater or equal zero, co-contraction of the muscles is allowed here. Only during calibration this is impossible. After double-integrating the acceleration of the knee joint for one timestep Δt=10ms into the future we get the desired angle from $\mathbf{S}_{t+\Delta t}$. Obviously this could be done for more joints (e.g. hip, ankle), but in our experiments currently only the knee joint is powered, thus we only need to compute q_{knee}.

Experiments

The experiment described here was performed in an upright standing position with the left foot on the ground. The right thigh and shank have been raised and lowered in a random pattern in sagittal plane as shown in Figure 4. When interpreting the diagram it is important to take into consideration the hip angle, which is also shown there. In the first case the actuator was not attached to the orthosis so that unhindered movement was possible. As can be seen, the post-processed EMG signals of the knee flexor

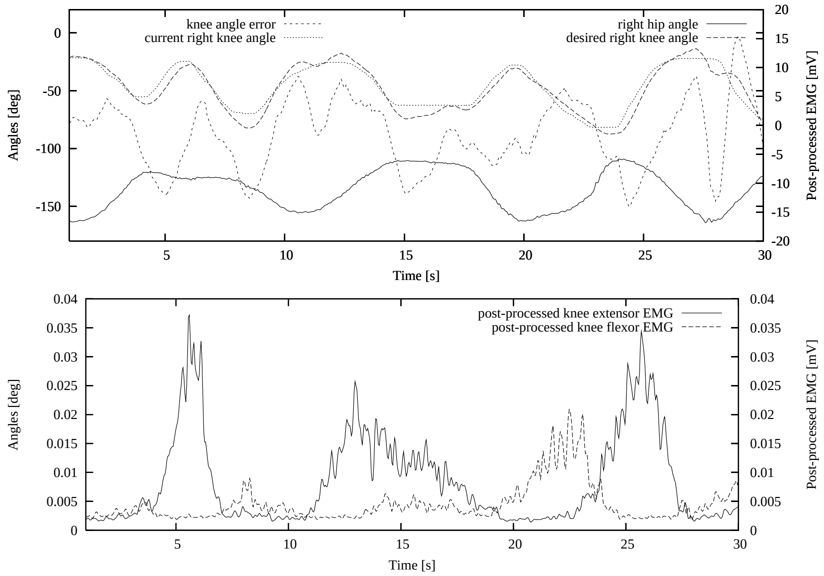

Figure 4: This diagram shows the angles of the right hip and right knee with the actuator not attached. Zero degrees means upright standing position, positive angles stand for hip flexion and knee extension. Also shown is the error between the current and predicted knee angle and the post-processed EMG-values feeding the prediction for the knee muscles.

and extensor lead to a knee angle prediction similar in shape to the performed motion. The maximum error is 15.4 degrees, the average of the absolute error is 4.9 degrees and the standard deviation of the error is 5.9 degrees. The relative error is not meaningful since the amount is important independently of the angle where it appears. The shifting in time is mostly a result of the low-pass filtering of the EMG values and a simple friction function that is used to simulate the effects of tendons and joint end stop.

In the second experimental setup the EMG signals have been calibrated during unhindered motion at the beginning. After that, the actuator has

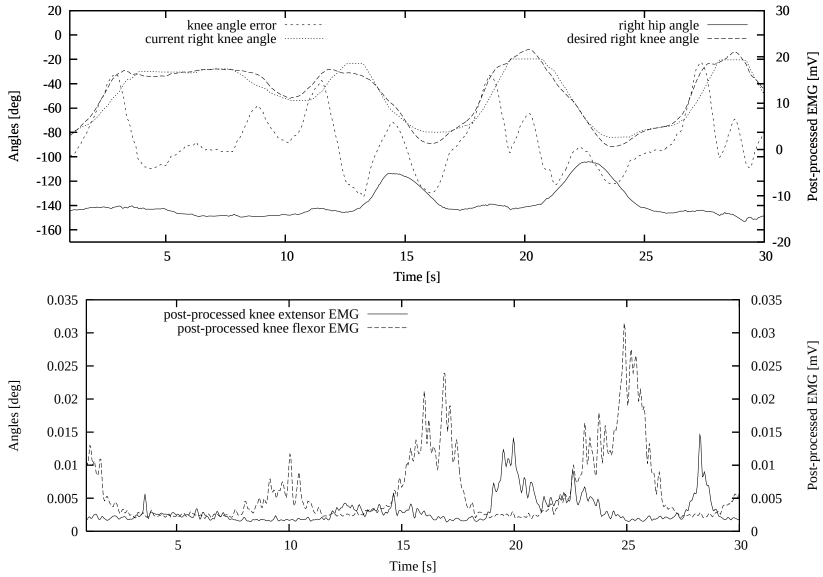

Figure 5: This figure shows the motion of the right leg with the actuator attached and powered by the motion controller. Due to safety reasons the maximum current to the motor was limited resulting in a slower response to the desired angle.

been attached to the orthosis and powered by the motion controller. Results from this setup can be seen in Figure 5. Due to safety reasons the output current of the servo amplifier was limited resulting in limited accelerations of the actuator. Also some peak angles could not be reached due to lack of resulting knee torque. Unfortunately, due to the delayed response of the system to the desired angles, a subjective feeling of stiffness was perceived making it a little bit harder to perform the motion than without the actuator. Due to the difference in the performed motions (slight differences in angle configurations or velocities are sufficient), the EMG signals cannot be compared easily to show this effect. Additional force sensors are necessary to detect the forces of the human leg acting on the orthosis (in the case of no external contact of the orthosis).

Discussion

In this paper an approach has been presented and experimentally examined that allows the estimation of the intended motion of a subject wearing a leg orthosis by evaluating EMG signals from certain muscles.

As shown in the previous section, the motion prediction algorithm is working well in predicting the desired motion, although the raw and post-processed EMG signals are quite unsteady and unreliable by nature. As was explained before, the delay between raw EMG signals and the resulting prediction for the knee torque has a strong effect on the performance of the system. The next steps in research will be to shorten this delay to allow the orthosis to be more supportive and to incorporate more muscles crossing the knee to make the model robust against contact from the environment while walking or climbing stairs.

Hopefully in the near future this research will lead to an intuitive human-to-robot interface to control powered orthoses.

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