TORQUE CONTROL OF AN EXOSKELETAL KNEE WITH EMG SIGNALS

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Abstract
This paper introduces a control scheme and algorithm for a powered orthosis. Recognizing the intended motion is based on real-time evaluation of EMG signals recorded from the operator's leg muscles. The desired motion is executed with a torque controller for an electric linear actuator. In contrast to most of the previous approaches for similar applications, this is performed without pattern classification and without a dynamic biomechanical model of the human body.

1 Introduction

Exoskeleton systems for human operators offer a wide range of possible applications: They can offer assistance to patients during their rehabilitation by guiding motions on correct trajectories to help re-learning motion patterns, or give force support to be able to perform certain motions. In factory environments they could remove load from the body of workers during strenuous physical work. Depending on the size, weight, and handling of the devices, they could even be beneficial in everyday life at home, especially for elderly people.

Exoskeletons also offer a unique way of giving force feedback to the human body. They can act as haptic interfaces for telemanipulation, games and entertainment, and muscle and motion training devices for athletes.

Since numerous applications for exoskeletons can be imagined, many groups have shown interest in this topic. Pioneer work in this area has been performed by the research group of Vukobratovic: A full body exoskeleton robot was developed supporting a completely paralyzed patient while moving on predefined trajectories [10, 11]. The influence of the patient was completely ignored but a motion controller modified the trajectories to keep the exoskeleton balanced.

Especially in recent years several projects have emerged. Among others there are: the Berkley Lower Extremity Exoskeleton (BLEEX), a military exoskeleton to aid soldiers carrying heavy loads [4]. The Hybrid Assistive Leg (HAL) is an actuated body suit for both legs [3], in the latest version (HAL-5) extended for both arms. It is designed for multiple purposes, such as supporting elderly people or as rehabilitation device. The powered lower limb orthosis described in [9] has been developed to assist during motor rehabilitation after neurological injuries by re-learning gait patterns.

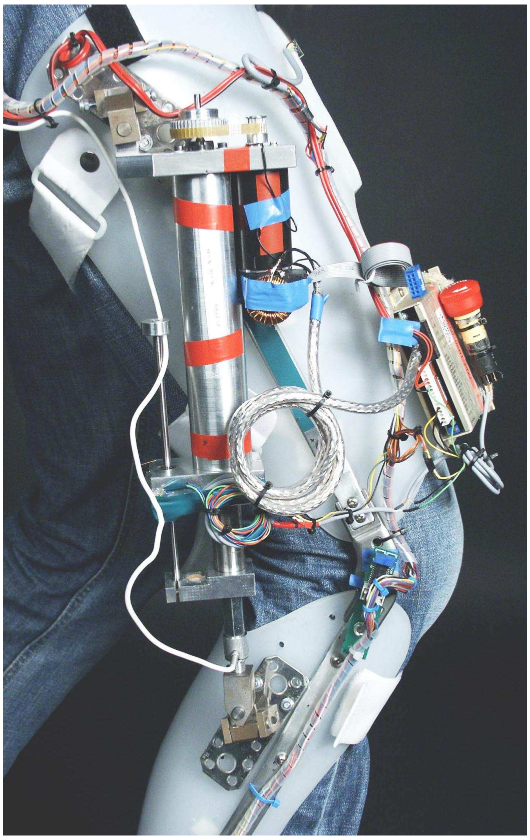

Figure 1: The exoskeleton for knee support.

As the applications are very diverse, many approaches for the interfaces between the operator and the patient exist. It is necessary to develop an intuitive interface that allows continuous control of the exoskeleton, since standing, walking, and climbing stairs while keeping a stable pose are complex and very dynamic tasks. Activating predefined motion patterns is not possible in our setup since variable interferences from outside (contact forces) or the operator (swinging with the arms, leaning forward etc.) will interfere with the stability of the precalculated motions.

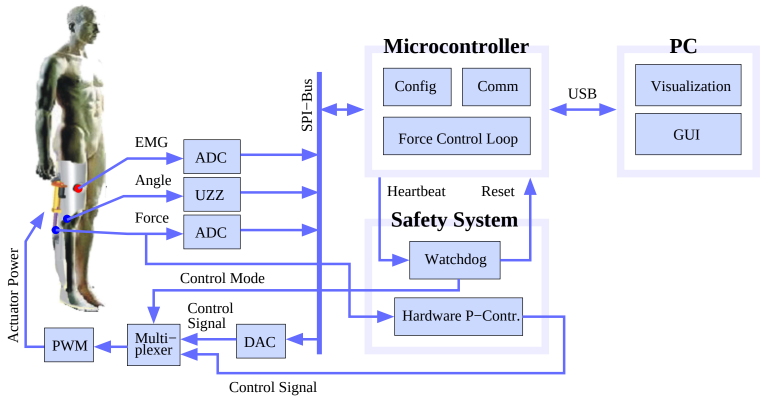

Figure 2: Overview of the components of the system.

In most of the developments one out of two alternatives is chosen: Either the desired motion is recognized by force sensors between the human and the mechanical construction or biosignals are taken from the subject. The differences between the approaches are found in the underlying interpretation of the signals and the control algorithms.
Recently more focus has been put on controlling robot arms and exoskeletons with EMG signals [2, 7]. In Lloyd [6] a promising but very complex musculoskeletal model is presented that takes into account 13 muscles crossing the knee to estimate the resulting knee torque that could be used to control an exoskeleton, although the analysis presented there was not performed in real-time.
In [8] EMG signals of the Biceps Brachii and Triceps Brachii where used to estimate the elbow joint moment. With this estimation a moment controller was fed to allow control of a two-link exoskeletal arm to lift an external load with the hand. This approach is very similar to the one described here, but applied to a different environment.
The advantage of EMG signals compared to other means of input is that they form an intuitive interface and can be used with every operator 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 can still be detected.
The drawback of using EMG signals is that the operator has to be able to activate his or her muscles in an orderly manner to execute a certain motion. Considering patients, this restricts the group of users to a certain level of rehabilitation.

2 System Description

As can be seen in Fig. 1, the exoskeleton consists of an orthosis that covers the right leg and an actuator attached to it. This actuator is able to perform knee flexion and extension and support the subject wearing the exoskeleton with additional torque in the knee joint.
The role of the control system is to determine the intended motion of the operator and support him or her with additional torque from the actuator during execution. The main components of the system are: The orthosis with the sensor and actuator hardware, the microcontroller together with the control software, the hardware safety system, and the PC for data visualization and user interaction (refer to Fig. 2).

2.1 Hardware

The central connection between all sensors, actuator, and the Atmel Mega 32 microcontroller is realized by a real-time capable SPI bus. The PC is connected to the microcontroller during calibration, debugging and development via USB (non real-time).
Three Delsys 2.3 differential electrodes are used to measure the muscle activations. They are connected to a single reference electrode to minimize interferences from outside and have an inbuilt amplifier with a gain of 1000 V/V and a bandpass filter from $20Hz$ to $450Hz$. The signals are sampled with a MAX1230 12-bit D/A-converter. The knee angle is measured by a Philips KMZ41 Hall sensor and its output is evaluated and digitized by a Philips UZZ9001. The actuator force is measured with a GS XFTC300 force sensor, amplified and also digitized with a MAX1230. Sampling rate for all converters is set to 1 kHz.
The actuator consists of a ball screw powered by a standard DC motor (Maxon RE35, $90W$) and is driven by a PWM amplifier (Copley 4122Z) that is connected to the SPI bus by an AD5530 D/A-converter. The possible range of motion is between $0deg$ (straight leg) and $-98deg$ (maximum flexion). The force sensor is attached to the actuator in-line to measure the force between the thigh and shank.

2.2 Safety System

The safety system is divided into two parts: the software system and the hardware system. The software system checks the EMG signals, the control output for the actuator and the current knee angle against minimum and maximum ranges to avoid undesired behaviour of the orthosis.
The hardware safety system monitors the periodical heartbeat of the microcontroller. In case of a failure the heartbeat stops and the separate watchdog switches to a secondary controller: This controller is a hardware p-controller driven by the force sensor. Depending on the current motion that is performed, different target values have to be applied ($0N$ for free motion during swing phase, a predefined maximum force during floor contact). The EMG sensors have no influence here. The input of the PWM amplifier is switched from microcontroller to hardware p-controller with an analog multiplexer by the watchdog circuit. Switching back to software control has to be performed by hand for safety reasons.

2.3 Human Body and Actuator Models

The control loop described in Sec. 2.4 needs the resulting knee torque produced by the thigh muscles of the operator as input (refer to Fig. 3).
To achieve this, the recorded EMG signals have to be post-processed before they can be converted into muscle forces: The signals are offset corrected, rectified, and low-pass filtered with a cut-off frequency between $2Hz$ and $4Hz$ (depending on the experiment and support ratio) forming the activation envelope $s_n(t)$ where n is the index of the electrode and muscle.
To convert the muscle activation s_n into a muscle force, an EMG-to-force function is applied (based on [6]):

$$F_n(s_n) = \frac{e^{A_n s_n s_{n,max}^{-1}} - 1}{e^{A_n} - 1} \cdot F_{n,max}, \tag{1}$$

where $F_n(t)$ is the force produced by muscle n with $n = 1 \dots N$ (N: number of recorded muscles), s_n the post-processed EMG signal and A_n the non-linear shape factor of the transfer function. $s_{n,max}$ is the maximum recorded post-processed EMG signal during calibration with the corresponding maximum measured force $F_{n,max}$. A_n was limited to $-10 < A_n < 0$ in our setup.
The parameters A_n, $s_{n,max}$ and $F_{n,max}$ have to be determined for each muscle. No other properties of the muscle have been modeled to keep the number of parameters to be calibrated low.
The body model that incorporates the muscles and calculates the resulting knee torque sums up the torque contributions of every muscle for the resulting knee torque T_m:

$$T_m = \sum_{n=1}^{N} \left(\left| \vec{I}_n \times \frac{\vec{I}_n - \vec{O}_n}{|\vec{I}_n - \vec{O}_n|} \right| \cdot F_n \right), \tag{2}$$

where $\vec{O}_n$ and $\vec{I}_n$ are the points of origin and insertion of the muscle in the thigh and shank and have been chosen in analogy to human anatomy. The knee joint lies in the origin of the coordinate system. Obviously this sum allows co-contraction and co-activation but does not handle them explicitly. No other properties of the human body like joint stiffness or friction are modeled.
One important assumption for the chosen muscles is made: It is assumed that they represent a group of muscles that are activated at the same time and that the group has a force output that is related exponential to the post-processed EMG signal of the selected muscle. Those groups should be the major sources for the resulting knee torque during all phases of the motions. The selected muscle does *not* have to be the main contributor of the group.
Obviously this is a very demanding assumption and certainly cannot be followed for all motions. On the other hand the goal is to control an actuator and not performing detailed muscle analysis and experiments have to show if this requirement is sufficiently fulfilled (refer to Sec. 3).
The actuator model is as simple as possible: The moment arm of the actuator converts the measured force F_a into a knee torque contribution of the actuator T_a:

$$T_a = \left| \vec{A}_t \times \frac{\vec{A}_t - \vec{A}_s}{|\vec{A}_t - \vec{A}_s|} \right| \cdot F_a, \tag{3}$$

where $\vec{A}_t$ is the point of attachment of the actuator to the thigh and $\vec{A}_s$ the point of attachment to the shank. The knee joint lies in the origin of the coordinate system.
During parameter calibration (Sec. 2.5) the force measurements are also low-pass filtered with the same frequency as the EMG signals to avoid misalignment of data. During normal operation mode the unfiltered force values are used to avoid possible oscillations resulting from a delay.

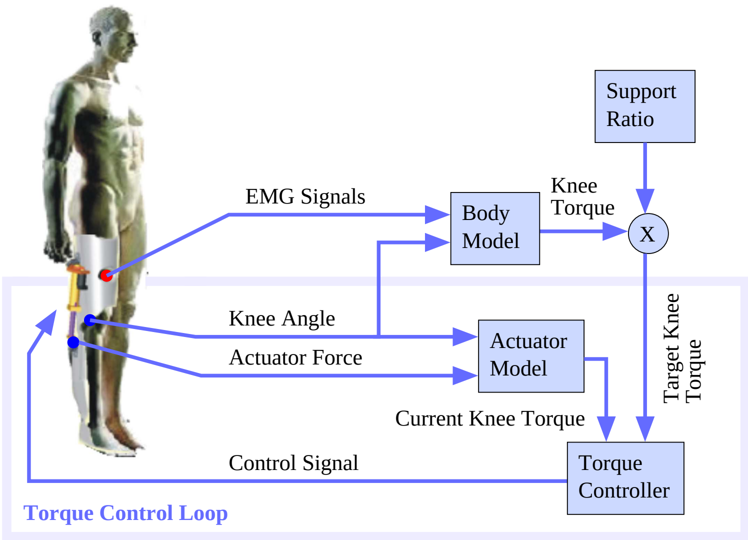

Figure 3: Torque control loop of the microcontroller.

2.4 Control Algorithm

The control system consists of two nested loops: an outer loop that evaluates the muscle activations and an inner control loop that is responsible for producing the control value for the PWM amplifier (refer to Fig. 3).
The outer loop calculates the resulting knee torque T_m from the EMG signals. This is an estimation of the torque contribution of the operator to the intended motion and passed to the inner control loop. The inner loop is responsible for adding additional support torque T_s to the knee joint with the actuator to aid the operator.
T_s is calculated using an amplification function G:

$$T_s = G\left(T_m\right) \text{ with} \tag{4}$$
$$G(x) = x \cdot S, \tag{5}$$

where S is an amplification factor that defines the support ratio.
T_s is interpreted as the target torque for the p-controller. The current knee torque T_c is derived from the force sensor that is connected between the actuator and the orthosis by a similar calculation as in Eq. 3. Both torques yield the control deviation of the torque controller

$$E = T_s - T_c. \tag{6}$$

2.5 EMG Parameter Calibration

In Sec. 2.3 the parameters A_n, $s_{n,max}$ and $F_{n,max}$ have been introduced for the EMG-to-force function F_n. Unfortunately the EMG-to-force relationship depends on many variable factors like muscle condition, electrode placement, moisture on skin, blood circulation, and many more. This relationship has to be calibrated before every experiment.
For practical use it is desirable that the calibration is not too complex and time-consuming and can be performed with the orthosis alone and no external devices that might introduce inconsistencies. With focus on patients with disabilities the required motions have to be simple.
In our setup the calibration is performed with isometric contractions of the knee flexor and extensor muscles without floor contact of the leg. The muscles that are recorded are the m. rectus femoris, m. vastus lateralis and m. semitendinosus. During the contraction the actuator is locked, immobilizing the knee joint. In an angle between $-45deg$ and $-100deg$ the operator has to try to extend and flex the knee. The activations of the muscles, the force value, and the knee angle are measured.
The idea of the calibration algorithm is to store the EMG and force values in tables. Each muscle has an associated table and each entry of the table contains the activations of all recorded muscles and the force value from the same point in time (refer to Fig. 4). The table entry where the values are stored is selected by a linear function that maps the activation of the muscle to an entry index. As a result, all tables will contain unique information about different levels of muscle activations and resulting knee torques. Since the entries of the tables are indexed by activations of different muscles and not by time, redundancy of information is kept low, minimizing the costs of the optimization independent of the complexity of the necessary motion and without letting the amount of data grow unreasonably high or weighting certain activations stronger because of longer durations.

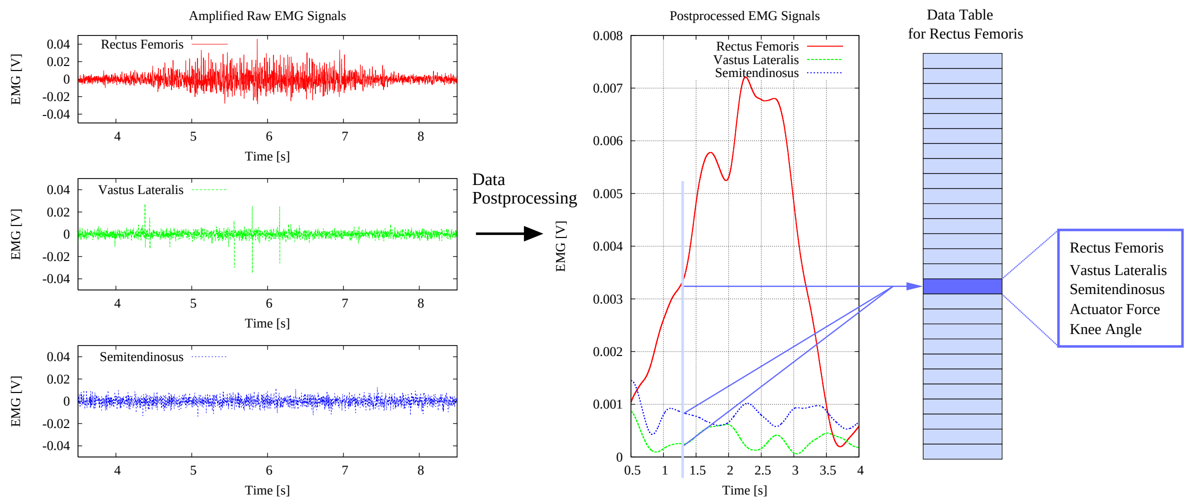

Figure 4: Overview of the data collection for the calibration.

The error function of the optimization process calculates the sum of the squared differences between T_m and T_a for all entries:

$$E = \sum_{i=1}^{M} \left(T_m\left(i\right) - T_a\left(i\right)\right)^2, \tag{7}$$

where M is the number of valid entries in the table, i is the i-th valid entry. $T_m(i)$ is the knee torque calculated from the EMG values and angle stored in entry i by using the current parameters of the optimization process. $T_a(i)$ is the actuator torque contribution derived from the force sensor measurement and stored in entry i.

To reduce the dimensionality, the parameter $s_{n,max}$ is directly taken from the uppermost table entry. $F_{n,max}$ could also be taken from the same entry, but experiments have shown that the curve fitting is more accurate if it is also a parameter that is optimized due to measurement errors. It can be limited to a small interval about this value. Since A_n can be bounded to values between $0 < A_n < 10$ (upper boundary has been determined experimentally) the optimization can be performed by sub-space search.

Experiments have shown that the measured knee torque has a different time offset to the EMG signal emitted by the muscle during contraction and relaxation. Since this property of the muscle is currently not considered, the data for the calibration tables are only collected during rising muscle activations (refer to Sec. 4).

The optimization is started for the first time when 80% of the entries are filled and restarted if 60% have been updated.

During the optimization only parameters of the currently considered muscle are optimized, all other muscles (for which optimized parameters exist) are evaluated with their EMG signals to account for co-contraction and co-activation. This greatly reduces the dimension of the optimization but requires repeated optimization as soon as parameters from other muscles are changed.

3 Experiments and Results

For the experiments presented here, three Delsys 2.3 differential electrodes are placed on the thigh on top of the m. rectus femoris, m. vastus lateralis, and m. semitendinosus. The muscles have been selected due to their large contribution to the knee flexion and extension torque and their easy accessability for the measurements.

The experiments have been performed with an healthy subject that is able to perform all motions on his own accord without any support. Due to safety issues it is currently not possible to perform experiments with patients with disabilities.

Nevertheless the results underline the usefulness of the system. The motion performed during the experiments are chosen by their relevance for everyday-life, although normal gait is not considered yet (refer to Sec. 4). For every experiment two trials are presented: The first one is an example of an unsupported motion, where the controller is neither supporting nor hindering the motion (within its possible range of velocity and acceleration). This can be verified by checking the force sensor values: throughout the unsupported trials the values are close to zero indicating that the actuator is not adding any forces (positive or negative) to the knee motion. The second trial is showing the motion performed again, this time with actuator support. Unfortunately the repeatability is not very accurate because of the human inside the device and different postures and accelerations lead to different muscle activations and torques.

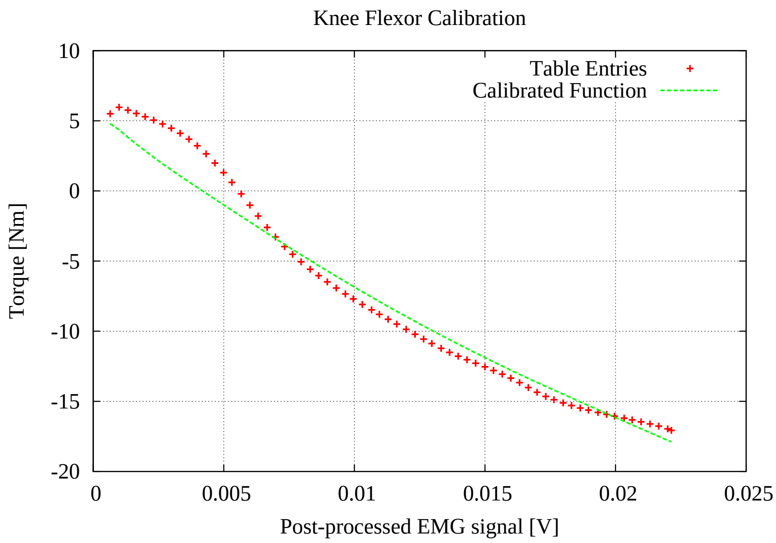

Figure 5: Results from the calibration prior to the motion experiments. Parameters of F_n are: $A_n = -0.666$, $s_{n,max} = 0.024V$ and $F_{n,max} = 246.58N$.

But the usefulness of the system is documented by the similar knee angle trajectories when comparing the trials. This shows that the intended motion can be performed and the absolute actuator torque values are evidence that the actuator adds additional torque of significant amount to the motion.
Each diagram contains curves for the estimation of the resulting knee torque of all three muscles, the calculated knee torque based on the force sensor values and the current knee angle, and the knee angle itself ($0deg$ means straight leg, negative values indicate knee flexion).
In the next section the setup for the calibration is described followed by the actual experiments.

3.1 Calibration

The calibration was performed as described in Sec. 2.5: The knee angle was at $-91.3deg$ when the subject tried to extend and flex the knee against the resistance of the locked actuator (isometric contraction). The leg was held at the thigh so that shank and foot were not touching the ground.
First of all the m. rectus femoris was calibrated, because during this contraction the m. vastus lateralis and m. semitendinosus were almost not activated at all. After that, the m. semitendinosus was calibrated during isometric contraction of the knee flexor muscles. Fig. 5 shows the contents of the calibration table for the m. semitendinosus: The measured knee torque against the activation of the associated muscle. The calibrated curve shows the calculated knee torque using the optimized parameters of the EMG-to-force function over the muscle activation.
The vertical torque offset of both curves is a result of the influence of gravity: When the muscles were relaxed the force sensor measured a knee torque because the center of mass of the shank, foot and lower part of the orthosis was not exactly below the knee joint. When all thigh muscles are relaxed the force sensor measures only the constant influence of gravity during the following isometric contraction. This value can be taken as offset.
Last of all, the m. vastus medialis was calibrated during a stand-up like motion. Contractions in this pose are very hard to perform because it is very fatiguing and voluntary relaxation in a half-standing pose on one leg supported only by the orthosis is very difficulty. The results of the m. vastus lateralis calibration had to be edited manually.

3.2 Standing Up

Fig. 7 shows results of standing up from a chair and sitting down again. The left side of the diagram shows the motion without actuator support, the right side shows the motion with a support ratio of 1.0.
In general it can be said that the shape of both knee angle trajectories are very similar showing that the motion can be controlled by the human. This is a very important fact, since the subject is also able to perform the task on his own. Adding significant torque influences the motion and the operator has to take this effect into account to react properly to it.
In the right diagram it can be seen that the strong torque support at $t = 5.7s$ leads to an unexpected quick motion to which the operator reacts immediately resulting in a reduction of muscle activation to slow down the motion. This in turn leads to

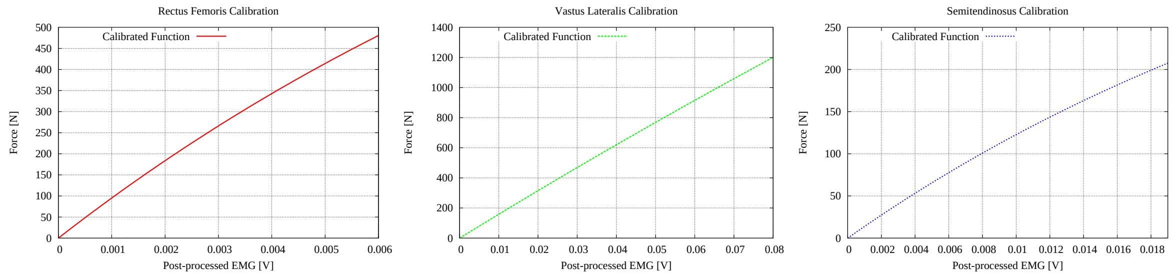

Figure 6: Results from the calibration prior to the motion experiments. Parameters of the curves are: M. rectus femoris: $A_n^r = -0.431$, $s_{n,max}^r = 0.006V$, $F_{n,max}^r = 480.52N$. M. vastus lateralis: $A_n^v = -0.131$, $s_{n,max}^v = 0.08V$, $F_{n,max}^v = 1200.52N$. M. semitendinosus: $A_n^s = -0.666$, $s_{n,max}^s = 0.024V$, $F_{n,max}^s = 246.58N$.

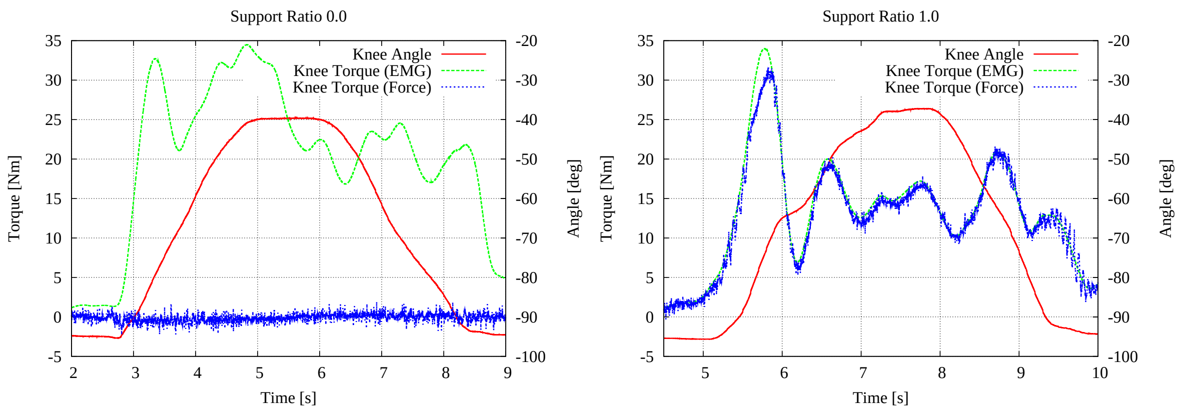

Figure 7: Standing up from a chair and sitting down experiment.

a smaller torque support. Between $5.9s < t < 6.4s$ a small dent in the angle trajectory is a result of this decrease. After that the muscle activation is increased again with a smaller slope leading to an increased support. Another smaller dent follows between $6.9s < t < 7.1s$ as a result of the second reduction of muscle activation.
The sitting down motion starts at $t = 7.9s$. The reduction in muscle activation to sit down results in a lower torque support in the knee as expected. For the operator the resulting knee flexion motion is unexpected quick leading to an increase of knee extensor muscle activation between $8.2s < t < 8.8s$ to compensate that. The velocity of knee flexion is reduced to a comfortable degree and the extensor muscle activation is reduced again. At $t = 9.1s$ this behaviour is repeated with a smaller amplitude.
Comparing the shape of the torque curves based on the EMG signals reveals that the EMG signals are significantly reduced over the whole motion except for the first peak: Before the actuator support is recognized by the operator the same muscle activation as in the unsupported case is used (out of habit). But this activation is immediately adapted as described.

3.3 Stair Climbing Motion

Fig. 8 shows the result from this experiment. In the left diagram the unsupported motion is shown: The torque support of the actuator is almost zero during the whole motion.
In the left diagram the supported motion ($S = 1.0$) can be seen: At $t = 2.1s$ the right leg is raised and at $t = 3.3s$ the leg is lowered onto the stair and the knee extensor muscles are getting activated. At $t = 3.5s$ the knee extensors are strongly activated to step up. At $t = 4.6s$ the knee is almost straight again.
As in the stand-up experiment the conscious adaption of the muscles activation by the operator can be seen in the torque curves: Between $4.0s < t < 4.6s$ the habitual muscle activation together with the actuator support leads to a quick knee extension so that the operator reduces the muscle activation immediately resulting in a dent in the knee trajectory at $t = 4.2s$. As can be seen, the shapes of both knee trajectories are very similar, indicating that the system is still controllable. During push-up between $3.5s < t < 4.5s$ the torque produced by the subject's muscles is reduced significantly.
Unfortunately it is not possible to directly compare the sum of the actuator torque and the muscle torque from the first trial with the second trial since different body poses and accelerations in the other joints affect the values.

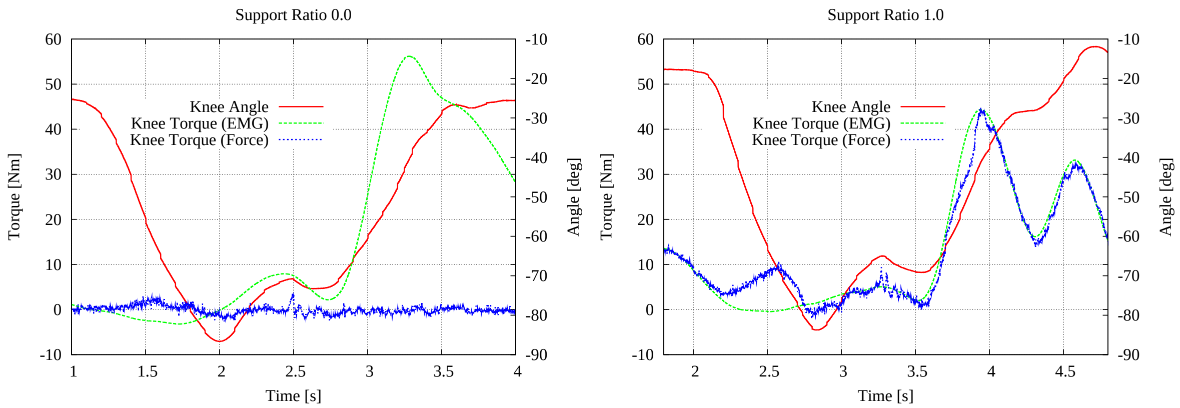

Figure 8: Stair climbing experiment.

4 Conclusion

In this paper a control system for an exoskeleton system was presented that can add torque support to the knee during common motions like climbing a stair or getting up from a chair. Also presented was an improved version of the calibration algorithm from [1] for the necessary parameters of the human body model.

The experiments and results presented in Sec. 3 show that the operator was able to perform certain motions while receiving torque support from the exoskeleton.

But some interesting effects need closer investigation: The interaction between the operator and the orthosis resulting in an oscillation - although decaying quickly - is undesired, because it leads to artifacts in the knee trajectory. In this context the maximum amplification has to be experimentally determined, depending on the reaction time of the subject, to avoid large overshoots.

During normal gait the torque support has to be investigated and applied only very carefully if at all. The thigh muscles are active during the swing phase only for short bursts that guide the motion initiated by the hip motion. Those bursts should not be amplified because they could not be regarded by the brain so quickly. Torque support should only be applied during floor contact with the foot.

Also the muscle model has to be improved to consider the different delays of the force output changes during contraction and relaxation. Preliminary results have shown that this might be achieved through another optimization of muscle parameters. The error function of this process can be the difference between two calibration curves: one for calibrating the rising activations and one for the declining activations.

Other interesting aspects of research include improving the calibration for the m. vastus lateralis and examining different relationships between the support torque and the torque based on the EMG evaluation: Using non-linear relationships for $G(x)$. This might feel more comfortable and the behaviour of the orthosis might be more predictable leading to smaller overshoots during motions. In practical environments this could help reducing the potential muscle degeneration for factory workers if only strong activations are amplified and the support during normal motions is minimal.

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Curricula Vitae

Christian Fleischer was born in 1974 in Berlin, Germany. He studied computer engineering at the Berlin University of Technology with strong emphasis on real-time systems and robotics and finished his diploma in 2001. After seeing some beautiful sights of the world and working as a freelancing computer scientist he returned to University. Since 2003 he is working on the exoskeleton project and his Ph.D. as a research assistant.

Günter Hommel received his diploma degree in Electrical Engineering from TU Berlin in 1970. He first joined the Department of Electrical Engineering and then the Department of Computer Science at TU Berlin where he received his Ph.D. in Computer Science. In 1978 he joined the Nuclear Research Center in Karlsruhe working in the field of real-time systems. From 1980 he was the head a research group in Software Engineering at the German National Research Center for Information Technology (GMD) in Bonn. In 1982 he was appointed professor at the Institute for Computer Science of TU Munich, where he worked in the fields of real-time programming and robotics. Since 1984 he has been professor at the Institute for Computer Engineering of TU Berlin heading the Real-Time Systems and Robotics Group. In 2002 he received an honorary doctorate (Dr. h.c.) from the Moscow State Academy of Instrument Engineering and Computer Science. In 2004 he was appointed Advisory Professor at Shanghai Jiao Tong University. In 2005 he was nominated Director of „TU Berlin - Shanghai Jiao Tong University Research Labs for Information and Communication Technology“ in Shanghai.