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Application of EMG signals for controlling exoskeleton robots

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Abstract

Exoskeleton robots are mechanical constructions attached to human body parts, containing actuators for influencing human motion. One important application area for exoskeletons is human motion support, for example, for disabled people, including rehabilitation training, and for force enhancement in healthy subjects. This paper surveys two exoskeleton systems developed in our laboratory. The first system is a lower-extremity exoskeleton with one actuated degree of freedom in the knee joint. This system was designed for motion support in disabled people. The second system is an exoskeleton for a human hand with 16 actuated joints, four for each finger. This hand exoskeleton will be used in rehabilitation training after hand surgeries. The application of EMG signals for motion control is presented. An overview of the design and control methods, and first experimental results for the leg exoskeleton are reported.

Keywords: human body model; human-machine interaction; powered orthosis.

Introduction

One of the key issues for successful application of exoskeletons is reliable motion control. The challenge is to achieve cooperation between the human and the robot with permanent direct contact. Depending on the application, different approaches can be applied to realise this cooperation. One possible approach is to suppress the human influence on the exoskeleton, as demonstrated in pioneer work carried out by the Vukobratovic group at the end of the 1970s using a full-body exoskeleton robot in walking support of a fully paralysed patient [1, 2]. The exoskeleton was moved along precomputed trajectories, which were slightly modified by a motion controller to maintain balance. However, most practical applications of exoskeleton robots need to account for human motion, and reaction to the imposed motion or even detection of the human intention to perform some tasks.

The common approach to control exoskeleton robots is based on using force sensors [3, 4]. In this approach, force sensors are placed between human body parts and the mechanical construction or between different parts of the mechanical construction. The force signal serves as a measure of the discrepancy between motion desired by the subject and the real motion of the exoskeleton. The advantage of this method is the simplicity of the force signal measurement: once calibrated, the force sensors provide reliable signals. However, there are problems in using this approach. The first problem is related to natural delay in the control loop, which is caused by neuronal signal propagation from the brain to the muscles, as well as by biomechanical characteristics of the muscle contractions and limb motion. This delay leads to problems in using large gains in the motion control loop (desired for better system performance).

The second problem occurs if the mechanical construction is in contact with the environment: It is difficult to separate the measured force signal from the subject and from the environment. Unfortunately, these situations occur regularly in practice, e.g., during foot contact with the floor.

In our opinion, the use of EMG signals in control has the potential to improve the performance of exoskeleton devices. Measured EMG signals are related only to the subject's intention (for healthy individuals), so that the above-mentioned ambiguity in force sensor signal during contact with the environment is avoided. Theoretically, proper interpretation of EMG signals should allow computation of the desired human motion in advance – before the muscles contract and reaction with the mechanical construction takes place. Therefore, the delay described in the control loop can at least be reduced.

In this work, two different approaches for application of EMG signals for motion control of exoskeleton robots are presented. In the first approach, called a dynamic human body model (DHBM), the intended human motion is calculated using EMG signal processing and an elaborate biomechanical model of the human body. The predicted human motion (positions and velocities) is used as input for actuator controllers. In the second approach, called direct force control (DFC), the EMG signals are converted to forces acting on limbs and compared to current forces measured in actuators attached to the corresponding limbs. The difference between these forces is used as input for the actuator controller.

In both approaches the EMG signals are directly incorporated in the control loop, in contrast to the HAL system [7], where the controller feedback signal is based on joint angle measurements, and EMG signals are used to calculate a correction term for system input.

One of the main issues of the approaches presented is conversion of the measured EMG signals into muscles forces (often referred to as a myoprocessor in the literature). The EMG signals depend very much on the subject, on skin properties such as skin moisture, as well as on muscle fatigue. The main contribution of this paper is

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the adaptive algorithm presented for the myoprocessor and integration of the calibration procedure necessary into the system. In contrast to other work [5], we use a simplified model for the EMG signal-muscle force relationship with only a few parameters. EMG-driven motion control is then demonstrated on a leg exoskeleton, whereas Rosen et al. used an arm exoskeleton [5] with a method similar to the DFC approach.

Both approaches presented in this work are based on physical models with some simplifications and parameter adaptations. Other groups have reported interesting results using neuro-fuzzy techniques for control of exoskeletons by means of EMG signals [6].

The paper is organised as follows. First, the leg exoskeleton is described (Figure 1). The DHBM and DFC approaches are explained and compared, and experimental results are presented and discussed. Second, the hand exoskeleton (Figure 2), and algorithms for its control are described. Finally, conclusions are drawn.

Exoskeleton for the leg

The current system is composed of an orthosis with an actuator, a microcontroller connected to a PC, and EMG, force, and Hall sensors. The linear actuator is attached between the thigh and shank with a force sensor in-line to generate the supporting torque in the knee (Figure 1).

Data acquisition and processing

Three Delsys 2.3 differential electrodes (Delsys, Inc., Boston, MA, USA) are placed on the rectus femoris, vastus lateralis, and semitendinosus muscles in the thigh. These muscles were selected because of their large contribution to knee flexion and extension torque and for ease of recording.

The electrodes have an inbuilt amplifier with a gain of 1000 V/V and a bandpass filter between 20 and 450 Hz. The EMG and force signals are sampled with a 12-bit A/D converter. The knee angle is measured using a Hall sensor and is also digitised.

Recorded EMG signals are offset-corrected, rectified, and low-pass filtered with a second-order Butterworth filter with a cutoff frequency of 2 Hz, leading to the post-processed signal $s_n(t)$, where n is the index of the electrode and muscle.

The force measurements are also low-pass filtered at 2 Hz during calibration to avoid misalignment of data. During normal operation mode, unfiltered force values are used.

Muscle and actuator models

Both control loops that are presented in the Control methods section need estimations of the muscle forces that the operator produces to derive the necessary support. The post-processed EMG signals are converted into muscle forces by the EMG-to-force function (based on [8]):

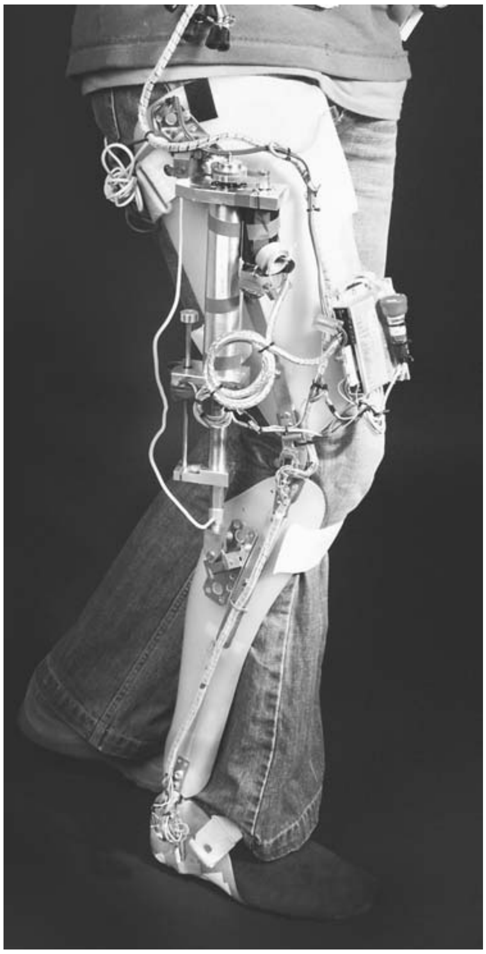

Figure 1 Leg exoskeleton composed of the orthosis with an actuator and sensors.

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

where n is the muscle index, A_n defines the shape of the curve, and $f_{n,\max}$ is the maximum force output for the maximum EMG signal $s_{n,\max}$. The parameters A_n and $f_{n,\max}$ have to be calibrated for each muscle. The resulting knee torque is:

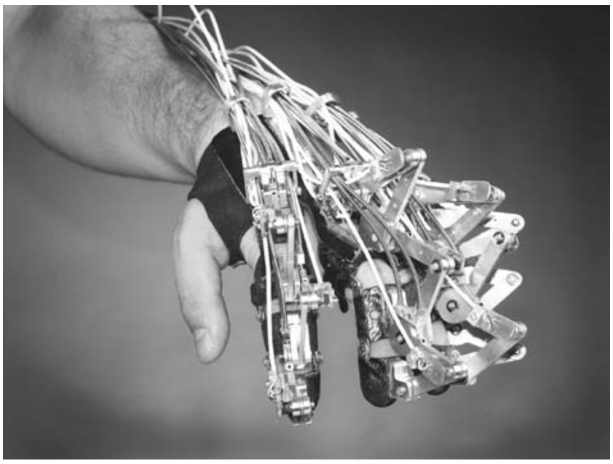

Figure 2 Hand exoskeleton with the mechanics for 16 degrees of freedom (motor unit not shown).

$$T_{EMG} = \sum_{n=1}^{N} \left(\left| \vec{I_n} \times \frac{\vec{I_n} - \vec{O_n}}{\left| \vec{I_n} - \vec{O_n} \right|} \right| \cdot F_n(s_n) \right),$$

where N is the number of muscles measured. The knee joint lies at the origin of the coordinate system. O_n and I_n are the origin and insertion of muscle j in the thigh and shank, and were chosen by analogy to human anatomy. No other properties of the human body are taken into account. The torque produced by the actuator is calculated as follows. The values of the force sensor attached to the shaft of the actuator are converted into the knee torque contribution $T_{actuator}$ through the moment arm of the actuator.

Control methods

Two approaches were investigated by our group: the first utilises a dynamic human body model, and the second DFC of the actuator.

In both systems, a hierarchy of two control loops exists. The high-level control loop evaluates EMG signals and the current state of the human body and the orthosis. The output of this loop is the desired motion expressed, as either the desired knee angle or torque. The low-level loop controls the actuator with a PID controller.

Dynamic human body model

The general idea is to simulate a simplified dynamic model of the human body that is affected by three muscles spanning the supported knee and external reaction forces applied to both feet and hip. As shown in Figure 3, the recorded EMG signals are converted into muscle forces and used as an input to the body model together with the joint angles and floor contact information. The model outputs the desired knee angle of the operator, which is passed to the low level control loop as the target value. The model computation is performed by solving the system of equations

$$M(q)\dot{u} = f(q,u) + g(q)T$$

for $\dot{u}$ (forward dynamics) and T (inverse dynamics), where q is the vector of generalised coordinates for the joint angles and coordinates of the reference point (sagittal plane only), u is the vector of generalised velocities $\dot{q} = u$, M is the mass distribution, f represents inertial forces and gravity, T takes into account all joint torques and external reaction forces at the feet, and $g(q)$ is a non-linear function representing the current system configuration and geometry.

To be able to calculate the accelerations $\dot{u}$, the external forces and joint torques T that affect the model have to be calculated. The torque in the supported knee joint is calculated by evaluating the EMG signals. All other joint torques and external forces are approximated by computing the inverse dynamics with the current kinematic data for the system. The resulting torques and forces are assumed to be constant for a small time-step and used as the needed values for T during forward dynamics computation (very rough approximation). The body model is simulated for a small time-step of $\Delta t = 20$ ms, and the resulting knee angle is passed to the low-level loop and converted into encoder ticks of the actuator to allow position control. Owing to the amount of computation, the high-level loop runs at 100 Hz, whereas the low-level loop runs at 1 kHz.

If a greater number of actuated joints are added, the overall model complexity is similar: inverse dynamics computation for this joint is no longer needed, but the EMG signals from additional muscles have to be evaluated and the corresponding elements of $\dot{u}$ have to be computed and integrated for the controller.

Direct force control

The DFC method does not use a dynamic model. As in the previous approach, the resulting knee torque from the muscle activation T_{knee} is calculated in the high-level control loop from the EMG signals. This can be interpreted as the torque contribution of the operator to the motion. The supporting torque T_{supp} is calculated by multiplying T_{knee} by the amplification factor S_{ampl}, which can be chosen according to the support required (the upper boundary of S_{ampl} has to be determined experimentally). T_{supp} forms the target value for the low-level loop (Figure 4).

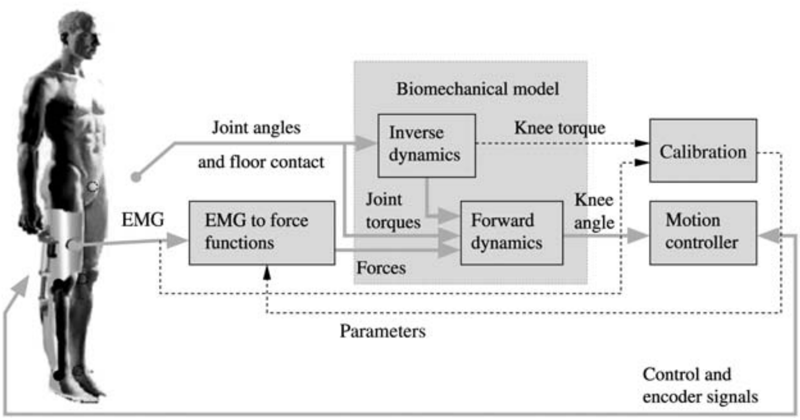

Figure 3 Orthosis and the dynamic body model system.

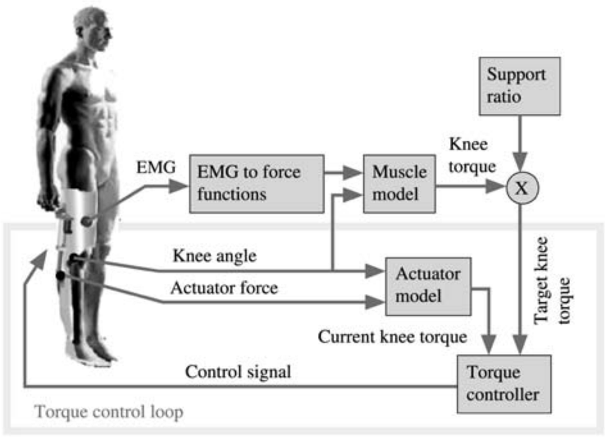

Figure 4 Orthosis with the operator and the direct force control system.

The error input of the P controller is calculated according to:

$E = T_{\text{supp}} - T_{\text{actuator}}.$

Both loops run at a frequency of 1 kHz.

The complexity increases linearly with the integration of additional joints.

EMG parameter calibration

In both approaches, the parameters A_n and $f_{n,\max}$ of $F_n(t)$ need to be determined. Unfortunately, the relationship between muscle activation and the EMG signal depends on many different factors, such as electrode placement, muscle size, moisture on skin, etc. These parameters have to be calibrated at the beginning of every experimental session. The calibration is performed using isometric contractions of the knee flexor and extensor muscles without floor contact for the rectus femoris and semitendinosus muscles. Currently, the vastus lateralis muscle is not optimised automatically.

The idea of the calibration algorithm is to store the EMG and force values in tables. Each muscle has an associated table and every entry of the table contains the activations of all recorded muscles and the force value from the same point in time. The table entry where the values are stored is selected by a linear function that maps the activation of the muscle to which the table belongs to an entry index. This ensures that for the following optimisation process data with many different levels of activation are used without letting the amount grow unreasonably high or weighting certain activations stronger because of longer durations. The error function of the optimisation process calculates the sum of the squared differences between T_{knee} and T_{actuator} for all entries. The optimisation yields values for A_n and $f_{n,\max}$ (the parameters are bounded, and sub-space searching is possible).

Experimental results

The experiment presented here is a typical example from a series and consists of climbing a single step with two different levels of support in which the supported leg initiates the motion. The experiment was performed with a healthy person and the DFC method. Figure 5 shows the knee angle, together with the torque computed from the EMG signals and the torque produced by the actuator. The leg is straight at an angle of 0°, and negative angles indicate knee flexion. The upper diagram shows the motion without support (the supporting torque is almost zero during the motion, the orthosis is "evading" the leg), and the lower diagram shows motion with support of 1.0: the actuator torque contribution follows the torque produced by the muscles. As expected, the knee torque derived from the EMG signals is significantly lower compared to the trial without support. At $t = 3.8$ s, an overshoot can be observed: the operator was activating his muscles as usual, but when the feedback of the actuator support was recognised, muscle activation was immediately reduced. This results in a dent in the angle trajectory after $t = 4.1$ s. At $t = 4.3$ s, the operator increases muscle activation again to finish the motion with a second small overshoot.

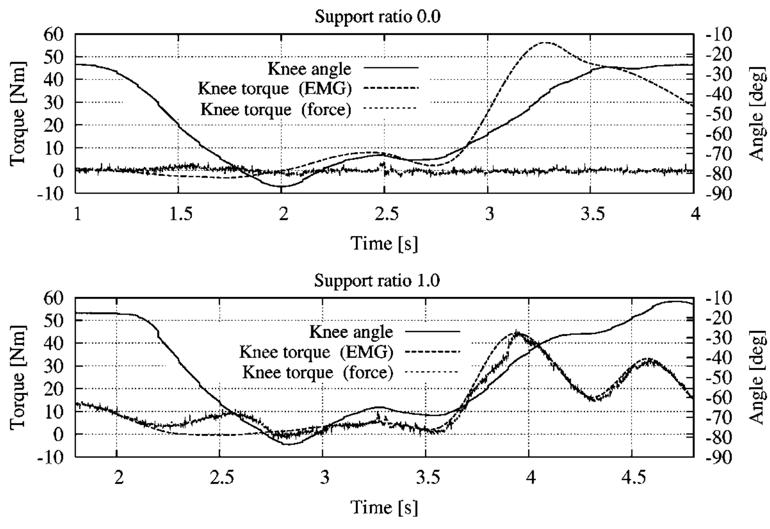

Figure 5 Knee angle and torques during the experiment with a support of 0.0 (top) and 1.0 (bottom).

The actuator support is documented by the force that is added to the system, resulting in decreased muscle activation over the whole motion compared to the unsupported motion, as can be seen in Figure 5.

Discussion

Both of the above-mentioned algorithms can be used to control an exoskeleton, but there are differences in application, as well as in the ease of use.

The DHBM approach is more complex in terms of the calculations necessary. To obtain a solution to the inverse dynamic calculation that represents muscle activation or influences by external contact forces, all sensor data have to be accurate and consistent. Only during experiments in which the supported leg had no contact with the environment was this possible. During experiments involving climbing a step, inconsistent sensor readings lead to partially incorrect target motions. On the other hand, this algorithm calculates the trajectory of the human body, and allows integration of algorithms to maintain stability based on solving dynamic equations with motion constraints. It is also possible to predict the intended motion as if the orthosis is not attached to the subject by disregarding it during forward dynamics computation.

The DFC method is more robust because the influence of all properties such as inertia, joint velocity, and unmeasured muscle activations, as well as all external contact forces, are implicitly taken into account by the force sensor, regardless of where they act on the operator or the orthosis. The force sensor acts as a substitution for the body model. The computation is not performed by simulation, but by measuring the resulting behaviour of the body parts in reality. No data between sensors can be inconsistent. Integration of algorithms solving postural stability issues is not possible, since no constraint equations can be solved without introducing a dynamic model again.

Interestingly, although calibration of the muscle parameters and the muscle model is very simple, support of the motion is possible.

Although the exact amplification factor of the operator's muscle force is unknown (because the calibration uses only a few representative muscles from different groups), significant support can be achieved. The absolute torque support can be read from the force sensor. An important aspect is that the trajectory of the knee angle was similar in both trials, showing that the operator was able to adapt to the support. Currently we have no objective criterion for evaluating the quality of the support.

The main focus now is on improving the DFC method in terms of the interaction between the operator and the orthosis to smooth the executed motion and minimise undesired overshoots.

Exoskeleton for the hand

The hand exoskeleton was designed to support rehabilitation and diagnostics after hand surgery or stroke. The following motions are supported in each finger: flexion and extension of the metacarpophalangeal (MCP), proximal interphalangeal (PIP) and distal interphalangeal (DIP) muscles, and abduction/adduction in MCP joints. The thumb is currently not actuated. The palm is free of mechanical elements to allow interaction with the environment. The fingers are moved by a construction of levers actuated through pull cables guided by flexible sheaths (Figure 2). Pulleys at the levers allow bidirectional movement.

Finger joint angles are measured by Hall sensors integrated into the mechanical construction. Angles of the axes at the motor units measured by optical encoders correspond to the angles measured by the Hall sensors. Because of varying tension in the connecting cables, both values for joint angles deviate. Force sensors integrated between the levers and finger attachments measure forces during flexion and extension at the finger joints. Surface EMG electrodes (Delsys 2.3) measure muscle activity at eight points on the forearm.

Control methods

Currently the hand exoskeleton supports two control modes based on joint angle and force sensor values. EMG sensors can be used for diagnosis, but are not used for control yet.

The first control mode allows trajectories determined by the supervisor (e.g., physiotherapist or physician) to be followed. This allows reliable repetition of exercises with high accuracy. Force and EMG sensor readings allow the progress of rehabilitation to be assessed.

The second control mode uses force sensors to determine the motion of the exoskeleton. The force sensor readings are used to calculate a motion using an open-loop admittance control scheme. The exoskeleton can thus follow the motions of the hand. This control mode is needed to teach new motions and is useful for diagnostic purposes.

However, as mentioned earlier, the force sensors cannot distinguish between internal and external contact forces. Therefore, they are insufficient to measure the subject's motion intention during contact with the environment (e.g., grasping), which is common during rehabilitation. Integrating a greater number of force sensors to distinguish between internal and external forces is not practical for the hand exoskeleton owing to the constricted space.

EMG for control of hand motions

Similar to the leg exoskeleton, EMG sensor data can be used to control the hand exoskeleton without measuring all contact forces. However, there are several difficulties in application of the algorithms.

The first problem is that not all muscles responsible for hand motion can be measured by surface EMG sensors. Thus, only a subset of the muscles responsible for finger and hand movement is sampled by surface electrodes. Therefore, it is not possible to use EMG signals alone to control arbitrary motions in all supported degrees of freedom.

The second problem is that, owing to the high density of different muscles in the forearm, EMG signal separation is particularly relevant. For later application, the signals have to be processed to recover the underlying original signals. As described by Farina et al. [9], blind source separation can be used to solve this problem. After separation, the signals can be used for control purposes. Physicians can also use the recovered muscle signals in concert with the motion and force data for diagnosis.

Another idea is to use EMG signals to recognise the user's intention for a specific gesture (e.g., grasping an object, pointing at something). EMG-controlled prostheses that do this are commercially available. However, these devices often evaluate muscles that are not naturally used for controlled movement, as the original muscles are no longer fully functional. These devices require some training of the patients. Zecca et al. described the control of multifunctional prosthetic hands by EMG signals [10].

However, the exoskeleton is intended for use during rehabilitation of patients where muscle signals may be available. Therefore, muscles that are responsible for controlled movements will be used to control the hand exoskeleton. Several groups used this approach to control other devices, such as hand prostheses and robotic hands [11]. Benjuya and Kenney reported on a simple hand orthosis with one degree of freedom controlled by EMG signals [12].

The hand exoskeleton presented here will be used to extend existing work on EMG motion control to more complex movements. For application of the direct-force control method presented in the Control methods section, several modifications are necessary. The first step is blind source separation of the measured muscle signals. Second, force contributions of muscles that are not measured by EMG sensors have to be estimated. One method is to derive these from measured muscle signals by assuming a specific gesture that can be identified by pattern recognition. After these steps, the DFC or DHBM method can be used to control the resulting motion. Further research needs to identify which of the two methods is superior for the hand exoskeleton because of multiarticular muscles.

Conclusion

The application of EMG signals for controlling exoskeleton robots was demonstrated for the leg exoskeleton. The application of EMG signals can improve control schemes for exoskeleton robots based on force sensor measurements. This was shown with experimental results presented for the leg exoskeleton. For this system, different control schemes were described. An interesting fact is that even simple control schemes based on EMG signals without complicated dynamic models provide remarkable performance. In addition to the advantages for motion control, integration of EMG sensors into exoskeleton robots opens interesting new applications in rehabilitation and diagnostics.

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