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An EMG-position controlled system for an active ankle-foot prosthesis: An initial experimental study

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Abstract—**Although below-knee prostheses have been commercially available for some time, today's devices are completely passive, and consequently, their mechanical properties remain fixed with walking speed and terrain. To improve the current performance of below-knee prostheses, we study the feasibility of using the amputee's residual limb EMG signals to control the ankle position of an active ankle-foot prosthesis. We propose two control schemes to predict the amputee's intended ankle position: a neural network approach and a muscle model approach. We test these approaches using EMG data measured from an amputee for several target ankle movement patterns. We find that both controllers demonstrate the ability to predict desired ankle movement patterns qualitatively. In the current implementation, the biomimetic EMG-controller demonstrates a smoother and more natural movement pattern than that demonstrated by the neural network approach, suggesting that a biologically-motivated, model-based approach may offer certain advantages in the control of active ankle prostheses.**

I. Introduction

Although the potential benefit of powered prostheses for both upper and lower extremity amputees has been well documented, most of the research and commercial activity has focused on active upper limb devices [1]-[4]. Today, commercially available ankle-foot prostheses are completely passive, and consequently, their mechanical properties remain fixed with walking speed and terrain [5]. In distinction, normal human ankle stiffness varies within each gait cycle and also with walking speed [6][7]. Furthermore, some studies have indicated that one of the main functions of the human ankle is to provide adequate energy for forward progression of the body [6]-[8]. Not surprisingly, below-knee amputees that use passive ankle-foot prostheses exhibit non-symmetric gait patterns and higher metabolic ambulatory rates [5]. Thus, in order to mimic the behaviour of the human ankle and to increase gait symmetry and walking economy, a prosthetic ankle-foot device should be able to actively control joint impedance, motive power, and joint position.

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When developing an active ankle-foot prosthesis, a key challenge that needs to be addressed is how to measure and respond to the amputee's movement intent. For some time, researchers have attempted to use electromyographic (EMG) signals measured from the residual limb as control commands for an external prosthesis [9]-[13]. However, most of these systems only provide discrete or binary levels of motion control whereas daily activities require a continuous limb movement control.

The main difficulty with using EMG signals as the continuous control command for prostheses is the non-linear and non-stationary characteristics of EMG sensory information [10]. Some researchers have applied neural networks to solve this problem because such networks can acquire nonlinear mappings of data [10]-[12]. However, when using such an approach, it is not clear whether the prosthesis will behave in a manner comparable to a natural human limb. For these reasons, some researchers have developed EMG-controllers for prostheses and exoskeletons, based on neuromuscular control models of human limbs [13]-[15]. Researchers have argued that this class of controller could allow the amputee to experience a more subconscious control over the prosthetic limb, and consequently, the amputee might require a much shorter time period to learn how to operate the prosthesis compared with a control model that does not explicitly model biological limb dynamics.

In this paper, we propose two EMG-controllers for an active ankle-foot prosthesis: a biomimetic muscle model approach and a neural network approach. We specifically address the problem of position control of an active prosthetic ankle joint. Active ankle position control is one of the most basic functionalities of the human ankle. It allows for foot clearance during the swing phase and maintains proper landing of the foot during foot-strike [16]. We evaluate and compare the performance of these two approaches based on EMG signals measured from an amputee for various target ankle movement patterns. We anticipate that the biomimetic EMG-controller will demonstrate a smoother and more natural movement pattern as compared to the neural network approach. Experimental data are used to train each model, and then using an independent data set, model predictions are compared with desired ankle movement patterns.

II. EMG CONTROLLER DESIGN

In this study, the purpose of the EMG-controller was to estimate the intended ankle movement of an amputee according to measured EMG signals. In the following section, we propose two EMG-controllers that are based on biomimetic and neural network approaches. With these controllers, the prosthesis predicts the amputee's movement intent, or the desired ankle trajectory, based on EMG signals measured from the residual limb.

A. Biomimetic EMG-controller

A biomimetic EMG-controller is a controller that obtains the estimation of the amputee's motion intent by simulating the dynamics of the missing limb's neuromuscular system [10]. In this study, we formulated a neuromuscular model that describes the human ankle joint. The model is shown in Figure 1. To simplify the model, we focused only on the dynamics of the ankle joint for sagittal plane movements, since in normal walking, the majority of ankle movement occurs in that plane. We modelled the human ankle as a revolute joint with one degree of freedom. The foot was modelled as a rectangular box of mass m and length l, attached to the shank (fixed) through the revolute joint.

In Fig. 1, muscles A1 and A2 represent effective plantar flexor and dorsiflexor muscles, respectively. For simplicity, these muscles attach to the foot at fixed moment arm r. Since the knee was held in a fully extended posture during experimentation, and the Gastrocnemius and Soleus were activated at the same time (section *Experimental Setup,* Fig. 5), we modelled the Gastrocnemius and Soleus as one effective muscle. Since there are many ligaments, tendons and tissues that act about the human ankle, we included passive damping and stiffness in the model. The general dynamic model for the human ankle is described in Equation (1), and the corresponding notations are listed in Table 1.

$$I\ddot{\theta} = r(F_d - F_p) - B\dot{\theta} - K\theta \qquad (1)$$

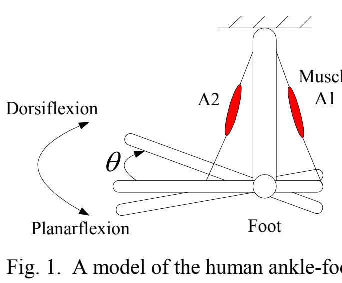

Fig. 1. A model of the human ankle-foot system.

From the literature, it has been stated that ankle joint stiffness dynamically changes throughout each gait cycle [6]. To capture this essential behaviour, a bilinear muscle model was used in which the slope of the muscle force-length curve varied proportionally with activation level. It is also noted that when transitioning from terminal stance to swing, ankle rotational velocity is sufficiently large in walking. In the model's development, it was therefore decided that muscle force-velocity behaviour should not be ignored. In the bilinear muscle model, the force-velocity characteristic was considered as linearly dependent on activation level.

The bilinear muscle model is defined as:

$$F^b = (k_o + k\alpha)(x_{eq} - c\alpha - x) - (b_o + b\alpha)\dot{x} \qquad (2)$$

where

x_{eq} = Isometric muscle length

α = Activation level

x = Actual muscle trajectory

k, k_o = Muscle stiffness factor and offset, respectively

b, b_o = Muscle damping factor and offset, respectively

F^b = Muscle force.

Using the bilinear muscle model, the overall dynamics of the ankle model are:

$$F_d^{\,b} = (k_{od} + k_d\alpha_d)(x_{d,eq} - c_d\alpha_d - x_d) - (b_{od} + b_d\alpha_d)\dot{x}_d \qquad (3)$$

$$F_p^{\,b} = (k_{op} + k_p\alpha_p)(x_{p,eq} - c_p\alpha_p - x_p) - (b_{op} + b_p\alpha_p)\dot{x}_p \qquad (4)$$

$$I\ddot{\theta} = r(F_d^{\,b} - F_p^{\,b}) - B\dot{\theta} - K\theta \qquad (5)$$

Variable definitions are listed in Table 1.

Since muscle parameters have been shown to vary from person to person, it was necessary to set model parameters on the basis of experimental data collected from the amputee subject. Given EMG signals and the corresponding desired ankle-foot trajectory, we estimated the parameter values using the Matlab Optimization Toolbox.

TABLE 1 SUMMARY OF NOTATION

Variables	Definitions
$\theta, \dot{\theta}, \ddot{\theta}$	Angular position, velocity, and acceleration of the human ankle, respectively. Joint position is zero when the foot is perpendicular to the shank.
F_p, F_d	Muscle forces generated by the effective plantar flexor and dorsiflexor, respectively.
$x_d, \dot{x}_d$	Muscle length and contraction velocity for the effective dorsiflexor, respectively.
$x_p, \dot{x}_p$	Muscle length and contraction velocity for the effective plantar flexor, respectively.
α_p, α_d	Muscle activation level for the effective plantar flexor and dorsiflexor, respectively.
r	Moment arm about the ankle joint.
B, K	Stiffness and damping factors for the ankle joint, respectively (due to the passive tissues around the ankle).
k_d, k_{od}	Muscle stiffness factor and offset for the effective dorsiflexor, respectively.
k_p, k_{op}	Muscle stiffness factor and offset for the effective plantar flexor, respectively.
b_d, b_{od}	Muscle damping factor and offset for the effective dorsiflexor, respectively.
b_p, b_{op}	Muscle damping factor and offset for the effective plantar flexor, respectively.
$x_{d,eq}, x_{p,eq}$	Isometric muscle lengths for the effective dorsiflexor and plantar flexor, respectively.

B. Neural Network EMG- Controller

A standard multi-layer, feedforward neural network was adopted in this controller. The structure of the network was 20-30-1 and was determined experimentally. The transfer function used in the input layer was a hyperbolic tangent sigmoid function while linear transfer functions were applied in both the hidden and output layers. The network was trained using a standard back-propagation algorithm. The inputs and output of the network were pre-processed EMG signals from the residual muscles and the estimated ankle position, respectively.

III. Experiment and Discussion

A. Experimental Setup

To obtain the input-output training data for the EMG controllers, we developed an ankle-foot training platform to allow an amputee to learn how to control an active prosthetic ankle using residual limb muscle activity. Here a training platform was used to communicate desired ankle positions and stiffnesses to the amputee. Fig. 3 and Fig. 4 depict the experimental setup and the ankle-foot graphical display of the EMG training platform. EMG signals were measured and sampled at 1080Hz through the DAC (PC-CARD-DAS16/16-AO) to a laptop computer. The graphical display and the rest of the software were developed using the Virtual Reality Toolbox and the Realtime Window Target of Matlab.

During the experiment, the amputee subject controlled the residual muscles, which previously actuated his ankle, to mimic pre-programmed motion trajectories of the graphical display. Here we assumed that the amputee's intended ankle-foot trajectory coincided with the desired ankle-foot trajectory defined by the graphical display.

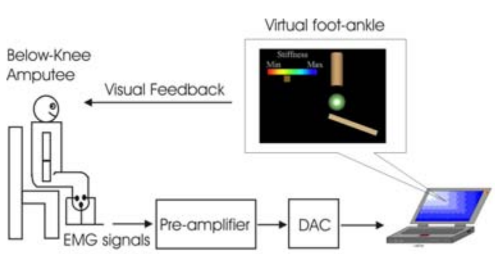

Fig. 3. The experimental setup.

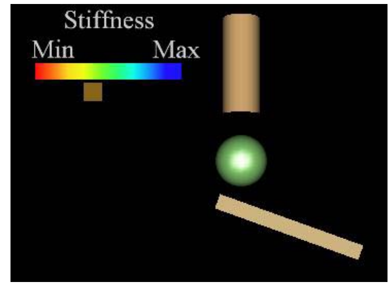

Fig. 4. The graphical display of the ankle-foot training platform. In the display, the green sphere and lower rectangle represent the human ankle and foot, respectively. The colour bar communicates desired ankle stiffness. During the experiment, the foot moves to communicate desired ankle-foot movement patterns to the amputee.

B. EMG Signal Processing

Since the goal of this investigation was to develop an EMG-controlled, ankle-foot prosthesis that mimics natural human ankle movements, it was desirable to measure EMG signals from those residual limb muscles that previously actuated the biological ankle before amputation. Thus, using fine wire electrodes (Motion Lab Systems, Inc), we recorded from the Gastrocnemius and Soleus muscles for prosthetic ankle plantar flexion control, and from the Tibialis Anterior for prosthetic ankle dorsiflexion control. Signals were amplified and sampled at 1080 Hz.

We pre-processed the raw EMG signals before their use as control commands. The raw EMG data were rectified, low-passed filtered, and normalized with respect to the maximum voluntary contraction (MVC) level of the amputee [10]. A 7^{th} order Butterworth low-pass filter with a cut-off frequency of 5 Hz was adopted. After normalization, the pre-processed EMG signals were within the range of [0,1], where a value of 1 represented the maximal voluntary muscle activation. Fig. 5 shows the pre-processed EMG signals measured from the residual muscles when the amputee tracked a sequence of consecutive plantar flexion (negative angle) and dorsiflexion (positive angle) movement patterns depicted by the graphical display. As expected, the Gastrocnemius and Soleus EMG signals were active during plantar flexion, while the Tibialis Anterior EMG signal was active during dorsiflexion. It is noted here that since the knee was held in a fully extended posture, both the Gastrocnemius and Soleus muscles were active, but the mean amplitude of EMG signal from the Gastrocnemius was much larger than that from the Soleus.

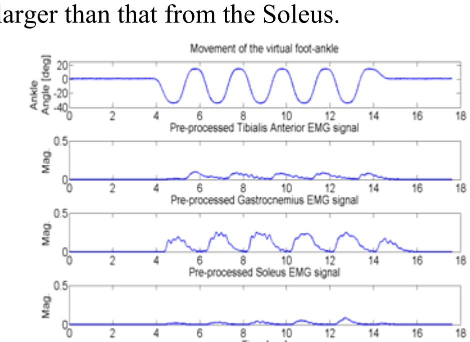

Fig. 5. Preprocessed EMG signals from the amputee's residual limb.

C. Results

We conducted a series of experiments with the ankle-foot training platform on a below-knee amputee. In these experiments, the preprogrammed motion trajectories of the graphically depicted ankle-foot comprised a sequence of plantar flexion movements (step response), sinusoidal movements of various frequencies, and random movements. Using the recorded data, we constructed the biomimetic and neural network EMG-controllers for the amputee.

Based on these offline-EMG data, we evaluated the controllers. Fig. 6 shows model predictions for a sequence of plantar flexion movements at 0.5Hz. Both controllers demonstrated the ability to predict ankle movement qualitatively as their predicted trajectories have a similar profile compared with the desired trajectories from the graphical display. Fig. 7 shows the ankle joint trajectory of a healthy subject following the same desired ankle-foot movement patterns depicted from the graphical display.

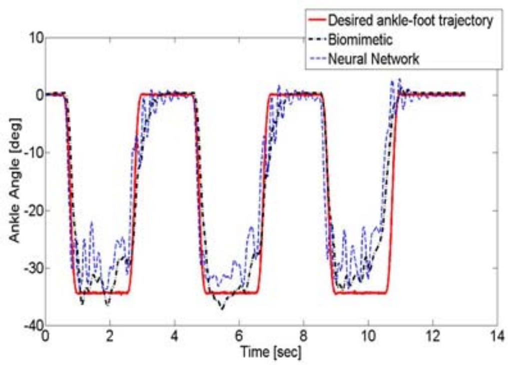

Fig. 6. Prediction of ankle joint position.

The biomimetic EMG controller appeared to generate a smoother, more natural ankle movement pattern than the neural network EMG-controller. Using frequency analyses on ankle trajectories, we found that the average frequency for normal human ankle movements was 4.5Hz ± 0.5Hz similar to that found for the bilinear controller output trajectory, or 5.4 ± 0.2Hz. Conversely, the average frequency for the neural network controller was one-fold greater, or 10.5 ± 0.5Hz. Thus, the trajectories generated by the biomimetic controller were found to be smoother than those trajectories generated by the neural network controller. This apparent difference between the controllers was perhaps due to the fact that the integrators in the biomimetic controller were acting as low-pass filters to smooth the corresponding ankle trajectory estimate.

A key assumption in this investigation was that the amputee's intended ankle-foot trajectory should closely coincide with the graphically-depicted ankle-foot trajectory (Fig. 4). However, based on the control experiment with the normal subject, we found that even a healthy biological ankle-foot could not accurately follow the desired ankle-foot movement patterns from the display (Fig. 7). To alleviate this problem, in future investigations human ankle kinematic data will be graphically displayed as desired ankle trajectories. In addition, in this investigation we did not address the problem of temporal variations in EMG patterns due to muscle fatigue or other factors. These issues suggest a need for real-time learning algorithms for EMG-based controllers that compensate for variations in muscle response.

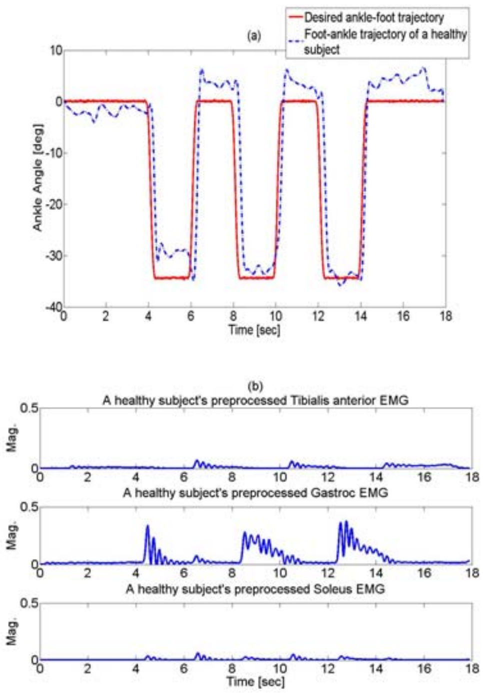

Fig. 7. A healthy subject follows the desired ankle-foot movement: (a) actual ankle trajectory vs. desired ankle-foot trajectory, and (b) EMG signals.

IV. Conclusion

In this investigation, we evaluate both biomimetic and neural network control approaches for predicting ankle movement intent from EMG information measured from the residual limb of an amputee. We find that both controllers demonstrate the ability to predict desired ankle movement patterns qualitatively. In the current implementation, the biomimetic EMG-controller demonstrates a smoother and more natural movement pattern compared with the neural network approach, suggesting that a biologically-motivated, model-based approach may offer certain advantages in the control of active ankle prostheses. In future studies, we plan to develop real-time learning algorithms for EMG controllers where the system adapts to variations in EMG temporal patterns. In addition, EMG controllers that employ vibro-tactile afferent feedback to the amputee will be investigated.

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