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„Finding Best Predictors for the Control of Transfemoral Prostheses“

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Finding Best Predictors for the Control of Transfemoral Prostheses

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Introduction

Various actuated transfemoral prostheses have been developed to restore walking after above-knee amputation. Big challenges when developing actuated prostheses are the user interface and the control of the device. Most approaches adjust the behavior of the prosthesis depending on the estimated gait phase. However, it has been shown in a clinical study with the commercial C-Leg prosthesis, which also uses gait-phase dependent control, that highly active patients feel controlled by the behavior of their prosthesis [1]. Our recently developed approach called *Complementary Limb Motion Estimation* does not try to estimate gait phases, but instantaneously generates the motion of the missing limb based on residual body motion. The aim is to allow a more direct control by the user. In a pilot study, an above-knee amputee was able to walk on a treadmill, as well as to ascend and descend stairs [2]. The knee joint was position-controlled, with the reference knee position continuously generated by a linear combination of hip- and knee angles and angular velocities of the healthy leg, thereby creating a virtual coupling between the healthy leg and the prosthesis. The coupling parameters were obtained by statistical regression on data of healthy subjects.

A major disadvantage of stiff position control of a transfemoral prosthesis is that interaction with the environment is ignored; when the prosthesis hits the ground, the knee joint does not absorb the impact, in contrast to what muscles around a physiological human knee do. A force or impedance control scheme could resolve this issue. While still using residual body motion to control the prosthesis with such a scheme, two problems need to be solved: identifying the appropriate force or impedance parameters, and finding suitable signals in residual body motion to predict those parameters. The second question can be tackled in parallel to the first, because muscle activity indirectly encodes impedance [3] and can be used as a preliminary output of the prediction. In this paper, we investigate which kinematic variables of the residual body could serve as predictors for such a control scheme. This is done by looking at data from healthy subjects, where kinematic variables are considered as predictors (inputs), and EMG of a thigh muscle is considered as the output (Figure 1). The statistical method we use selects the inputs which are most important to predict the output [4].

Materials and Methods

From measurements of five subjects (two female, three male) obtained in a standard gait lab (optical tracking system, EMG, ground reaction forces), we select five full gait cycles (from right heel strike to right heel strike) where all optical markers are available during the full cycle. Due to its important contribution to the knee torque during gait, EMG of the right vastus medialis is considered the representative output to be estimated, and 16 marker positions on the residual body (i.e. excluding the right leg) are taken as candidate predictors (Figure 1). For the sake of completeness, markers from the arms are also considered, even though it would be very undesirable for an amputee to depend on the arm movement for control of the prosthesis. Each marker provides three Cartesian world coordinates,

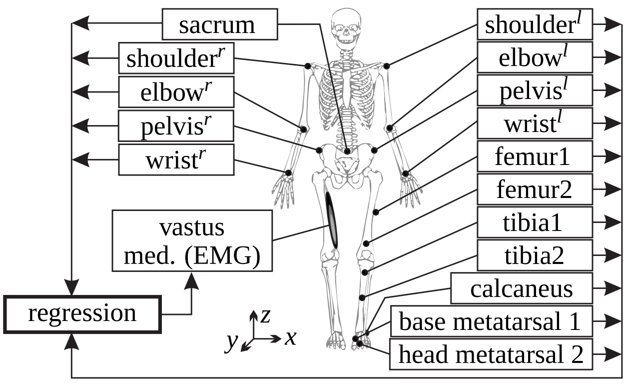

Figure 1: Regression scheme and input/output signals.

which yields 48 input signals in total. These coordinates are transformed into a body coordinate system by subtracting the signals from the marker positioned at the sacrum. The coordinates of the sacrum remain in world coordinates. In order to reduce inter-subject variability, the signals are normalized for each subject by subtracting the mean value and dividing by the standard deviation of the respective signal. The raw EMG signal (sampled at 2 kHz after applying an analog anti-aliasing filter) is digitally filtered with a third-order Butterworth bandpass between 10 Hz and 500 Hz, and it is full-wave rectified. It is divided by the mean EMG value $\overline{\mathrm{EMG}}$ over all five gait cycles of the respective subject. This normalization method has been shown to reduce inter-subject variability [5].

In order to determine which input signals are the best predictors for the output signal, an iterative algorithm is used

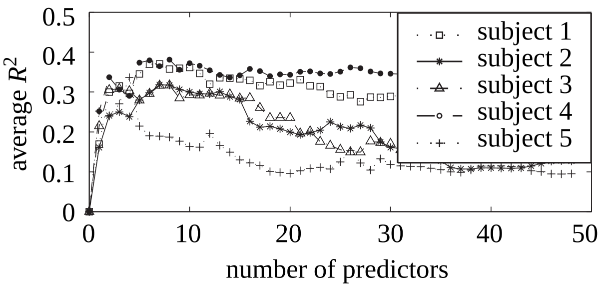

Figure 2: Correlation coefficient (R^2) for a given number of predictors, averaged over 5 gait cycles.

which computes the unique contribution from each input to the output, and the input with the smallest contribution is eliminated at each iteration. This yields a ranking of each signal, with the most important signal remaining until the last iteration. The algorithm is described in detail by Westwick et al. [4]. We run the algorithm on a leave-one-out basis, obtaining five combinations: In each combination, one of the subjects serves as validation subject, and the data from the other four subjects is used to compute the best predictors. We refer to one such set as a *validation set*.

Once the input signals are sorted according to the ranking, we successively apply the regression to the remaining subject for validation, with subgroups of 1-48 input signals.

Results

Reconstruction accuracy obtained from cross-validation (in terms of R^2) already reaches a local maximum for three predictors (Figure 2). The ranking of the most important predictors differs for the different validation sets (Table 1). The reconstructed EMG signal qualitatively matches the measured signal using only three predictors (Figure 3).

Table 1: Best predictors for different selection data sets (detailed marker positions see Figure 1).

Rank	Set 1	Set 2	Set 3	Set 4	Set 5
1	tibia1_y	metata.2_y	metata.2_y	calcaneus$_y$	femur1_y
2	tibia2_z	tibia1_z	tibia2_z	sacrum$_z$	femur1_z
3	tibia1_x	calcaneus$_z$	shoulder^l_x	tibia1_x	metata.2_y

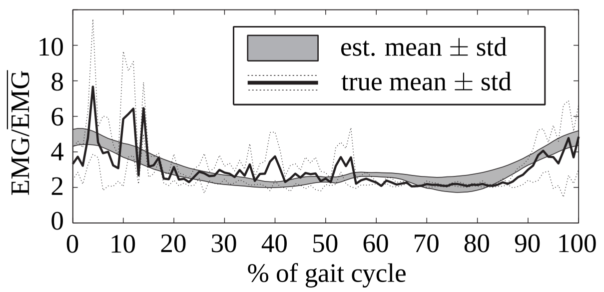

Figure 3: Measured (true) and predicted (est.) EMG signal for subject 2, which had the lowest R^2 value when using 3 predictors. Mean and std. dev. of 5 gait cycles are shown.

Discussion

Even though the most important predictors found for each validation set differ, the reconstruction accuracy is similar and a qualitatively good estimate of the output signal can be achieved with very few inputs. This indicates that the best predictors in different sets are highly correlated and equally suited for all five subjects.

We currently filter the EMGs only mildly (bandpass between 10 Hz and 500 Hz); while filtering with a moving average of 100 ms greatly increases the value of R^2, it does not influence the estimated output considerably. However, we noticed that normalization of input signals and output signal had a strong impact on the resulting estimate. We normalize the signals from the validation subjects with their own mean and standard deviation; when these predictors are later to be used to control a prosthesis, these two parameters have to be adjusted for each predictor.

Conclusion

In this paper, we show that the EMG signal of the vastus medialis muscle can be qualitatively reconstructed by using as few as three predictors from a pool of kinematic input signals. The results suggest that a similar reconstruction accuracy can be achieved for a range of different inputs. Should that prove to be true in future work, selection of inputs could be continued based on more practical factors, for example the reliability of real sensors for the specific kinematic signals.

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