COMPUTER-AIDED PROSTHETIC ALIGNMENT FOR LOWER-LIMB AMPUTEES

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Abstract: For a below-knee amputee using an artificial limb, proper alignment of the prosthesis is critical for optimal comfort and function. In this research, a layered perceptron artificial neural network was trained to use prosthesis force data to recognize and correct misalignment. The accuracy of a preliminary network was encouraging though not within clinical precision. Data from a larger patient population will significantly enhance performance.

I. INTRODUCTION

For lower-limb amputees using artificial limbs, proper positioning of the prosthetic foot relative to the socket is critical for restoration of function of the missing extremity. With optimal alignment of the foot and socket, the amputee is comfortable, stable, and energy efficient. Misalignment, however, can cause instability, fatigue, and ultimately tissue damage which may require amputation at a higher anatomical level in severe cases.

Current clinical alignment is a qualitative, costly, and time-consuming process that cannot guarantee optimal alignment. The clinician visually analyzes the patient's gait style to identify 'abnormal' gait characteristics and combines that information with the patient's verbal assessment of fit to establish appropriate modifications. Alignment fitting sessions are lengthy procedures, typically one to two hours, but are critical for the amputee because an incorrect alignment can induce tissue injury causing pain with restricted mobility and function.

Previous laboratory research has demonstrated that parameters associated with prosthetic gait force/time curves are related to the alignment of the prosthesis. Force maxima [1], gait phase durations, and step-to-step repeatability [2] are examples. Though single studies investigating prosthetic alignment relationships to one or two gait features have been conducted, a method for fusing this information into a composite clinical decision for alignment modification is lacking. The objective of this research is to use computational intelligence techniques to predict alignment based on prosthesis force data. The technique will have use as a clinical tool to facilitate the speed and accuracy of alignment and a prosthetics research tool to improve understanding of prosthetic gait.

II. METHODS

Instrumentation: To develop a method for characterization and pattern recognition of gait data, a device is required to measure forces and moments in the prosthesis during ambulation. An aluminum prosthetic shank pylon was instrumented with twenty strain-gages to record all six force and moment components [3]. Single-slit collars, which helped to ensure uniform hoop stress at the connections and minimize crosstalk error, were used to connect the shank to custom-designed inserts fastened to the socket above and the foot below. Signal conditioning instrumentation was contained in a backpack box attached to the instrumented shank pylon with a multi-conductor cable. All data were stored to a data acquisition computer which was connected to the backpack box using a multiconductor cable.

Studies to date: Prosthetic force data were collected on three male unilateral below-knee amputee subjects in concert with interface stress measurements [3]. Subjects walked the length of an 18 meter hallway twelve times, four times at each of three different angular alignment settings: plantarflexion, zero, and dorsiflexion. Zero was optimal alignment as deemed by a team of prosthetists, and plantarflexion and dorsiflexion were angular adjustments from zero. Approximately fifteen steps were collected for each of the three alignment settings for each subject.

Waveform Characterization and Pattern Recognition: The goal is to identify relationships between the force data and the alignment setting. These relationships are nonlinear and nontrivial. Our six-axis force transducer, however, provides abundant experimental data representing that relationship. An artificial neural network (ANN) is appropriate for this problem since there is a need to fit complex functions and learn from examples.

ANN's are nonlinear modeling systems very loosely based on biological networks [e.g. 4,5]. The basic element is a node ('neuron') which computes a scalar output from a simple function of its inputs. Many nodes are connected into a network and communicate their activities to each other via weighted links ('synapses'). In the layered perceptron neural network, nodes are grouped into a series of layers sandwiched between the inputs and the outputs. Error backpropagation, a method of gradient descent on the mean squared output error, is the most commonly-used network training technique. To guard against misleading results due to overfitting, the performance of the network is usually tested on a separate validation set, i.e. data the network did not see during training.

III. RESULTS

Two preliminary networks were tested and gave the results described below. Both were trained by backpropagation. The output in each case is the number of turns of the adjustment screw needed to optimize alignment. The maximal acceptable error, established by practicing clinicians, is 0.25 screw turn. For comparison, a nearest neighbor classifier (on raw data) gives 2.61 screw turns RMS error, which is not within the acceptable limit.

(1) The first neural network was trained on a low resolution representation of the actual waveforms. As illustrated in Figure 1, the 100 samples for each of the 6 measured shank

force vectors were reduced to 5 samples for each variable by averaging over blocks of 20 samples ('section-averaging method'). These were then presented to a network with 30 inputs, two hidden layers of 5 and 6 units, and 1 output. The network was run for both one subject and three subjects. Tables 1 and 2a,b summarize the results.

(2) A second network was trained using prosthetic force waveform features identified by 'experts' (clinicians and bioengineers) of relevance to alignment. Selected features were: (i) the sagittal bending maximum, normalized by subject weight; (ii) the torsion maximum in the second half of stance phase, normalized by weight and limb length; and (iii) the ratio of the axial force minimum trough over the axial force first peak. A scatter plot of feature (iii) is shown in Figure 2. The data shows a correlation with the alignment, however there is considerable noise and subject dependence.

Several network architectures were tested. The architecture used to achieve the results below had 3 inputs, 2 hidden units, and 1 output unit and was trained by backpropagation. Data from only one subject were used. Results for three alignments are shown in Table 2a,b.

IV. DISCUSSION

For both networks, the fact that test error was much larger than the training error indicates a need for more data or that the network has too many degrees of freedom. Too many degrees of freedom can cause the network to classify each of the three alignments rather than to form a regression. Thus data for more alignment settings are also needed.

For the waveform-sectioning network, results are better for a single subject than for all three subjects. This indicates large subject--to-subject variability and a need for data from more subjects to normalize out the walker dependence.

TABLE 1: Screw-turn root mean square error from section-averaging method.

	E_{train}	E_{test}
single subject	0.074	0.712
three subjects	0.65	1.24

TABLE 2: Scre-turn root mean square error for a single subject for both section-averaging method and feature method.

(a) Training Set

	from section-averaged data		from feature data	
target alig	mean	std	mean	std
8	7.999	0.033	7.972	0.159
0	0.007	0.082	-0.043	0.575
-5	-4.966	0.095	-4.936	0.523
	E_{train} = 0.074		E_{train} = 0.420	

(b) Test Set

	from section-averaged data		from feature data	
target alig	mean	std	mean	std
8	7.990	0.058	7.879	0.155
0	0.224	0.775	-1.030	1.371
-5	-4.558	0.833	-5.516	0.281
	E_{test} = 0.712		E_{test} = 1.02	

V. CONCLUSION

From a limited patient database, we were able to generate results nearly commensurate with that required for clinical accuracy. It is expected that finer grain training data from a larger patient population will significantly enhance the performance of the system.

REFERENCES

[1] Jones D and Paul JP: *Prosth Orthot Int* 2:161-166, 1978

[2] Pinzur MS: *7th World Congress ISPO* 371, 1992

[3] Sanders JE: PhD Thesis, University of Washington, 1991

[4] Eberhardt RC, Dobbins RW: *Neural Network PC Tools: a Practical Guide*, Academic Press, 1990

[5] Sanchez-Sinencio E, Lau C (eds): *Artificial Neural Networks*, IEEE Press, 1992

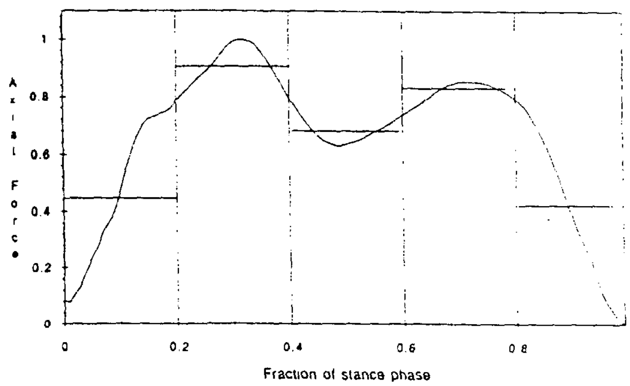

FIGURE 1: For the first neural network, an average value was calculated for each of the five sections.

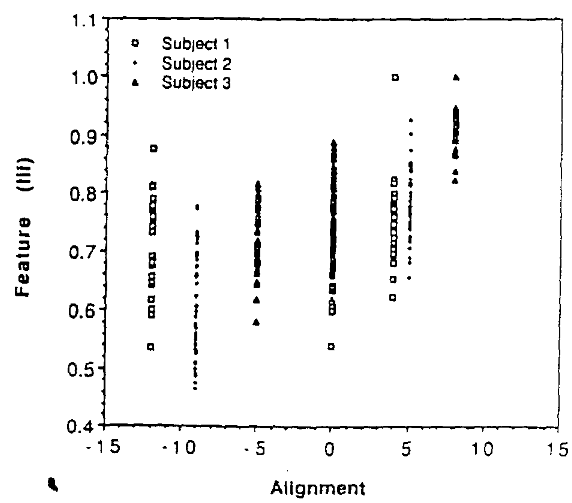

FIGURE 2: Scatter plot results for feature (iii) used by the second neural network.