Neural Network Aided Prosthetic Alignment

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Abstract

Some 43,000 lower-limb amputations are performed in the United States each year. Current procedures for fitting a prosthesis to an amputee are somewhat time-consuming and costly, requiring the subjective judgement of trained prosthetists, but necessary to avoid discomfort and ensure successful rehabilitation of the patient. We consider a neural network model which automatically recognizes certain types of misalignments using data obtained from an instrumented shank. Training procedures and partial results are described.

Introduction

Some 43,000 lower-limb amputations are performed in the United States each year [3] and most patients are fitted with a prosthesis of some kind. For successful rehabilitation, it is necessary that the prosthesis be properly aligned. The current fitting procedure is a rather time-consuming iterative process in which a trained prosthetist observes subtle features of the gait and interprets the subject's comments about the 'feel' of the prosthesis. Automatic detection of at least some forms of misalignment could aid less experienced prosthetists and might allow quicker diagnoses.

This paper describes a neural network model which detects certain types of misalignments from dynamic force and moment data measured in an instrumented shank as the patient walks. Descriptions of the instrumentation and some preliminary results are provided in [5, 6, 4]. This paper describes data processing procedures and the neural network model.

The Data

Six channels of force and moment data are collected from an instrumented shank as the subject walks. Fig. 1 shows data from a typical session. Each row represents one segmented step. Column AX is the axial force, i.e., the vertical compression; SS and SB are the sagittal shear and sagittal bending components; FS and FB are the frontal shear and frontal bending components. The misalignment is the same for all the steps shown.

Five different components of misalignment are considered: anterior–posterior angle (toe–up *vs.* toe–down), anterior–posterior shift (forward–backward shift), medial–lateral angle (sideways tip of the shank), medial–lateral shift (side to side shift), and toe angle (turned in *vs.* turned out). Training data was collected at a series of known misalignments. Compound misalignments involving more than one alignment component at a time were not considered.

Preprocessing consists of extracting the steps from the raw data, discarding the between–stance swing time, and eliminating abnormal steps (due to stumbles, turning, etc.). Steps are resampled to 100 time–points per step to normalize for variability in duration. The result is a 600–dimension vector for each step. For prediction experiments, these are further subsampled by dividing each step into 10 sections and averaging the points in each to give a 60–dimension vector. The 1165 steps were divided into 781 training and 384 test cases.

One might expect that gait distortion increases monotonically with misalignment so a reasonable first test is to check how well a linear approximation fits the data. Table 1 summarizes the results of a minimum mean squared error linear fit. The last line, 'device error', reports the RMS error in the units of adjustment significant to the prosthetist: screw turns for AP and ML angles, cm

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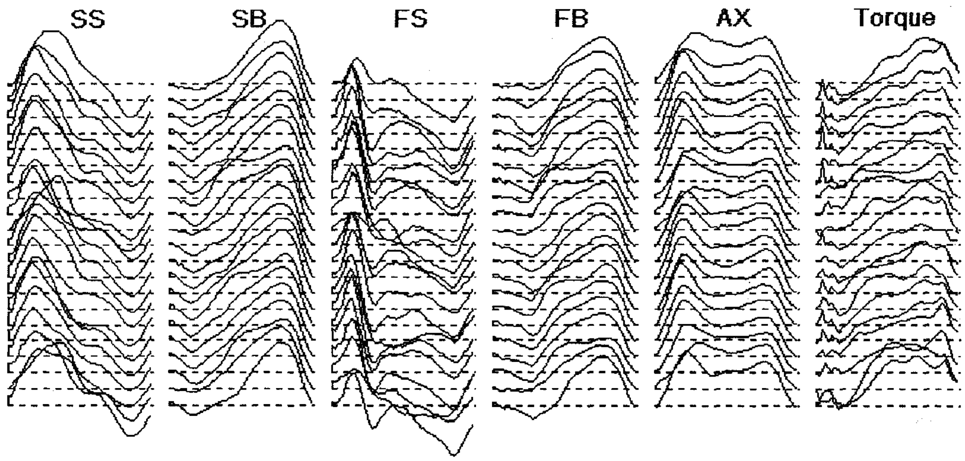

Figure 1: Typical prosthetic data. Six force components are measured by strain gauges in the prosthetic shank as the subject walks. Each row represents one step.

Table 1: Prosthetic misalignment detection, linear fit results

	AP angle	AP shift	ML angle	ML shift	Toe Angle
Training Data					
Target means	-0.0338	0.0093	-0.0039	0.0029	-0.0128
Target std–dev	0.2305	0.2148	0.2239	0.2289	0.1741
RMS error	0.0683	0.1076	0.0694	0.1187	0.0724
Normalized error	0.2963	0.5006	0.3099	0.5186	0.4160
Test Data					
Target means	-0.0317	0.0391	-0.0039	-0.0126	-0.0047
Target std–dev	0.2117	0.2230	0.2393	0.2156	0.1792
RMS error	0.0760	0.1150	0.0746	0.1232	0.0833
Normalized error	0.3589	0.5159	0.3115	0.5716	0.4649
Device error	0.63 turns	0.25 cm	0.37 turns	0.20 cm	1.37 degrees

for AP and ML shifts, and degrees for toe angle. The normalized error is the RMS error divided by the standard deviation of the target value —the error that would be observed if the mean target value were used as the prediction. Although the linear fit explains much of the variation, better results are required. For comparison, practicing clinicians are accurate to within 0.25 screw–turns in the AP component, for example.

Discriminant Analysis Projections

Five neural networks were trained to detect the misalignments (one network per alignment component). Linear discriminant analysis (LDA), e.g. [1], was used to reduce the dimensionality to a manageable level. It has been shown [7, 2] that a *linear* network with a single hidden layer trained with a 1–of–N target representation forms a hidden–layer representation which is similar to a discriminant analysis projection. LDA has dimensionality reduction properties like principal components analysis, but also accounts for class information in forming the projection. Fig. 2 shows a 2–dimensional LDA projection obtained by grouping the AP angle targets into discrete classes. Symbols $A, B, \ldots I$ correspond to AP angle targets of 0.55, 0.36, 0.18, -0.18, -0.36, -0.55, -0.73, -0.85, and -0.91. Symbol '0' represents zero misalignment. (These are scaled val-

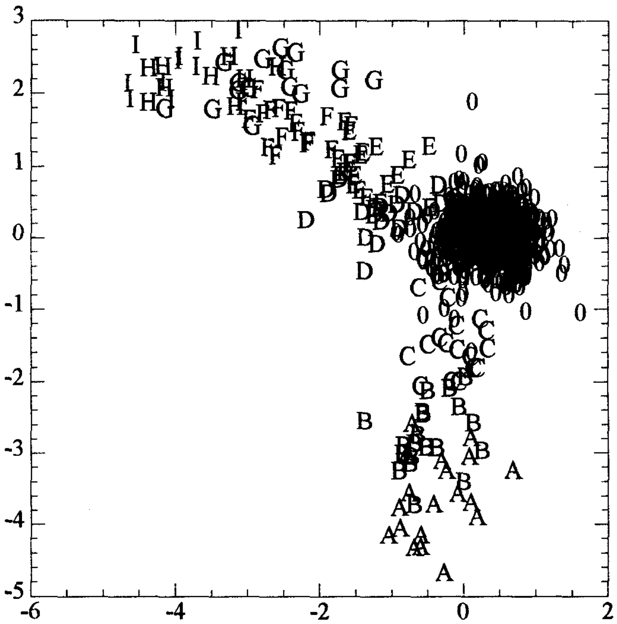

Figure 2: A 2–dimensional discriminant analysis projection of 60–dimensional prosthetic alignment data separates the classes reasonably well. Symbols $A, B, \ldots I$ correspond to AP angle misalignments of 0.55, 0.36, 0.18, -0.18, -0.36, -0.55, -0.73, -0.85, and -0.91. Symbol '0' represents zero misalignment.

ues from the actual adjustment units to the -1,+1 range.) Although there is some overlap of neighboring clusters, they follow a clear trajectory from $A, B, C, 0, D, E, \ldots I$ corresponding to decreasing target values. The trend is almost linear, but positive and negative misalignments are not quite symmetric with each other about zero. (Prosthetists say that positive and negative misalignments have qualitatively different effects on the gait.) 2–dimensional plots for the other misalignment directions also show reasonable grouping of the target classes.

This suggests that the 2–dimensional projection contains enough information to classify the target and that a nonlinear system should be able to improve on the linear approximation results. Table 2 summarizes the results obtained by training five networks (one for each misalignment direction) using 3–dimensional LDA projections as inputs. Each network had 3 inputs, 5 hidden nodes, and 1 output node. An extra benefit of the LDA projection is that the training times are much shorter because of the reduced network size. Test set errors are reduced by about 40% relative to the linear fit. The network is trained to detect misalignment based on data from a single step, but a typical data series consists of about 10 steps with the same misalignment. The last line of the table, 'with averaging', indicates errors can be further reduced by averaging single–step predictions in the same series. These results are within range of the 0.25 screw-turn error accepted by practicing clinicians.

Remarks

These single–subject results are promising, but a useful system must be subject independent. This is a harder problem because of subject–to–subject variabilty due to personality, sex, age, physical condition, extent of injury, stage of rehabilitation, etc. Earlier tests with three subjects suggest that useful results may be obtainable, but this is the subject of continuing work.

The LDA projection is useful preprocessing that greatly reduces the dimensionality of the classification problem and makes the problem presented to the network much simpler. Without

Table 2: Prosthetic misalignment detection, neural network results

	AP angle	AP shift	ML angle	ML shift	Toe Angle
Training Data					
Target means	-0.0338	0.0093	-0.0039	0.0029	-0.0128
Target std–dev	0.2305	0.2148	0.2239	0.2289	0.1741
RMS error	0.0356	0.0673	0.0326	0.0559	0.0297
Normalized error	0.1543	0.3132	0.1458	0.2440	0.1708
Test Data					
Target means	-0.0317	0.0391	-0.0039	-0.0126	-0.0047
Target std-dev	0.2117	0.2230	0.2393	0.2156	0.1792
RMS error	0.0402	0.0825	0.0415	0.0745	0.0352
Normalized error	0.1900	0.3699	0.1734	0.3458	0.1967
Device error	0.33turns	0.18cm	0.21turns	0.12cm	0.58degrees
With averaging	0.15turns	0.12cm	0.13turns	0.07cm	0.34degrees

the projection, network training times are considerably longer because of the high dimensionality plus there is uncertainty that an adequate number of hidden nodes have been allocated. The LDA projection provides the researcher with information about the structure of the data and, in this case, gives confidence that the problem is solvable and indicates that only a few hidden units are necessary.

Its effectiveness here is probably due to two factors: (1) the input variables are interdependent so the effective dimensionality is much smaller than the apparent dimensionality, and (2) the underlying function is only weakly nonlinear since increasing amounts of misalignment tend to cause increasing amounts of the same sort of gait distortion.

References

[1] K. Fukunaga. *Introduction to Statistical Pattern Recognition.* Academic Press, New York, 1972.

[2] P. Gallinari, S. Thiria, F. Badran, and F. Fogelman–Soulie. On the relations between discriminant analysis and multilayer perceptrons. *Neural Networks*, 4(3):349–360, 1991.

[3] H.W. Kay and J.D. Newman. Relative incidences of new amputations: statistical comparison of 6000 new amputees. *Orthot Prosthet*, 29:3–16, 1975.

[4] J.E. Sanders, C.H. Daly, W.R. Cummings, R.D. Reed, and R.J. Marks II. A measurement device to assist amputee prosthetic fitting. *Journal of Clinical Engineering*, 19(1):63–71, 1994.

[5] J.E. Sanders, R.D. Reed, and R.J. Marks II. Computer–aided prosthetic alignment for lower–limb amputees. In *IEEE Engineering in Medicine and Biology Society Conference, San Diego, CA*, pages 1282–1283, 1993.

[6] J.E. Sanders, R.D. Reed, and R.J. Marks II. Dynamic alignment of a lower–limb prosthesis by computational analysis of gait force–time data. In *Canadian Society of Biomechanics, Symposium on Amputee Gait, Calgary, British Columbia*, 1994.

[7] A.R. Webb and D. Lowe. The optimized internal representation of multilayer classifier networks performs nonlinear discriminant analysis. *Neural Networks*, 3(4):367–375, 1990.