

Exploiting Kinetic and Kinematic Data to Plot Cyclograms for Managing the Rehabilitation Process of BKAs by Applying Neural Networks

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Abstract—Kinematic data wisely correlate vector quantities in space to scalar parameters in time to assess the degree of symmetry between the intact limb and the amputated limb with respect to a normal model derived from the gait of control group participants. Furthermore, these particular data allow a doctor to preliminarily evaluate the usefulness of a certain rehabilitation therapy.

Kinetic curves allow the analysis of ground reaction forces (GRFs) to assess the appropriateness of human motion.

Electromyography (EMG) allows the analysis of the fundamental lower limb force contributions to quantify the level of gait asymmetry. However, the use of this technological tool is expensive and requires patient's hospitalization. This research work suggests overcoming the above limitations by applying artificial neural networks.

Keywords—Kinetics, kinematics, cyclograms, neural networks.

I. INTRODUCTION

THE diseases which lead to amputation mainly affect the cardiovascular system, including diabetes and peripheral arterial disease causing infections or gangrene. Tumors are also regarded as causes of amputations as, due to cancer growth and metastasis, and would require a limb to be amputated not to incur more severe consequences. In industrialized countries like United States of America and United Kingdom, diseases cause approximately 65% of all amputations performed each year [1]. In the literature, elderly people (over 60) are usually those who get amputations due to diseases. Poor blood circulation associated to cardiovascular diseases is one of the most widespread causes of amputation nowadays [2]. By limiting the flow of arterial blood to the lower extremities of the body, such disease causes ulcers and gangrene, which usually lead to amputations.

Diabetes is another common cause of limb loss. There are an estimated 177 million people with diabetes in the world [3]. Complications of diabetes involve a decrease in blood circulation and sensorial feedback from the limbs as well. This can result in ulcers and infection because of the unexpected and abnormal pressures on the extremities of the body (especially the feet) which may lead to amputations.

The most frequent level of amputations in general is below the knee, BKA or transtibial amputations, with an occurrence of 47% of the cases [4].

II. COMPENSATION MECHANISMS IN UNILATERAL TRANSTIBIAL AMPUTEES

As transtibial amputees do not have plantar flexors, their locomotion results to be impaired, considering that this muscle group contributes to up to 80% of the biomechanical power required to perform a full gait cycle. Around the hip joint the amputated leg will experience abnormally increased absorption and energy generation rates and this can be regarded as the fundamental compensatory mechanism developed by unilateral transtibial amputees during ambulation [5].

III. THE BIOMECHANICAL MEANING OF KINETIC AND KINEMATIC CURVES IN GAIT ANALYSIS

Kinematic curves wisely correlate vector quantities in space to scalar parameters in time to assess the degree of symmetry between the intact limb and the amputated limb with respect to a normal model derived from the gait of control group participants. Furthermore, these particular curves allow a doctor to preliminarily evaluate the usefulness of a certain rehabilitation therapy. Kinetic curves allow the analysis of ground reaction forces (GRFs) to assess the appropriateness of human motion.

IV. THE INNOVATIVE APPLICATION OF NEURAL NETWORKS IN REHABILITATION ENGINEERING

Electromyography (EMG) allows the analysis of the fundamental lower limb force contributions to quantify the level of gait asymmetry. However, the use of this technological tool is expensive and requires patient's hospitalization. This research work suggests overcoming the above limitations by applying artificial neural networks [6].

Artificial Neural Networks (ANN) have been extensively used in research projects (such as applications in biomimetics for designing prostheses activated by PIC microprocessors) related to gait analysis to predict leg's misalignments from the normal gait mostly with EMG signals [7]. Instead, this study proposes, for the first time, to use them in conjunction with raw gait data (GRFS) in Excel. Using raw gait data with neural networks to classify patient's gait asymmetries can be very efficient and useful to improve the design of mechanical prostheses, and to define the most suitable rehabilitation therapy for each patient.

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V. FIRST APPROACH: USING SELECTED TIME FRAMES

A. NN Architectures Used for Data Classification

As this study involves dealing with long-range data sets, neural networks such as the Multilayer Perceptron (MLP) and Radial Basis Functions (RBF) have been chosen for pattern recognition tasks and classification purposes [8]-[9]. The attractive features of simultaneous data handling and the concept of contextuality make such ANNs potentially useful tools in the automated recognition of various gait patterns. [10].

B. Pre-Processing of the Raw Gait Data

Once the raw gait data are converted from the .TXT to .XLSX format, they may present gaps in the measurements taken. Hence, 57 time frames (from the 47th to the 103rd) of a gait cycle have been selected as an example, in which the greatest number of repetitions for each prosthetic foot expected to be tested at each walking speed were included. Each time frame has to correspond to one triplet of angular kinematic data (ankle-hip-knee joint angles), for each prosthetic foot assessed at a certain speed.

In the first place, different spreadsheets should be used to distinguish between the prosthetic foot attachments taken into account as well as with respect to the walking speed.

The first data encoding approach consists of including a selection of 9 (over 57) time frames, for instance, equally spaced by six frame units (i.e. according to the convention followed, the time frames 1, 7, 13, 19, 25, 31, 37, 43 and 49), and considering these triplets of joint angles as inputs along with each relative walking speed.

In summary, the input vector is composed of 28 components, - columns - the first reports the type of walking speed and the remaining 27, i.e. 9 triplets of joint angle (ankle-hip-knee) data. The desired output vector includes the two columns to distinguish the first prosthetic device from the second device.

Once the data is randomized, the first 35 rows have been selected as training set, the following 12 rows of data for cross-validation and the last 12 rows have been used as testing set for testing the accuracy of the MLP neural network.

These subclasses of the whole batch of data respect the widely accepted rule of thumb for neural networks whereby 60% of the data set should be used as training set, 20% for cross-validation to avoid overtraining / over-fitting and the remaining 20% as testing set [11]. The MPL architecture is now composed of fifteen hidden neurons and two output neurons. The MLP is trained, on the abovementioned data, over different runs, where each run corresponds to 1000 training cycles. The best results obtained with this encoding approach are discussed in the subsequent section.

C. Results

Fig. 1 shows the percentage of accuracy obtained on the testing set after having trained the MLP over three runs (3000 epochs) on the training set.

Three different performance reports (see Fig. 1 below) are shown in order to underline also the variability of the results.

Output / Desired	First	Second
First	5	2
Second	1	4

Performance	First	Second
MSE	0,202631968	0,202631496
NMSE	0,810527872	0,810525984
MAE	0,301081221	0,3010809
Min Abs Error	0,0029773	0,002977284
Max Abs Error	0,96130606	0,961306032
r	0,533753932	0,533754903
Percent Correct	83,33333333	66,66666667

(a)

Output / Desired	First	Second
First	6	3
Second	0	3

Performance	First	Second
MSE	0,210541089	0,1800653
NMSE	0,842164356	0,7202612
MAE	0,401512823	0,375567822
Min Abs Error	0,065159579	0,024001968
Max Abs Error	0,795761991	0,692788489
r	0,405747271	0,558222532
Percent Correct	100	50

(b)

Output / Desired	First	Second
First	5	3
Second	1	3

Performance	First	Second
MSE	0,236822458	0,219094038
NMSE	0,947289833	0,876376153
MAE	0,382099517	0,365514053
Min Abs Error	0,032871923	0,01194645
Max Abs Error	0,924489435	0,956442423
r	0,394038133	0,437006843
Percent Correct	83,33333333	50

(c)

Fig. 1 The percentage of correct classification obtained on the testing set after having trained the MLP on the testing set for three runs (3000 epochs), (a), (b) and (c) representing each run. The MLP has 2 outputs and one hidden layer with fifteen processing elements (PEs).

The reports are referred to the first approach used in this research work.

The three training runs (3000 epochs) are needed in order to improve the MLP accuracy, since with only one run the accuracy was lower and even more variable, as it can be seen from the two performance reports illustrated in Fig. 2, where the training has been made on only one run (1000 epochs). The MLP architecture is the same as in Fig. 2.

In addition, decreasing the number of runs of training reduced the correlation number (r) (see reports in Figs. 1 and 2). Hence, with three runs of training the final accuracy of the MLP neural network is not only higher, but also more reliable on a statistical viewpoint. This is because of the higher value of correlation coefficient ($r = 0.39-0.56$) indicates that there is a good correlation among the variables used for classifying whether the patient was wearing either the first prosthetic device or the second device.

Output / Desired	First	Second
First	3	2
Second	3	4

Performance	First	Second
MSE	0,349704318	0,354732199
NMSE	1,398817271	1,418928798
MAE	0,443186322	0,415634475
Min Abs Error	0,00380312	0,000149927
Max Abs Error	0,998783702	0,992892662
r	0,146228776	0,206097386
Percent Correct	50	66,6666667

(a)

Output / Desired	First	Second
First	4	3
Second	2	3

Performance	First	Second
MSE	0,331591663	0,363716822
NMSE	1,32636665	1,454867286
MAE	0,399799181	0,431532534
Min Abs Error	0,003785385	0,005799101
Max Abs Error	1,043409372	1,046026685
r	0,263673736	0,198015293
Percent Correct	66,6666667	50

(b)

Fig. 2 Two performance reports obtained on the testing set for two runs (2000 epochs) with the same MLP architecture respectively represented by (a) and (b). The reports are referred to the first approach used in this research work.

Considering the first approach followed in my experiment (see both Figs. 1 and 2), the obtained MSE results to be higher with respect to the MSE resulting by adopting the second approach. This aspect emerges from a comparison between the results reported in Figs. 1 and 2 on one side and the results shown in Figs. 3 and 4 on the other side, as described in the following section of my research work.

This is because more data have been included, i.e. nine time frames have been considered, rather than one triplet of

averages of the modules for the three joint angles (ankle, hip and knee joint angles). However, overtraining occurred much faster, as it can be observed from the very few epochs in the cross-validation after which the neural network simulator had to stop the training process of the MLP neural network in order to avoid overtraining.

The negative values of the angles were thought to have influenced the final accuracy of the classifier significantly and, therefore, their sign have been discarded and only their modules have been considered.

This amendment slightly decreased the rate of change in accuracy given by the neural networks, giving us 70-72% of accuracy as average with three runs of training (Fig. 1) and 58% of accuracy as average with one run of training (Fig. 2), as shown in the previous reports and confusion matrices.

VI. SECOND APPROACH: EXPLOITING THE MAGNITUDE OF THE JOINT ANGLES

A. Materials and Methods

The resultant 57 components for each joint angle (ankle, hip and knee) formed a linear vector with the speed relative to each repetition/walking trial and the averages of their modules were used as input for the MLP classification network, thus resulting to an input vector of four components.

The limitation of this method consists of neglecting the time frames, but only considering the variation of the magnitude with respect to the walking speed.

After a randomization of the data, the two prosthetic devices have been used as desired outputs for the neural network.

As in the previous approach, the first 35 rows of data (i.e. the first 35 repetitions, randomized with respect to the speed relative to each walking trial) have been used for training. The following 9 rows have been deployed for cross-validation to avoid over-fitting/overtraining, whilst the last 15 rows were used for testing, in order to check the accuracy of the neural network in learning and classify data which it had not seen before.

B. Results

By testing the test set, the ability of the MLP model built to discern whether either the amputee was wearing the first prosthetic device or the second device has been ascertained, with an accuracy of classification respectively of the 77.78% circa and 75% (Fig. 3). The same accuracy level was obtained by applying the RBF to the raw gait data (Fig. 4), but this type of neural network architecture resulted to have a higher MSE (Fig. 4).

Therefore, the MLP did surprisingly model the gait data better than the RBF, as the RBF neural network was expected to model the batch of data better due to the few elements analyzed (59 repetitions, less than 100 elements) [12].

Output / Desired	First	Second
First	7	1
Second	2	3

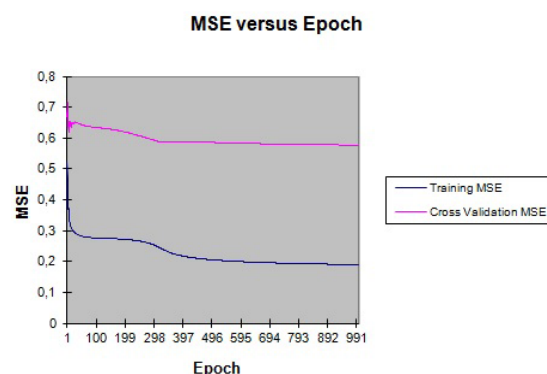
Performance	First	Second
MSE	0,164415535	0,182963247
NMSE	0,771839594	0,765021909
MAE	0,283076216	0,269711985
Min Abs Error	0,002850553	0,000409236
Max Abs Error	0,898671283	0,935404364
r	0,521385394	0,531011057
Percent Correct	77,77777778	75

Fig. 3 Report of MLP performance on the second approach

Output / Desired	First	Second
First	7	1
Second	2	3

Performance	First	Second
MSE	0,228827068	0,185562581
NMSE	1,074215949	0,871113225
MAE	0,468143014	0,40982753
Min Abs Error	0,289556849	0,138872101
Max Abs Error	0,641007375	0,604087994
r	0,463269505	0,474251938
Percent Correct	77,77777778	75

Fig. 4 Report of RBF performance on the second approach



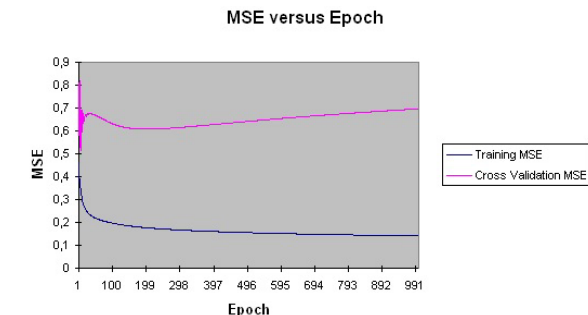
Best Networks	Training	Cross Validation
Epoch #	1000	1000
Minimum MSE	0,189545737	0,57692706
Final MSE	0,189545737	0,57692706

Fig. 5 MLP learning curves and Mean Squared Errors (MSEs), associated to the second approach

The MLP learning curves show that the Mean Squared Error (MSE) for both training and cross-validation data sets decrease by increasing the number of epochs up to 1000 (Fig. 5).

This suggested that the MLP neural network built with one hidden layer was preliminarily a good model for classifying the gait data inputted.

In fact, whilst the MLP learning curves are parallel to each other (Fig. 5), the RBF learning curves suggest a certain scarcity of ability in modeling the data (Fig. 6).



Best Networks	Training	Cross Validation
Epoch #	999	6
Minimum MSE	0,140948886	0,513173141
Final MSE	0,140948886	0,69646721

Fig. 6 RBF learning curves and Mean Squared Errors (MSEs), associated to the second approach

VII. DISCUSSION AND CONCLUSIONS

Taking the considerations on the two approaches analyzed in the previous sections of this research paper into account, the second approach has to be preferred with respect to the first method. Therefore, the rate of change in the three joint angles' magnitude, correlated to the walking speed only, resulted to be statistically more relevant than considering the change of joint angles through several time frames.

The findings indicate that, neural networks, such as the MLP built in the first approach followed in this research work, can discriminate between the two prosthetic foot devices with a reasonably high accuracy (77.78% and 75% for the first prosthetic device and the second device, respectively).

These results would provide a medical doctor with a tool to assess whether or not considering the kinematic data (i.e. the angles generated at each joint on the lower limb) would be relevant for each individual trans-tibial amputee, and would save time in assessing the performance of different prosthetic devices by choosing the most suitable criterion of analysis.

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