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Human Gait Analysed by an Artificial Neural Network Model

Rogério Rodrigues Lima Cisi, Euvaldo F. Cabral Jr.
Departamento de Engenharia Eletrônica, Escola Politécnica da USP
E-mails: rogerio@leb.usp.br, euvaldo@lcs.poli.usp.br

Abstract

In this paper a model proposed by Sepulveda et al. [1] will be revised regarding the use of artificial neural networks to map EMG signals and joint dynamics in the lower-limb. The original model will be used to analyse other aspects of human gait, like muscle recruitment, movement patterns and to study a problem from a patient with a lesion in the femur's region. Some theory on neural networks is applied to validate the model and train the network. New tests are used to verify other aspects of the human gait study. Analysis of the results showed some discrepancies in EMG/moments mapping but good results in EMG/angles mapping.

1. Introdution

The human motor control can be analysed at multiple levels depending on which aspect is been studied. The three common levels of analysis generally considered are cellular, network and movement [2]. The cellular level specifies the function of each neuron of the system, regarding biophysics aspects. The network level analyses strictly the central nervous system, namely, the neuron connection and the information through the network. Finally, the movement level takes into account the muscular system and the structural support system, studying the human movements after cortical and spinal commands.

Human Gait is included in the movement level study. It is a cyclic movement pattern repeated several times. The walk is a typical human gait that can be measure and give some information about our muscles and nerves involved with motor control. The human gait cycle is defined as the interval between two events repeated related to the same foot [3].

An artificial neural network (ANN) regarding the correlation between EMG signals and joint variables was first described by Sepulveda et al. [1] achieving good results. The authors used a *multi-layer perceptron* (MLP) making a mapping of 16 EMG signals and 3 joints angles and moments of the lower limb. The data used in the training and testing procedure were obtained from the literature [6]. After that, some other works were developed using neural networks to study motor control. In this paper will be given an overview of the original work, considering some aspects involved in the ANN design.

Actually, there are other strategies to represent the correlation between EMG signals and human gait, like mathematical optimization theory and algebraic methods (Hof et al., 1987). But in most of cases, artificial neural networks have been demonstrated superior than other methods, because of the simplicity of the arrangement, and the slow discrepancies between measurement and prediction.

2. Electrical Measures in Human Gait

A good way to analyse the muscle function is recording the electrical activity of the muscle. It was done using electromyogram (EMG) records. The EMG is the single best representation of neurologic control (activation) of skeletal muscle [6]. It represents the activity of the motor units, the basic unit of motor function, composed by one motor neuron and the group of muscle fibers it innervates. Each motor unit, when activated, produces a motor unit action potential that is an electrical signal measured by electrodes placed over muscles.

The EMG data presented in this paper were obtained by superficial electrodes because of the facility to measure, although needle electrodes produce better results [6].

During the human gait a group of muscles is recruited to produce the dynamics required. The EMG is used to verify which muscles are being recruited and in what manner they interact to produce the body movements.

3. Artificial Neural Network Model

In the field of artificial neural network there are some models based on biological systems, at least in their essence. For this reason, it is thought that artificial neural networks are appropriated to analyse natural systems, like spinal networks and pools of motor units. In our problem, we want to study the relationship between EMG signals and joint movements. The responsible structure for that is composed of several neural networks, spread over spinal cord and lower-limb.

We propose in this paper an extension of the original model, considering four artificial neural networks divided in two classes: moment networks and angle networks. Each class has two types, slow and normal cadence. With our model it is possible to analyse the human gait in several aspects regarding muscle recruitment, movement patterns and joint dynamics.

The four ANNs chosen (EMG/moments, EMG/angles - natural and slow cadence) are the traditional MLP [4], with backpropagation training algorithm (Figure 1). The choice was made based on cluster analysis. Taking the input vector, we proceed to a k-means study and it was shown that among 16 inputs (one for each muscle) there were some clusters with strong representation while others had only one representative (outliers). In this situation it is not possible to use a Radial Base Function network (RBF) to perform the mapping. RBFs are faster than MLPs and sometimes lead to the same or better performance, but they require the input vector to be well distributed over some clusters. The MLP, on the other hand, has generally the ability to separate the inputs in the same cluster improving the network response. The k-means analysis is shown in Table 1.

All networks constructed have the same structure, differing only in the training set. The networks have an input layer with 16 units that is associated with 16 leg muscles. The input units are described in Table 2. The hidden layer has 32 units, which are sufficient to separate all clusters present in the input layer. Completing the architecture, there are 3 output units associated with hip, knee and ankle dynamics, relating with moment or angle depending on the network type. Figure 2 illustrates the system structure.

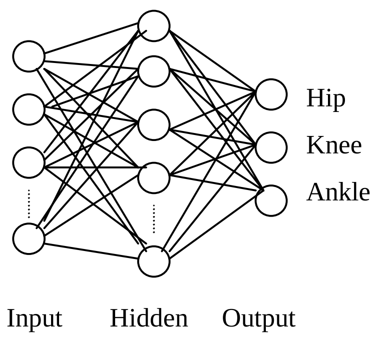

Figure 1: A classical structure of multi-layer perceptron. The neuron activation function is any kind of non-linearity. The most used are sigmoids. The input layer is feed up with EMG signals and the output layer represents angles, in one class of network, or represents moments in other class. Each network has two variants, slow and natural cadence.

Representatives – Cluster Spread		
4 clusters	**8 clusters**	**12 clusters**
14 - 1.5616	10 - 0.7565	10 - 0.7565
24 - 1.4431	10 - 0.6925	10 - 0.6925
7 - 0.7284	4 - 0.2311	4 - 0.2311
6 - 0.8402	2 - 0.0586	2 - 0.0586
	3 -0.2158	1 - 0.0000
	4 -0.3733	1 - 0.0000
	7- 0.2780	1 - 0.0000
	11 -1.1016	1 - 0.0000
		1 - 0.0000
		3 - 0.1286
		7 - 0.3044
		10 - 1.0272

Table 1: K-means analysis. The 51 input patterns were divided in 4, 8 and 12 clusters. The analysis shows that there are some clusters with many representatives while others have only one representative. Because of that response, the MLP is used instead of the RBF.

In other papers [8, 9] it was also used different kinds of ANNs to study movement generation. In that case, it was necessary to use a recurrent network, to achieve the pattern generation. Elman Network [5], that is a three-layer network with feedback from the hidden layer to the input layer input is generally used in this cases. Because of this feedback process, the network is capable of detecting and generating time-varying patterns, for instance, movement patterns. Another alternative is described by Srinivasan et al. [8].

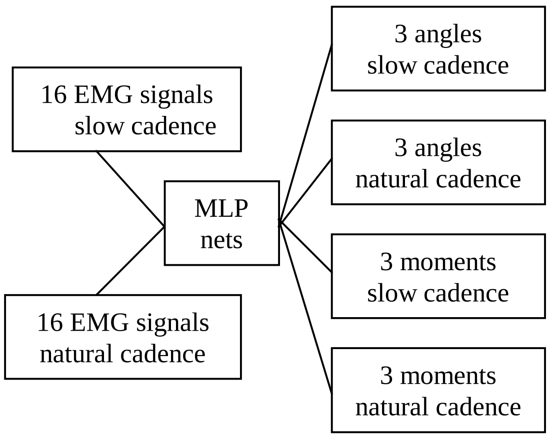

Figure 2: The system structure. Each output block defines a different network. For slow cadence the input is the upper block and for natural cadence the input is the lower block.

Input	Muscle
1	Gluteus medius
2	Gluteus maximus
3	Semitendinosus
4	Biceps femoris
5	Erector spinae
6	Sartorius
7	Rectus femoris
8	Vastus lateralis
9	Adductor longus
10	Adductor magnus
11	Tibialis anterior
12	Extensor digitorum longus
13	Medial gastrocnemius
14	Lateral gastrocnemius
15	Soleus
16	Peroneus longus

Table 2: Muscles associated with input units. These muscles are recruited in the human gait in a complex manner. The networks will be trained to execute the same tasks of the muscle ensemble, e.g., create the angles and muscles dynamics.

4. Methodology

In order to obtain an adjusted system it was necessary to train all the networks with an appropriated training algorithm. The backpropagation algorithm [4] was used achieving good results. Two approaches have been tested: linear and sigmoid neuron transfer function in the output layer. If possible, the use a linear function is a better approach because it is faster. Both input and output vectors were normalized before being applied to the network. The use of sigmoid functions was done considering the well-known formulation of standard MLP (using sigmoids as the neurons transfer function which requires outputs between 0 / 1, for example) and to having a normalized network suited to analyse data from different sources (see application session). After 5000 epochs the output error was less than 2% which is considered a good result because is lesser than the standard deviation.

The validation procedure was done testing the network with input vectors different from the training vectors. Applying a linear regression in the networks resulted in the following averaged coefficients:

$m = 0.9867 \quad b = 0.0034 \quad r = 0.9989$

which confirmed that the system became corrected adapted, because m and r coefficients are almost 1 and b coefficient is almost 0.

5. Application

After the previous steps, the system was applied to a real case - a register of a patient who had fractured his femur. After the recuperation, he was submitted to an EMG exam to verify the muscle activity. In static EMG tests no problems were found, but when the patient was evaluated in a gait analysis it was clear that there was a distortion in the walk. The drawback in this case is to identify which muscle was to be blamed to the bad performance. The system here described was applied to help achieving the diagnostic.

As EMG signals, angle positions and moment measures were normalized, the system could be used without any change. The strategy was to search for system outputs that were similar to that registered from the patient, e.g., outputs showing a distorted walk. A first assumption was that moment was not a better variable to be evaluated because the system was trained with averaged measures of people in perfect conditions, which was so many different of the patient measures. Then, the approach was to set up the angle outputs (hip, knee and ankle angles during the gait) to be similar to that shown in the patient records. Three patient trials were averaged during his gait and then were plotted graphics of angle positions *x* percentage of the stride.

The network in which the EMG signals and angle positions represents slow cadence was used because the patient executed a cadence like that. The main task to obtain similar angle positions was to feed the network with the EMG signals used in the training procedure but changing each muscle at a time, verifying whether this change had effect or not. After testing all muscle inputs, it was verified that 4 muscle inputs were responsible to fit the network output to the patient data, namely, biceps femoris, erector spinae, rectus femoris and lateral gastrocnemius. After several trials, the best input was configured as normal input in all muscles except a 10 times reduction in the four muscles related. This probably means that either in the ANN as in the patient these muscles are responsible to the walk distortion and need to be better evaluated. Figure 3 and Figure 4 show hip and knee curves of patient data and curves obtained from the network. Although these curves are not perfectly fitted they are the best approximation found. Ankle curve was not used because a linear regression demonstrated that this curve was not agreeing with patient data, probably because ankle has a great level of variability, being not suited for that analysis (see Table 3).

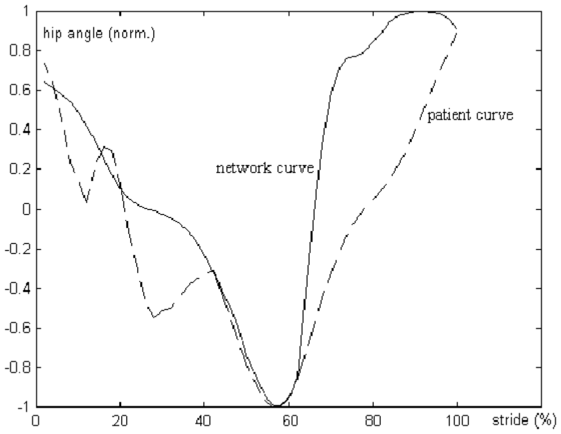

Figure 3: Hip angle *x* percentage of stride. Observe that in the beginning of stride the two curves were more similar.

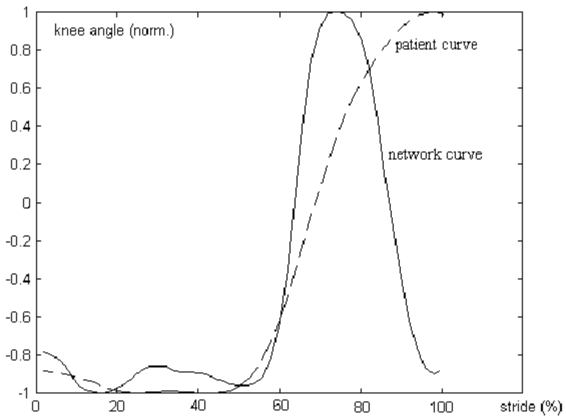

Figure 4: Knee angle *x* percentage of stride. Observe that in the beginning of stride the two curves were more similar.

	m	b	r
hip angle	0.6070	-0.1009	0.7673
knee angle	0.6307	-0.0334	0.5515
ankle angle	-0.9461	0.4322	-0.6853

Table 3: Linear regression coefficients between patient and network curves after adjusts in EMG input signals to fit the curves. Hip and knee angle curves was relevant but ankle curve was not so considered because of the great differences in the values observed.

6. Conclusions

The variables presented in human gait analysis interact with each other in a complex manner. In the study presented here there is a 16-dimension vector as the input set mapped in 6 dimension joint dynamics. Considering this complexity an artificial neural network approach is suited to this case because of its relative simplicity, easy manipulation and robustness.

In a real study, like that analysed in this paper, the data have to be carefully treated because the results, in many times, are not well established.

The analysis of that patient, who had problems in the walk even after the recuperation of a femur broken, showed us that the system reviewed here can be used to study the case, but not in a whole. The network that correlates EMG and moment showed discrepancies in the results. This is attributed to differences among each subject record, because their moments normally vary in a great range. So, this part of the system is not appropriated to our study. The other network type, EMG – angles, is more suited because angles is less affect to differences between the subjects. The first two system outputs, hip and knee angles could be approached to the patient record, showing that four muscles would be involved in the patient's problem. The biceps femoris and rectus femoris are more probably to be affected, because are femur muscles. Erector spinae and lateral gastrocnemius have to be more studied to confirm whether they take part into the problem or not.

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