Study of a FCMAC ANN for Implementation in the Modeling of an Active Control Transtibial Prosthesis

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***Abstract*— This article presents some topics that have been developed by the authors on the development of a model of posture and behavior control of a Active Transtibial Prosthesis, i.e., applied to individuals with amputation below the knee. It is intended to use a Neuro-Fuzzy ANN as the basis of this control. Specifically, we intend to use an FCMAC ANN Neuro-Fuzzy type. Such ANN has the ability of memorizing a region of operation and allow that for similar entries to those known in memory, know outputs may be generated. It is intended to show an early version of this work whose application was the modeling of the inverse kinematics of a leg in the sagittal plane.**

Keywords-component; Active Transtibial Prosthesis, Control, Artificial Intelligence, ANN Neuro-Fuzzy.

I. INTRODUCTION

The search to improve the quality of life for people who have suffered amputation is one of the goals of a branch of engineering called the Rehabilitation Engineering [1]. Using tools and techniques developed in large research centers, it is possible to obtain models of prostheses and orthoses that may allow greater comfort to its user, particularly for those with lower limb amputations.

Modeling the control of prosthesis or any device used in human rehabilitation allows for better interaction with its user and can ensure greater comfort in performing movements [2]. In particular, for prostheses applied to the lower limbs, their behavior during walking is a factor that can facilitate or hamper the movement of the user. In this context, some tools from studies in the area of Artificial Intelligence can assist in the implementation of the control of these devices for rehabilitation. Of these tools, we highlight the use of fuzzy systems and Artificial Neural Networks (ANNs) combined in a system called Neuro-Fuzzy ANNs. The fuzzy systems deal with linguistic sets that allow managing inaccuracies in a way to generate the output more plausible by rules [3]. In the other hand the ANNs seek to simulate the connectionist reasoning using processing units with nervous system biological inspirations. They are able to learn, generalize and classify the elements in the universe they have been trained. The combination of these two systems can leverage the best of each [3].

In this work, we intend to show the results of some studies done about a Neuro-Fuzzy called FCMAC. This ANN has great potential for use in real-time control and allows the memorization of the environment in which it will be applied in order to generate the closest know output [4]. The FCMAC ANN is used as a basis for implementing a posture and behavior control of an active prosthesis for transtibial amputees and, as a first version, the results generated in this study were applied to generate a modeling of inverse kinematics of a leg in the sagittal plane.

II. CHOICE OF A NEURO-FUZZY ANN

Among the various models of Neuro-Fuzzy ANNs, we highlight the ANFIS ANN (Adaptive Network-based Fuzzy Inference Sistem) and FCMAC (*Fuzzy-Cerebellar Model Articulation Controller*) ANN. In previous works [11, 12] we sought to determine which of these two types would be used in the implementation of the control of the active transtibial prosthesis. The following will show some characteristics about these two Neuro-Fuzzy ANNs.

A. ANN ANFIS

The ANFIS is one of the more widespread Neuro-Fuzzy ANNs and represent a type of RBF (Radial Basis Function) ANN in a system of type Fuzzy TSK (Takagi, Sugeno and Kang) [3]. It relies on the use of ANNs and Fuzzy systems whose output has not defuzzification processes. Figure 1 shows the layout and operation of such an ANN.

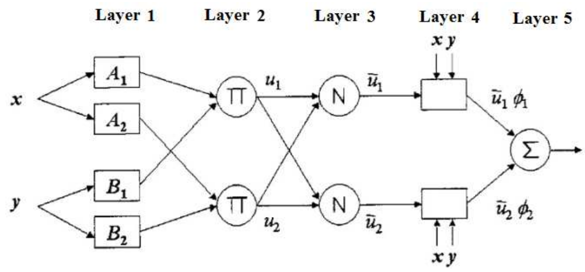

Figure 1. Model of Neuro-*Fuzzy* ANN of the *ANFIS* type [3].

In Figure 1, the first layer represents the fuzzification of the inputs x and y. Layer 2 is responsible for the activation of the outputs of layer 1. Layer 3 is responsible for normalizing the output of layer 2. Layer 4 presents

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parametric equations on the basis of inputs from the ANN and layer 5 is the sum of parametric equations whose biggest influence on the output comes from the parametric equations whose activations in layers 2 and 3 are larger.

This ANN presents two modes of construction [3]. The first is called Concatenated Model, whose entries are a concatenation of relevance vectors associated with each variable. The second is called the Combined Model and, unlike the previous, its entries are formed by combinations of fuzzy sets of the variables. In this last, to develop a complete system, all possible combinations for these assemblies must be considered.

B. The FCMAC ANN

The FCMAC ANN is an improvement of an architecture proposed by [5], called CMAC. The CMAC (*Cerebellar Model Articulation Controller*) ANN is a simplified model inspired in the cerebral cortex of mammals that operates through associative memories that relate the inputs of the ANN with appropriate outputs. A feature that should be mentioned is that the CMAC ANNs have a large number of receptive fields with finite boundaries [3, 4]. This means that it operates in a mapping by limited intervals of operation. The ANN initially proposed by [5] implements functions of the type shown in (1) and (2).

$$f : S \rightarrow A \tag{1}$$

$$g : A \rightarrow Y \tag{2}$$

In Equation 1, S is the space of input from ANN, A is the set of CMAC memories and Y is the output. The mapping of CMAC memories is done using functions of Boolean activation. The outputs of these activations are combined using an AND Boolean operator to enable or disable your memories. The memories that are activated are weighted by weights and summed to generate the output of the ANN. However, the use of activation functions of Boolean type in entries, makes some CMAC memories completely connected or disconnected. This makes its output response to present discontinuities, even for well-behaved inputs [6].

An alternative proposed by [7] to solve the problem of discontinuities in the output of the ANN was the adoption of activation functions of fuzzy logic. These functions work with concepts of pertinence of elements and allow use as a activation one degree trigger that allows certain memory locations that are not completely disconnected from the output pattern and are usually Gaussian or B-splaines [3, 6]. Thus some memory locations may contribute fully, partially or not contribute to the output, making that this way it can be continuous and smooth. The structure of a Fuzzy-CMAC ANN (or FCMAC) can be seen in Figure 2, where it notices that it is very similar to the CMAC ANN, differentiated only by the activation functions in the entries.

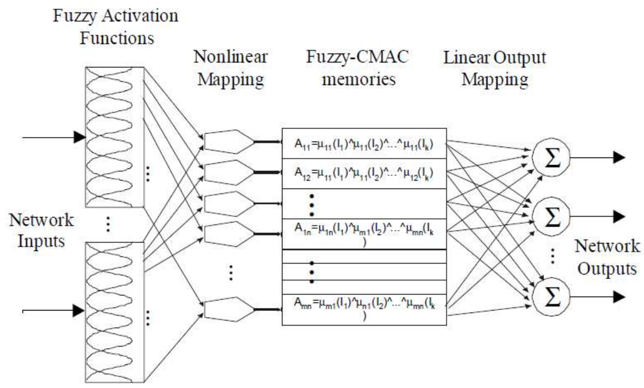

Figure 2. FCMAC ANN structure. Adapted from [6, 4].

C. Justification for the Selection of FCMAC ANN

Regarding ANFIS ANN, it appears that it seeks to preserve the properties of generalization of ANNs. Moreover, the knowledge of an expert can serve to start the ANN parameters so that during your training, it can give better results by already be closer to the desired setting. However, with regard to its constitution, it must be verified its limitations for problems not linearly separable, that is, with similar characteristics but belonging to different sets [8]. This is because in the case of the combined model, its application in project is subject to the number of entries in the ANN, since the number of combinations grows exponentially with the number of inputs, besides being more difficult to construct. Now with regard to the concatenated model, its construction becomes easier, however, the ANN becomes less robust.

Regarding the Fuzzy-CMAC ANN, a feature that should be mentioned is that their receptive fields act as memories of Fuzzy-CMAC ANN, by enabling or disabling certain ANN connections. Thus, only a few receptive fields will predominantly contribute to the output of the ANN while others will not contribute effectively. Thanks to this, it is possible to conduct a local training ANN only fields that contribute to output and allowing some information stored by the ANN are not lost. Moreover, the problem of discontinuities solved by the use of continuous functions of fuzzy logic, may apply a method of training using a gradient method [3, 6].

Thus, it appears that the Fuzzy-CMAC ANN is presented as a robust technique that can map the characteristics of the human gait. Memorize certain features of the walk can allow the prosthesis to have a consistent stance that can relate the user's intentions with the environment [12]. Given its characteristics, the aim is to use a Fuzzy-CMAC ANN as the basis to perform the modeling control of the active prosthesis for transtibial amputees.

III. Materiais e Métodos

A. Operation of FCMAC ANN

Likewise the CMAC ANN, the FCMAC also operates at finite boundaries, i.e., inputs are limited to their ranges of operation. At the entrance of ANN, μ values are calculated which are the degrees of pertinence of the input values in the range of operation. Thus the output of the activation functions are calculated in (3).

$$\mu_{ij} = \exp\left(-\frac{1}{2}\left(\frac{x_i - c_{ij}}{\sigma_{ij}} \right)^2 \right) \tag{3}$$

In Equation 3, μ is the value of the pertinence of input *x*, partitions of the interval *c* and *σ* are the center and support of the membership functions, *i* ranges from 1 to n inputs and *j* ranges from 1 to k number of membership functions. Then the combinations of the membership functions of the inputs are combined with each other as the operator E. For FCMAC ANN are used t-norm operators as minimum or algebraic product [9]. For this work, we used the algebraic product given by (4).

$$a_m = \prod \mu_{ij}(x_j) \tag{4}$$

The index *m* in (4) ranges from 1 to k^n number of rules or combinations of inputs, and *a* is an associative cell related to the FCMAC memory of this multiplicand, and related to the insert input. The associative cells activated by input values that are closer to the values entered in the ANN showed a higher value. With that they influence the output more than those with a lower value. However, all cells contributed to the output of the ANN that in this study was adopted as the (5) [6].

$$Y = \frac{\sum_{m=1}^{N} w_m a_m}{\sum_{m=1}^{N} a_m} \tag{5}$$

where *N* is the number of memories in the ANN.

B. Learning of FCMAC ANN

For the correction of the weights of ANN, one can use an equation similar to the correction of the weights of CMAC ANN. It is given by (6). It is also possible to adjust the Gaussian activation functions of the input layer. This adjustment is made using the backpropagation algorithm and the variables *c* (center) are modified and *σ* of the Gaussian functions. This adjustment improves performance at the ANN output [6].

$$\Delta w_{ij} = \eta (Yd - Y) \frac{a_j}{\sum_{m=1}^{N} a_m} \tag{6}$$

C. Reduction in the number of inputs combinations

A problem that occurs with this ANN is that the total number of possible rules, or combinations of functions grows exponentially in a relation between the number of entries *n* and the number of membership functions *k* as in (7). This is referred to as curse of dimensionality [3], since the number of entries of ANN may limit the application of the designer.

$$C = k^n \tag{7}$$

To reduce this problem, [6] used a limited number of combinations and adjusted the membership functions in the inputs so that the generated combinations could map the inputs in the best possible way. For this he treated the membership functions or activation using an algorithm of clustering or categorization that allowed these functions to initialize. The clustering algorithms used to start the membership functions was the Fuzzy C-Means. With this technique it is possible to calculate the centers of Gaussians activation functions so that they are well distributed in the input space. This allowed the number of combinations of inputs to grow linearly with the number of activation functions for each input, as shown in (8).

$$C = k \tag{8}$$

In (7) and (8), C is the number of possible combinations of inputs FCMAC. The Fuzzy C-Means algorithm is one of the algorithms most utilized for clustering and as well as other algorithms of the type, aims to minimize a function of the type presented in (9), which represents a cost function based on the distance of each point in the input assembly, in the position of each cluster and in the relevance of each point to the cluster [10].

$$J = \sum_{i=1}^{c} \sum_{j=1}^{P} \mu_{ij}{}^m d^2(x_j, v_i) \tag{9}$$

In (9), x_j is a sample of a point vector *P*, *c* is the number of desired clusters, *d* is the distance from x_j to the center v_i and μ_{ij} is the value of degree of relevance of the sample x_j to the center v_i, *m* is called fuzzy factor which typically is equal to 2 (the bigger *m is*, it is said the cluster is more *fuzzy* [10]) and *J* is called cost function.

D. Implementation of a FCMAC ANN

To implement a FCMAC ANN, it was necessary to list what are the elements that characterize an ANN of this type. Thus, some elements were listed, and as a result, was generated a data structure that could represent ANN as illustrated in Figure 3. To implement FCMAC ANN, it was used the computer álgebra ambient Matlab ® because it allows greater ease in the development of algorithms.

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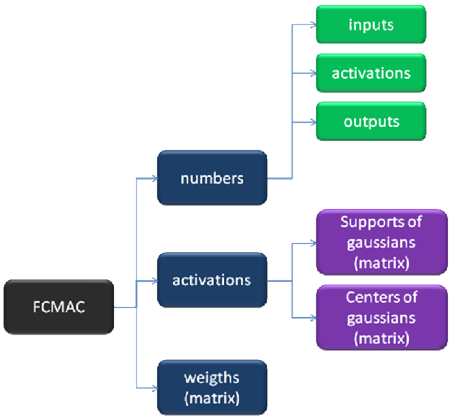

Figure 3. Data structure that represents the FCMAC ANN.

In Figure 3, the attribute numbers stores values corresponding to dimensions of ANN, such as number of entrances, activation functions and numbers of outputs. The attribute activations stores two matrixes that store the values of centers and supports of the Gaussian functions of the inputs. Finally, the attribute weights keeps the corresponding matrix weights of each output, each initialized with random values between -1 and 1 [6].

E. *Neuro-Fuzzy Control for a Active Transtibial Prosthesis*

The active transtibial prosthesis has a set of sensors that allow for the acquisition of kinematic and dynamic parameters during operation. As the initial proposal, the control of posture and behavior will not consider the bioelectric signals of the user, ie, will be used only dynamic kinematic parameters acquired by the sensors. For this purpose, it is intended to train a FCMAC ANN in order to bring consistent output based on the parameters obtained from sensors. Thus, based on previous work [11, 12], were collected some parameters that feed the FCMAC ANN:

- Distance d relative to the ground plane;
- Angle α between the sole of the prosthesis to the ground plane;
- Angles β between the sole and the leg prosthesis;
- Force F applied to the prosthesis due to the weight of the user;

With these parameters, it is proposed the control model shown in Figure 4 [13].

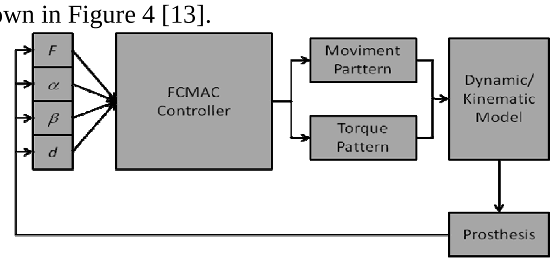

Figure 4. Proposed model to control the prosthesis [13].

In Figure 4, it can be seen that the output of FCMAC ANN should provide at its output the movement to be performed by the prosthesis and how much torque must be applied to a joint. This pattern of torque must be applied at the ankle and depend on the phase of gait. The movement pattern also depends on the phase of gait. These two standards should be adjusted according to the kinematic and dynamic model of the prosthesis so that your posture and behavior can be consistent.

IV. RESULTS

As a first version in the application of Neuro-Fuzzy FCMAC ANN in a control template for a Active Transtibial prosthesis, worked on a model of inverse kinematics of a leg in the sagittal plane. This means that one wishes to obtain the angles which allow the end of the leg may be located in a certain position. For this, it is considered a model with two segments and two degrees of freedom (degree of motion). The ANN which controls the position of the leg has as input parameters a position in which the point on the ankle is in the *xy* plane and an output, it is expected angles of the hip and knee. The structure of ANN used can be seen in Figure 5.

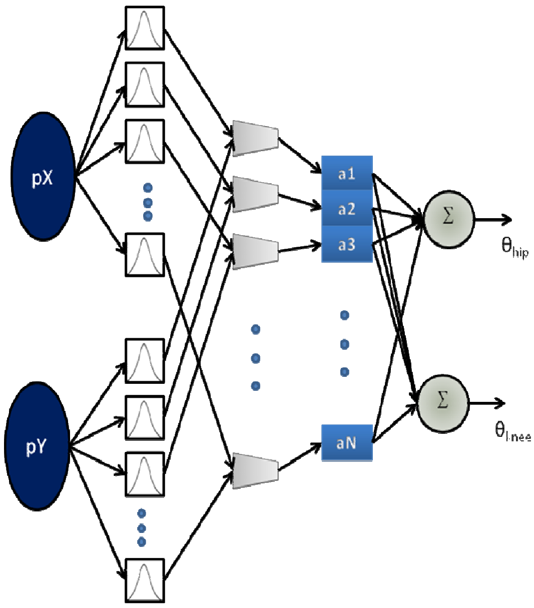

Figure 5. Structure of FCMAC ANN to control the leg where N = 100, that is, the ANN possesses 100 memories.

For training the ANN, it was generated a leg operation space in which its edge could be located. In this operating region, about 400 training points were generate, which were also used to generate a 100 clusters that serve as centers for the Gaussian functions activation inputs of ANN. The region restriction is shown in Figure 6, where two segments of line represents the leg segments and the red points are the clusters generated in this mapping.

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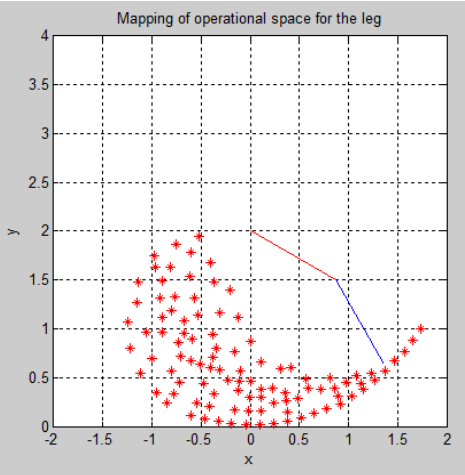

Figure 6. Mapping of the leg operation space. Strictly in this region, the FCMAC ANN can provide the desired output after training.

Established these points, began training a FCMAC ANN with about 100 activation functions on each input. After training, was traced a trajectory parameterized in the *xy* plane and tried to verify if the ANN would be able to perform the inverse kinematics of this trajectory to position the end of the leg in this plan. Figure 7 shows the trajectory traced to the end of the leg and the solution of inverse kinematics for the angles corresponding to this path.

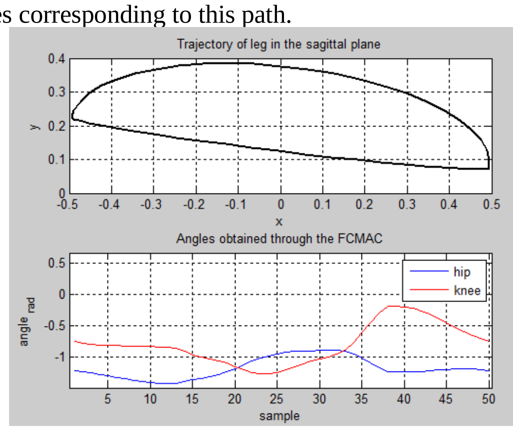

Figure 7. At the top of the figure has the trajectory desired to be approximate by FCMAC ANN. In the lower part there are the corresponding angles to this path

V. Discussion

When using a categorization algorithm, one can find some clusters that are positioned at locations around whose elements have some similarity. By doing so, it was possible to perform a mapping of the leg operation space with a limited amount of clusters equal to ¼ of data that would be used in training. This could allow a drastic reduction in the number of combinations of inputs needed so that the ANN could approximate the trajectory. Thus, for the ANN used, which had 100 functions in the activation of 2 starters, it took only 100 combinations of inputs instead of 1002 = 10000.

The FCMAC ANN training for this application was carried out in 500 times and wished the Mean Square Error (MSE) was 10^{-4}. However, at the end of training epochs, the NDE obtained was 1.6 x10^{-4}. However, ANN performance was satisfactory, because the behavior of the trajectories obtained in simulation was close to expectations as you can see in Figure 8, where they are shown briefly simulation performance of the FCMAC ANN to approximate the trajectory of the leg.

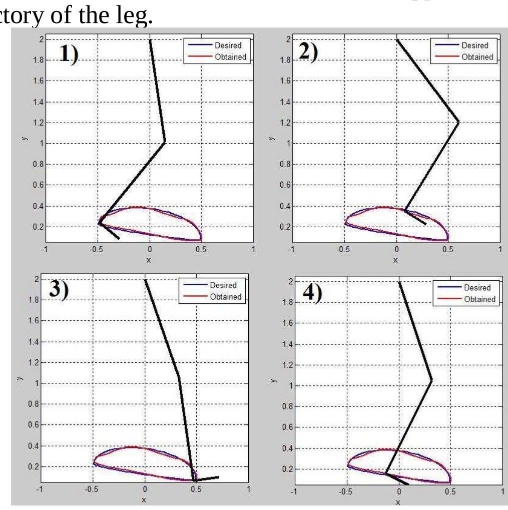

Figure 8. The figure shows a few moments of trained FCMAC simulation. The blue curve represents the desired trajectory and the red represents the trajectory obtained by ANN.

VI. Conclusion

Through this work, we can learn a few points about the capabilities of FCMAC ANN. It was found that in case of using all possible input combinations, their applications on design would be constrained by the number of entries as the number of combinations grows exponentially with the number of inputs and activation functions.

It was seen that the use of a categorization algorithm allows the number of input combinations is dramatically reduced to a linear complexity to the number of activation functions of the inputs. The Fuzzy C-Means algorithm allowed for mapping the operating region of the leg so that could distribute the activation functions of the inputs through this region.

As regards the application done, verified the ability of FCMAC ANN memorizing the operating region and allow the execution of any path in this region even without the known during training. That's why when associating various positions in the area of operation with the angles of the hip and knee for the training data, the ANN memorized these relationships. Thus, when designing a trajectory in this region, it checks the path which points are closer to the region known demand and provide an approximate output.

It should be noted also that the coordinates are entered in the input ANN were operating in the area, leaving the ANN

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would be inconsistent. Thus, mechanisms are needed to prevent these boundary conditions occur.

As a next step, we intend to use the data obtained in a simulation environment developed in [11, 12] to train a FCMAC ANN. The aim is also to obtain a model of posture control and behavior of active prosthesis for transtibial amputees.

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