DESIGN AND IMPLEMENTATION OF AN INTELLIGENT INTERFACE FOR MYOELECTRIC CONTROLLED PROSTHESIS

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Abstract – **In this paper, a discrimination system, using a neural network for electromyographic (EMG) externally controlled upper extremity prostheses is proposed. In this system, the Artificial Neural Network (ANN) is used to learn the relation between the power spectrum of EMG signal analyzed by Fast Fourier Transform (FFT) and the performance desired by handicapped people. The Neural Network can discriminate 7 performances of the EMG signals simultaneously. In order to prove the effectiveness of this system, experiments for discriminating the 7 arm performances of a healthy 23 year-old man, were carried out. For real-time operation, a Digital Signal Processor (ADSP-21061) operates over the resulting set of weights and maps the incoming signal to the stimuli control domain. Results show a highly accurate discrimination of the control signal over interference patterns.**
Keywords – **Upper limb prosthesis, Feedforward artificial neural network, electromyography signal, correlational analysis, data engineering.**

I. INTRODUCTION

There has always been a goal in biomedical research to design a myoelectric (EMG) controlled upper limb prosthesis, which can be used for amputated people.

The application of EMG controlled prosthesis using neuromuscular stimulation on a muscle mostly depends on the successful discrimination of the myoelectrical signal by which the control over the impeded movement shall be performed.

The *Universidad Nacional de Colombia*, has developed an upper limb prosthesis which successfully uses EMG signals from biceps and triceps to enable amputees to open and close their hands. However, the issues on palm flexion and dorsiflexion still remain unsolved.

Accordingly, there has been a lot of research trying to find ways to add two motions, wrist pronation and supination, to the capabilities of the prosthesis to create an upper arm prosthesis beyond the two degrees of freedom enabled by the arm made at *Universidad Nacional*. Approaches towards this issue have included signal filtering, spectral analysis and pattern recognition.

Most of the research studies carried out up to now have processed signals coming from the biceps and triceps. However, we presume that additional information might be extractable from the signals obtained by electrodes at special location in the upper extremity. Although these electrodes are located at places where there is relatively little EMG activity, which is an electrical manifestation of neuromuscular activities associated with a contraction muscle. It is expected that signals from these places reflect the spatial nature of the EMG signal. This approach has been in several research studies used [1, 2].

II. PROCEDURE

The purpose of this research is to develop a hardware implementation of a neural network. The neural network is used in this system to learn the relation between the power spectrum of EMG signal, analyzed by FFT, and the performance desired by handicapped people. The Neural Network can discriminate 7 performances of the EMG signals simultaneously; the myoelectrical features are extracted at first by the Fourier analysis and clustered using a neural network. This system consists of two parts: acquisition and discrimination.

A. Acquisition part

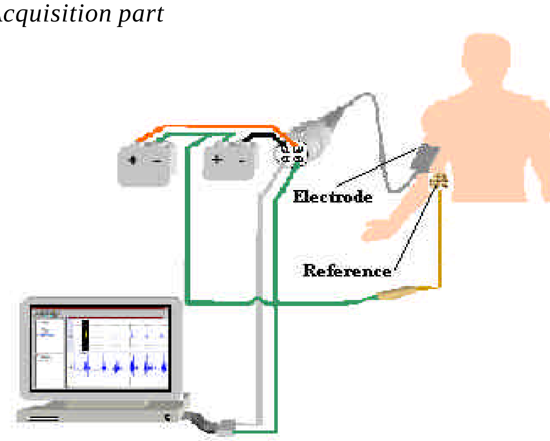

Fig. 1. Acquisition Part

The acquisition part (see Fig. 1) consists of Delsys® electrodes which are designed with a built-in gain of 1000 V/V and a built-in bandpass filter of 20-450 Hz.

They are designed using parallel-bar contact geometry to ensure signal stability, repeatability between recordings and optimal frequency content representation. The electrodes are constructed to maximize the EMG signal-to-noise ratio, the internal electronic components are completely shielded for noise immunity.

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25 Oct 2001	N/A	-

Title and Subtitle Design and Implementation of an Intelligent Interface for Myoelectric Controlled Prosthesis	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) GIDIC - Grupo de Investigacion y Desarrollo en Instrumentacion y Control Colombia, South America	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)
Distribution/Availability Statement Approved for public release, distribution unlimited	
Supplementary Notes Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom., The original document contains color images.	
Abstract	
Subject Terms	
Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU
Number of Pages 4	

Poor contact must be avoided. Therefore, the surface electrodes have to be fastened by tightening bands. Since different position of the surface electrodes causes different EMG signals (see Fig. 2), thus the position of the electrodes should be kept same.

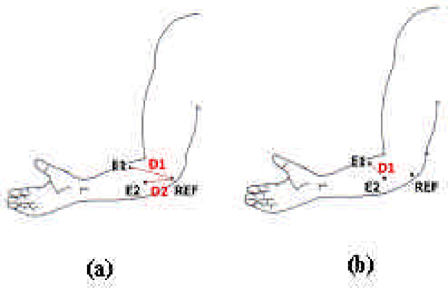

Fig. 2 Location of electrodes

The electrodes were organized as a circle form, using four electrodes one in front of the other, and adding an electrode as reference.

Given the strategies of training of the ANN, the form should be defined in terms of the databases, to conform several databases, according to the different combinations in the position of the electrodes.

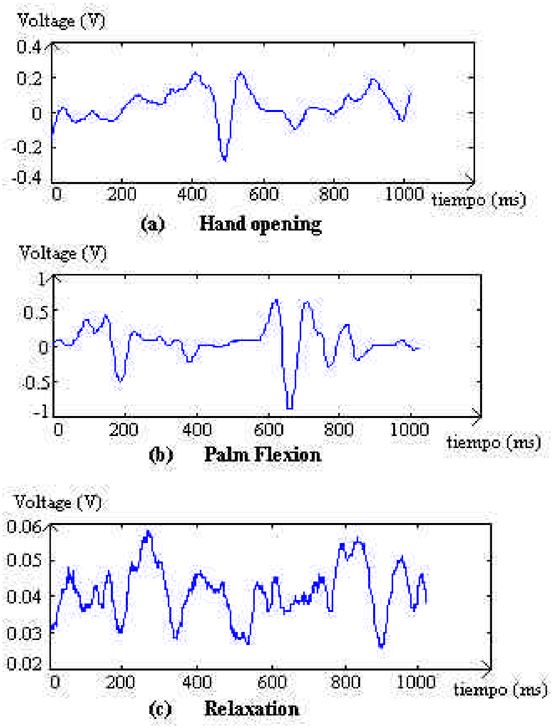

Fig. 3 EMG signals

Each electrode is measured regarding a common point of reference and four measurements are obtained (see Fig. 2a). A differential measure, it is made taking into account the values of pairs of electrodes (see Fig. 2b).

B. Discrimination part

The discrimination part is formed by the spectral calculation of the EMG signals, the process of the data engineering and the neural network.

Spectral calculation and Data Engineering

The EMG signals were collected from the right arm of a healthy patient, carrying out the following movements: Relaxation, hand opening and closing, palm flexion and dorsiflexion, wrist pronation and supination.

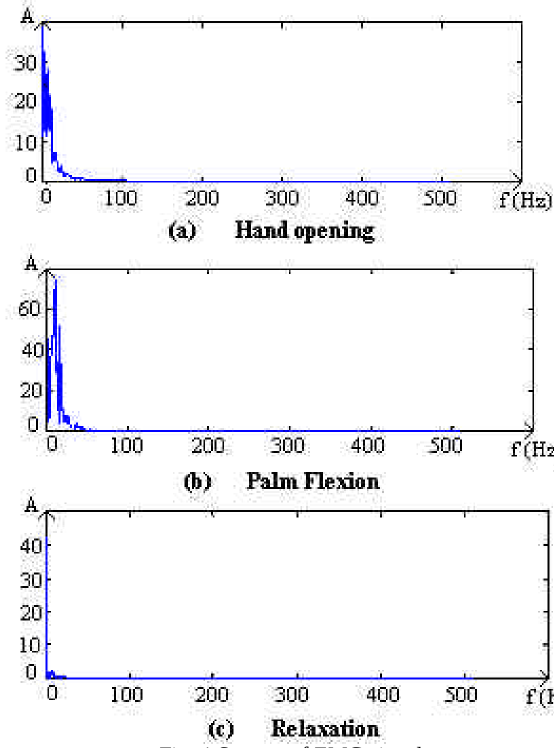

Fig. 4 Spectra of EMG signals

The EMG signal (see Fig. 3), a non-periodic signal, possesses all the characteristics of a random signal and consequently can be analyzed using Fourier analysis (FFT algorithm). The EMG power spectrum represents a continuous distribution of the power of the signal as a function of its frequency. Three examples of spectra are shown in Fig. 4., where you can appreciate some differences. Due the fact that the amplitude and frequency are related with many factors, that is, the contraction of muscles, the distance between the active muscle fiber and the detection site and so on, the information of the desirable performances of the handicapped is included in them.

A database was built and structured in 50 columns corresponding to the coefficients and 10.000 lines representing the examples of each movement.

In the database, not all the movements have the same number of samples, because statistically they do not have the same probability of happening; therefore the percentages are discriminated against each movement (see TABLE I).

TABLE I
Distribution of the Movements

J_1:	RELAXATION	60%

J_2:	HAND OPEN	7.5%
J_3:	HAND CLOSE	7.5%
J_4:	PALM FLEXION	6.25%
J_5:	PALM DORSIFLEXION	6.25%
J_6:	WRIST PRONATION	6.25%
J_7:	WRIST SUPINATION	6.25%

In order to select a set of features that contains essentially all the information of the patterns needed to classify the subpopulations more efficiently. It was necessary to map the pattern space into a reduced feature space through three steps to:

(i) retain as much of the original information as possible.

(ii) remove the redundant and irrelevant information, that could cause extraneous noise.

(iii) render the measurement data or variables that are more suitable for decision making.

The correlational analysis allows to determine the dependence among characteristic with the purpose of to reduce or to eliminate redundant information. The correlational analysis is sometimes practical, provided that the sample is large enough. It is useful to determine which ones depend strongly on which other ones, and eliminate the one is lower in order of importance. To do this, is important that exists a measure of dependency. The usual measure of dependence is the correlation coefficient defined in (1).

$$P_{ij} = C_{ij} / \sqrt{(C_{ii} C_{jj})} \quad (1)$$

The sample correlation of two features is defined in the same way as for attributes, by (2),

$$C_{ij} = Cov(X_i X_j) = (1/Q) \sum_{q=1}^{Q} E(X_i^{(q)} - m_i)(X_j^{(q)} - m_j) \quad (2)$$

where

Q	samples of patterns (each movement)
E	expected value operator
$X_i^{(q)}$	value for the i[th] attribute of the q[th] sample pattern.
$X_j^{(q)}$	value for the j[th] attribute of the q[th] sample pattern.
μ_i	expected value of the i[th] attribute over the sample population of size Q.
μ_j	expected value of the j[th] attribute over the sample population of size Q.

The correlation coefficient of (1) satisfies the Cauchy-Schwarts inequality (3)

$$-1 \le P_{ij} \le 1 \quad (3)$$

greater independence of X_i and X_j means P_{ij} is closer to zero ($C_{ij} \approx 0$).

Therefore, if any two features are other highly correlated, say, $|P_{ij}| > 0.707$, then more than half of the mean-squared variation of one feature is accounted for by the other (0.707^2=0.5) [3].

After applying those steps, the pattern attributes were reduced from 10.000 X 50 (rows by columns) to a smaller set of 10.000 X 30 features that intrinsically capture the relationships along the rows and columns.

Therefore, the principal database consists of 37 columns as follow: 30 belong to principal coefficients and 7 of the target .

Neural Network

The Neural Network learns (off-line) the teaching of data using a backpropagation algorithm as a supervised learning method.

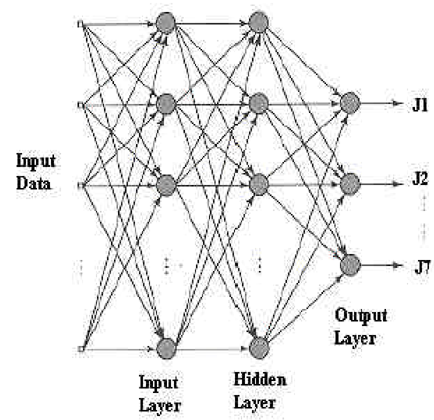

Fig. 5 Architecture of Neural Network

The architecture of a network consists of a description of how many layers a network has, the number of neurons in each layer, each layer's transfer function, and how the layers are connected to each other.

The neural network topology chosen was feedforward which includes multiple-layered perceptrons (MLP). It has a variety of layers; with one input layer (N), one hidden layer (M) and one output layer (J) (see Fig. 5). The output layer has a number of cells as many as the number of performances.

The process of ensuring general learning in an MLP consists of building three databases: (i) training, (ii) validating, and (iii) verification.

The straightforward procedure on a given 10.000 of original training exemplar pairs as follows: (i) 60% of the pairs to be used for training, (ii) take 15% of the exemplar pairs to be used for cross-validation, and (iii) take the remaining 25% of the original pairs to be used for verification testing of the MLP model (see TABLE II)..

TABLE II
Data distribution for learning the MLP

Movement	**Samples**	**Training**	**Verification**	**validation**
RELAXATION	6000	3600	1500	900
HAND OPENING	750	450	188	112
HAND CLOSING	750	450	188	112
PALM FLEXION	625	375	156	94
PALM DORSIFLEXION	625	375	156	94
WRIST PRONATION	625	375	156	94
WRIST SUPINATION	625	375	156	94
Total	10.000	6.000	2.500	1.500

The validation and verification together constitute the acceptance testing of a trained neural network.

The training process did not consist of a single call to a training function. Instead, the network was trained 5 times.

As a conclusion, the neural network needs 30 inputs and 7 neurons in its output layer to identify movements. The hidden layer has 45 neurons. This number was picked by guesswork and experience. If the network has trouble learning, then neurons can be added to this layer.

The neural network which has learned the relation between the EMG signal and the performance desired by the handicapped, it can discriminate the desirable performances.

III. IMPLEMENTATION

The neural network has been tested in a software implementation and has been shown to be capable of automatically generating patterns that are customized for an individual.

This hardware implementation is a step towards the development of low-power, portable and for real time operation. The implementation is based on the digital signal processor ADSP-21061[1] (it belongs to Analog Devices company) [4].

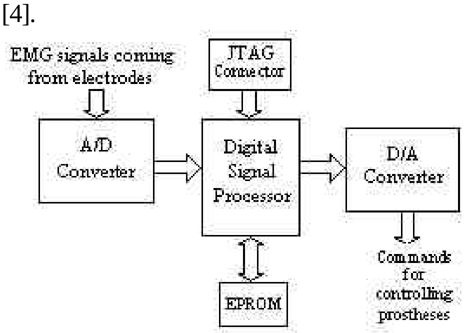

Fig. 6. Schematic diagram of an intelligent interface for myoelectrical controlled prosthesis

The size of the interface has always been a restriction fact, therefore, it was necessary to design this prototype, at the laboratory to come up with the right size.

An electromyographic power spectrum was computed after sampling the myoelectrical signal incoming from four surface electrodes. Using an A/D converter (AD73360)[2] performed digitization of the signal.

The sample rate was set to convert four channels at a frequency of 15.625 Hz, then the first program performed the acquisition of 1024 samples of each channel, window-weight by a Hamming function and transformed into the frequency domain. These data was downloaded to the host computer and saved.

Weights obtained were used in a second program executed on the ADSP-21061 for real-time testing.

The second program performed the upload of obtained weights and enter the endless loop of myoelectrical signal acquisition, Fourier transformation, recall phase and output the result through a D/A converter (AD5544)[3]. In terms of implementation, the neurode-input integration is easily coded, and executed by the ADSP-21061 with minimum computational cost.

IV. EXPERIMENTAL RESULTS

After teaching the neural network under the experimental parameters, on-line discrimination was carried out through our prototype (see Fig. 6).

As a conclusion it was found that the discrimination part could discriminate 7 performances from the EMG signal.

V. CONCLUSION

We have seen that a feedforward neural network learns in a more generalized fashion when there are not too many neurodes in the hidden layers. However, if there are not enough hidden neurodes, then the MLP will not learn to separate all of the performances.

The neural network architecture provides a twofold solution, a fast way of system customization to the patient and better patient adaptation to the system.

VI. FUTURE WORK

Prove the effectiveness of this system, experiments for discriminating the 7 performances of amputated people.

ACKNOWLEDGEMENTS

We express our gratitude to Analog Devices for their support through the DSP University program.

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[1] It is a member of the powerful SHARC® (Super Harvard Architecture) family of floating point processors. The ADSP -21061 is a 32-bit processor optimized for high performance DSP applications.

[2] The AD73360 is a six-channel, 16-bit, analog front end. It comprises six independent encoder channels each featuring signal conditioning, programmable gain amplifier, sigma-delta A/D converter and decimator sections.

[3] The AD5544 contains four, 16-bit, current-output, digital-to-analog converters respectively. Each DAC has its own independent multiplying reference input.