COMPARISON BETWEEN MLP AND LVQ NEURAL NETWORKS FOR VIRTUAL UPPER LIMB PROSTHESIS CONTROL

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***Abstract* - During the rehabilitation process, individuals who have experienced a total or partial loss of upper limbs are exposed to many risks. Besides this, a great mental effort is required during the training phase to adapt to a real prosthesis. In many cases, the use of Virtual Reality in Medicine has proven to be an excellent tool for evaluation and support as well as to mitigate risk and to reduce mental effort required. In order to be useful, virtual prosthesis must have a great similarity with the real world. For this reason, artificial neural networks have been explored to be applied in the training phase to provide real time response. The objective of this study is to compare the performance of the LVQ and MLP neural networks in EMG (muscle activity) pattern recognition. To achieve this, different feature extraction techniques for simulation and control of virtual prostheses are investigated.**

***Keywords* - Virtual reality, Neural networks, Rehabilitation, EMG pattern recognition, Feature extraction.**

I. INTRODUCTION

A prosthesis is a device that aims to recover an amputated limb function. The electromyographic signal (EMG), collected in the remaining muscles of the amputated limb, can be used to control myoelectric prosthesis. The EMG signal is an electric potential produced by a particular muscle contraction. By processing the EMG signal, it is possible to discriminate different upper limb movements. This application has become an important human-machine interface in many areas, such as prosthesis control (on-off and proportional), robotic hands control, and Force Display Devices (FDD) control in Virtual Reality (VR) environments [1]. Due to the its stochastic nature, pre-processing techniques (section B and C) capable of extracting EMG signal information are required before signal classification.

Artificial neural network (ANN) are systems that can recognize and classify patterns, such as EMG, from a learning model based on human learning [2]. A striking feature of ANN is its capability of generalization, after a training stage in which some input patterns are presented and processed by the network. In the execution stage, different patterns from those used in training stage may be processed properly by the network.

The use of VR techniques by myoelectric prosthesis in their training stage presents itself as a complementary tool that favors adaptation to artificial limbs [3]. VR techniques also enable performance evaluation of different control systems, ease wear during the training, and provide a good visual feedback [4]. Many authors have investigated the use of EMG signal in upper limb and prosthesis control: Huang et. al [5], Sebelius et. al [4] and Pons et. al [6]. They discussed the question around hands prosthesis control whilst Herle et. al [3], Nogueira et. al [7] and Soares et. al [8] treated the virtual arm control. EMG signal classification, pattern recognition, feature extraction, real-time signal processing, and realistic prosthesis simulation are among the main challenges faced by these authors.

This paper presents a comparative study of two classifiers using different feature extraction techniques. The main objective is to provide, during training stage, a better prosthesis control to the individuals who have experienced upper limbs lost.

II. MATERIALS AND METHODS

Feature extraction techniques presented in section C will be applied in each movement database. The database consists of hand movement investigated by Mattioli et. al [9] and arm movement, investigated by Soares et. al [8] and Nogueira et. al [7]. Five replicates were used for each movement: arm (isometric / isotonic contraction) and hand (isometric contraction). This movements will be used to generate the basics training patterns that will feed the LVQ and MLP neural networks. All patterns will be used during the training phase and application, since it is a virtual prosthesis for a single patient.

Configuration parameters of each neural network, such as: learning rate, learning rate decrease, tolerance, number of outputs units, number of hidden layer neurons and momentum, will be variated. In order to evaluate each network classification performance, efficiency (Equation 1) and training time will be computed for each different configuration.

$$E = 100 \times \frac{N_{correct}}{N_{total}} \% \qquad (1)$$

The desktop configuration used to run these tests is:

- Operational system: Ubuntu Linux, 10.04(kernel) 2.6.32;
- RAM 2Gb;
- Intel(R) CoreTM 2Quad E4700, 2.6GHz Processor;

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A. System architecture

Figure 1 shows the structure proposed in the following, all process stages will be detailed.

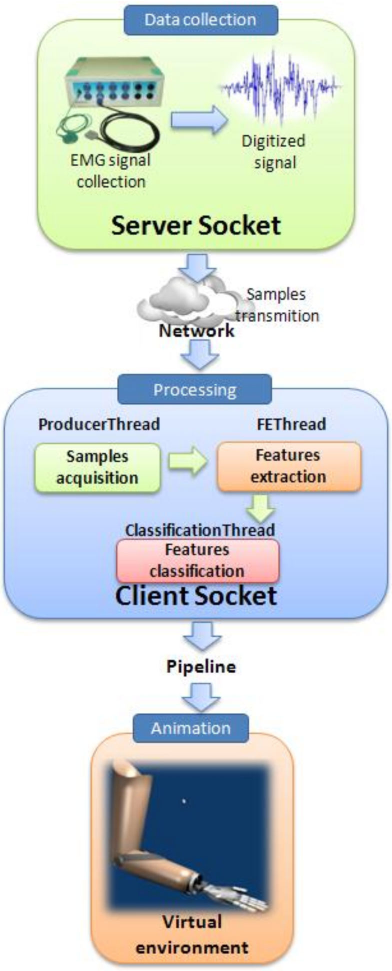

Fig. 1. System architecture.

The collection and transmission of samples are performed in "Data collection" stage, which are sent by socket to another block responsible by the "Processing".

All tasks related with samples processing are detailed in sections B, C and D.

B. Signal windowing

The first phase to be executed in the "Processing" stage is "Samples acquisition". Teager's energy operators (TEO), a real-time boundary detector method created by Peretta [10] and used by Mattioli et. al [11], will be applied to all samples received to extract only the significant parts of the signal. Once the relevant signal extracted it is divided into segments of each samples, similar to the procedure realized by Herle et. al [3].

C. Feature extraction

In order to reduce the amount of information to be presented to neural networks, two techniques of features extraction for each segment are presented: Time-domain features (TDF), used by Herle et. al [3], and Hudgins et. Al [12]; and autoregressive model (ARM), studied by Soares et. al [8].

1) TDF - Five features were defined: Mean Absolute Value (MAV), Mean Absolute Value Slope (MAVS), Zero Crossing (ZC), Slope Sign Changes (SSC) and Waveform Length (WL) [12] [3], all of those are calculated within each segment of 40 samples.

2) ARM - This is a representation of a specific signal which depends solely on the output values previously stored by the system. The $\hat{y}(n)$ variable value in a specific time of a ARM may be estimated from some previous variable values (y(n-1), y(n-2), ...). An ARM is defined by Equation (2) [8] and it is applied to each segment of 40 samples.

$$\hat{y}(n) = \sum_{m=1}^{M} a_m(n)y(n-m) + e(n) \quad (2)$$

Where: $\hat{y}(n)$ is a estimated value at time n; a_m is autoregressive (AR) coefficient of order m calculated for each samples within each segment; $e(n)$is an estimated error; and $M$the order of ARM which determines the number of coefficients a_m.

D. Classification technique

The feature vectors will be present to neural networks as an input. If TDF technique is used, only five features will be presented at a time for the network for each segment. Moreover, if ARM is used each sample will be represented by M numbers of AR coefficients, i.e., $40 \times M$ coefficients for each segment (of 40 samples) will be presented for the network.

After presenting the feature vector to each of the chosen networks, there's the classification of which movement that feature vector represents.

Two networks — LVQ (Learning Vector Quantization) and MLP (Multi Layer Perceptron) — with one hidden layer were chosen, considering that the work performed by Soares et. al [8] and Mattioli et. al [11] achieved a satisfactory performance.

Details on the classification techniques used are described by Mattioli et. al [9] [11].

E. Training environment prototype

The GUI of the training environment, is showed in Figure 2, in which the network training settings can be adjust.

A virtual prosthesis model was developed using 3Dstudio Max® [13] and after exported to Blende3D™. The GUI and 3D model are initiated at the same time. After three feature vectors correct classification by the network, a message is sent by pipeline to Blender that triggers an animation of the virtual upper limb prosthesis: The virtual prosthesis movements are: hand movements (extension, flexion, grasping and forearm pronation) and arm movements (elbow flexion, extension and forearm pronation, supination).

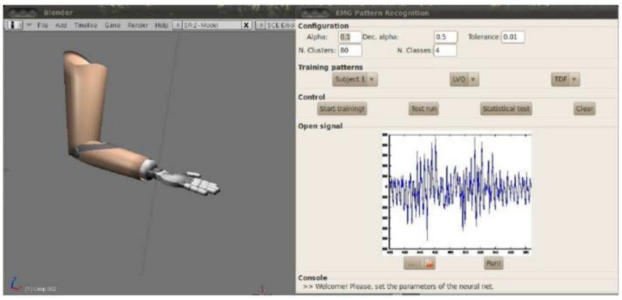

Fig. 2. GUI of the training environment.

F. Testing methodology

A single parameter will be variated at time, in order to understand its impact on results. The range of each parameter is described below:

1) Standard settings:

- **LVQ Network:** learning rate=0.1, reduce learning rate=0.5, and tolerance=0.01;
- **MLP Network:** learning rate = 0.1, tolerance=150, momentum 0.5 and number of neurons in hidden layer = 20;

2) Variable settings:

- **LVQ Network:**
  - Outputs units: The maximum percentage of output units will be up to 90% of the total (TDF-hand and arm) patterns, 22% of the total (ARM-hand) patterns and 11% (ARM-arm) patterns, learning rate and reduce learning rate 0.1 to 0.99 and tolerance is 0.01 to 0.099;
  - The number of repetitions for each test parameter is changed is: — TDF:, 100 repetitions; — ARM: (3^{rd},4^{th},6^{th},8^{th} and10^{th} order), 25 repetitions.
- **MLP Network:**
  - Learning rate: 0.1 to 0.7; tolerance: 100 to 300; number of neurons in hidden layer: 1 to 30;
  - 100 repetitions will be performed for each parameter variated, independent of the used feature extraction technique;

III. DISCUSSION

From the LVQ network performed tests follows that: Using TDF for hand movements has reached 97% of efficiency with only 72% of the training patterns. Using TDF for arm movements has reached a maximum of 80% of efficiency. Using the ARM for hand movements has reached 99% efficiency with only 11% of the training patterns as shown in Figure 3, and 97% efficiency for arm movements with only 10% of all training patterns.

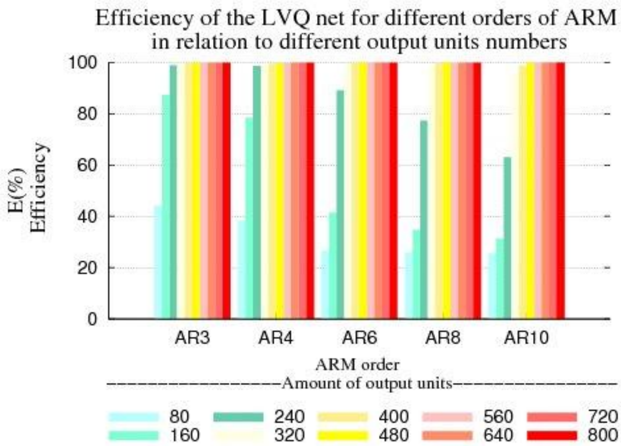

Fig. 3. LVQ network efficiency tests for isometric contractions of hand movement using ARM

The margin error of 20% for the arm movements increases the probability of error in the classification of the movement performed. Figure 4 illustrates an unacceptable feedback for a virtual training environment.

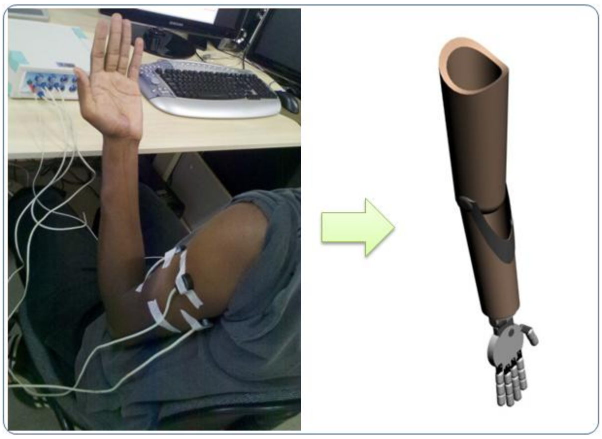

Fig. 4. Wrong visual feedback due to Neural network classification

Figure 5 shows the correct virtual movement due to high network efficiency.

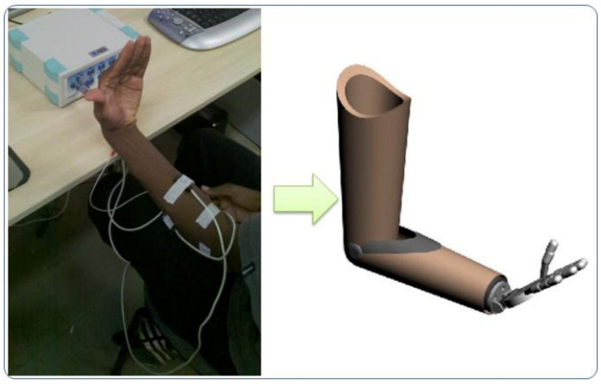

Fig. 5. Right visual feedback due to Neural network classification

The training time using TDF in both cases did not reach a second. The training time for an 3rd order ARM was 27 seconds.

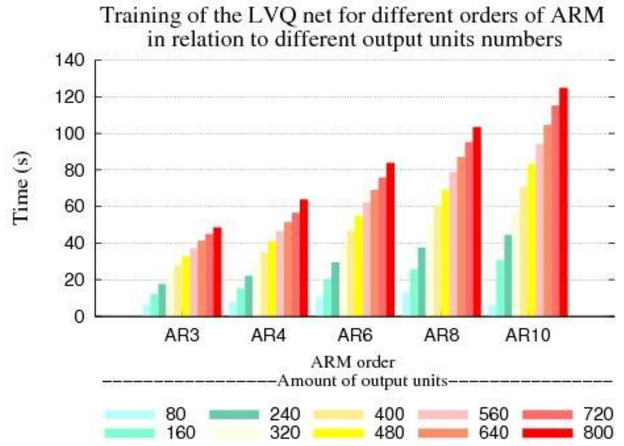

Fig. 6. LVQ network training time tests for isometric contractions of hand movement using ARM

In tests with MLP network performance rating above 85% was not observed for hand movements, and the average training time was 100 seconds, as shown in Figure 7 and 8.

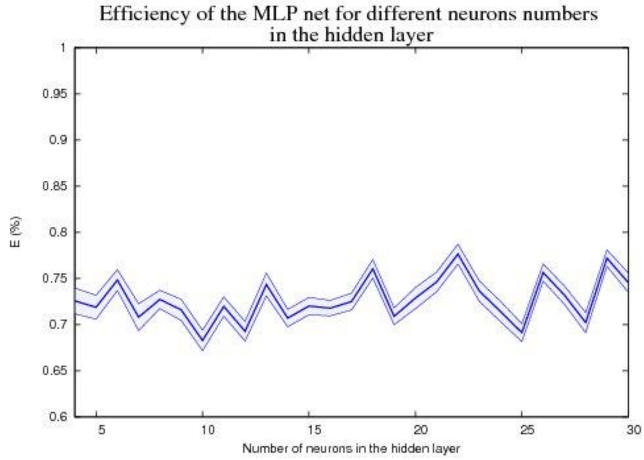

Fig. 7. MLP network efficiency tests for isometric contractions of hand movement using TDF

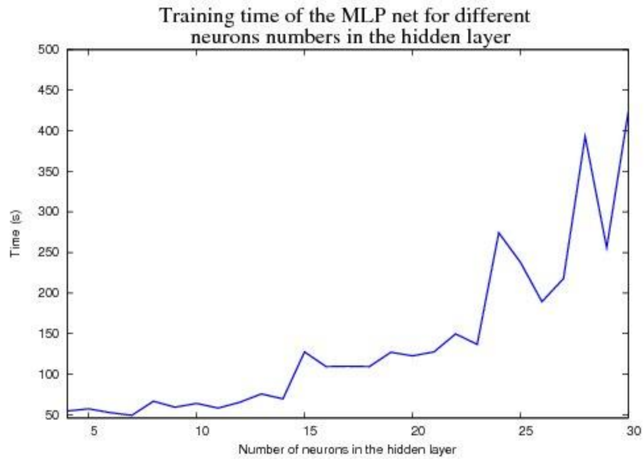

Fig. 8. MLP network training time tests for isometric contractions of hand movement using TDF

Results as the ones obtained in the MLP network to hand motions using TDF, and results for LVQ using ARM arm movements, are not suitable for controlling virtual prosthesis, since the error rate is too large.

IV. CONCLUSIONS AND FUTURE WORK

Machover [14] states that VR systems need to provide a consistent reaction to the user's movements, making the experience consistent. This emphasizes the importance of studying methods and techniques for increasing the efficiency of pattern recognition techniques, in order to have a correct classification of movements performed by the patient.

The results presented assert that the LVQ using ARM is a good alternative for controlling virtual prosthesis for upper limbs (arm and hand movements). This is an bright spot of this work, considering that all previous work tried to simulate only one movement at a time. In Soares et. al [8] it was necessary 50% of the training patterns to achieve the efficiency of 100%; and this work achieved the same only 10% of the training pattern.

Neural networks are often used for pattern recognition of EMG signals. Their efficiency depends on the used pre-processing technique and the way the signal is captured.

As a future work, the authors will perform a new data capture of hand movements signal with a greater number of capture channels and repeat the tests in MLP network using TDF.

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