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Classification of EMG signals using artificial neural networks for virtual hand prosthesis control

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***Abstract*— Computer-based training systems have been widely studied in the field of human rehabilitation. In health applications, Virtual Reality presents itself as an appropriate tool to simulate training environments without exposing the patients to risks. In particular, virtual prosthetic devices have been used to reduce the great mental effort needed by patients fitted with myoelectric prosthesis, during the training stage. In this paper, the application of Virtual Reality in a hand prosthesis training system is presented. To achieve this, the possibility of exploring Neural Networks in a real-time classification system is discussed. The classification technique used in this work resulted in a 95% success rate when discriminating 4 different hand movements.**

I. Introduction

In the past few years, Medicine and other human health related areas have benefited from the technological advances presented by Virtual Reality (VR) [1]. Specially when applied toward human rehabilitation, VR provides immersion that favors the patient's cognitive and motor abilities training [2].

The use of VR techniques by users fitted with myoelectric prosthesis in the training stage presents itself as a complementary tool that favors users adaptation to the artificial limbs [3]. Despite the high costs associated with these devices, the users' adaptation to the prosthesis can be seen as a major problem, regarding the fact that many patients still give up during the training process [3]. Besides making it possible to evaluate different control systems performance, the use of VR in the simulation of myoelectric prosthesis eases the problem of users' adaptation by providing the patients with a visual feedback channel. Therefore, the use of virtual prosthesis reduces significantly the patients' mental effort spent in the training stage [4].

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Myoelectric prosthesis control is based on the use of electromyographic (EMG) signals collected from remnant muscles [5]. An EMG signal consists in the electrical manifestation of the neuromuscular activation associated with a contracting muscle [6], [7]. This signal can be measured in the skin surface (surface EMG or sEMG) or by implanting sensors in the inner layers of the muscle. According to the medical literature, different forearm muscles are related to hand motion and EMG signals can be measured in these muscles even after hand amputation [8]. By analyzing and processing EMG signals, it is possible to classify and associate different hand motions to the corresponding signals, which consists in an important human-machine interface with wide application such as prosthesis control, robotic hands control and Force Display Devices (FDD) control in Virtual Reality environments [9]. Many authors have investigated the use of EMG signals in upper limb and prosthesis control: Sebelius et al. [4] and Pons et al. [10] studied the problem of real-time virtual hand prosthesis control, using different classification strategies; Herle et al. [3], Nogueira [11] and Soares et al. [5] addressed virtual arm prosthesis control, using artificial neural networks, feature extraction and a fixed signal windowing (200 ms) approach. Among the main challenges faced by these authors, one can highlight EMG signal classification, pattern recognition, feature extraction, real-time signal processing and realistic prosthesis simulation.

This work presents a VR training environment prototype that enables virtual hand prosthesis simulation/control using Artificial Neural Networks as the main element of the classification technique. EMG signals are classified by the network and a virtual prosthesis is controlled, performing 4 hand movements: grasping, flexion, extension and forearm pronation.

II. Materials and methods

In this work, a learning vector quantization (LVQ) neural network with 5 input units ($X_i, i = 1 \cdots 5$) and a varied number of output units ($Y_j, j = 20, 40, 60, 80$) has been used. Different numbers of output units were tested, obtaining satisfactory results (average performance above 80%) with 80 output units (20 units for each movement class) when performing offline cross validation on training data. A more detailed approach to performance calculation will be presented in Section II-B. Figure 1 presents the architecture of the network used in this work.

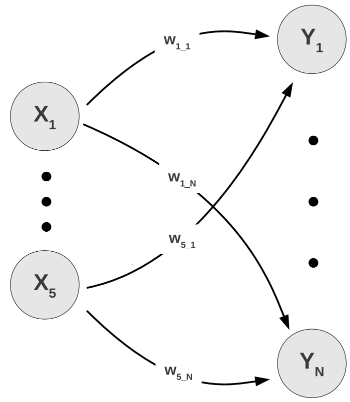

Fig. 1. LVQ network architecture (N = 20, 40, 60, 80)

A. Feature extraction

EMG signals were collected from the flexor carpi radialis muscle of 3 healthy subjects, using a single-channel bipolar recording technique. Inter subject variability in EMG generation was not an issue, since the network is trained and tested separately for each subject. Due to the EMG signal complexity, as proposed by Herle [3], it is necessary to reduce the network's input units number. In order to achieve this, the solution adopted in this work was to extract features from the EMG signal, mapping it to a smaller dimension vector, called feature vector. Previous work such as Englehart et al. [12] and Zecca et al. [13] suggests different approaches to improve the network classification performance by applying dimensional reduction to the input vector.

First of all, a signal windowing was conducted, in order to select only the signal intervals with relevant information. Windowing intervals were determined using the Teager's energy operators (TEO). These operators are useful for analyzing single component signals from the energy point-of-view, and can be used to determine signal's relevant information intervals [14], [15]. Equation 1 presents the Teager energy operator in the discrete domain, as defined by Kaiser [14]. Different thresholds to detect relevant signal intervals were tested. A threshold of $1 \cdot 10^6$ resulted in signal windows with great similarity with visually obtained windows.

$$\Psi[x(n)] = x_n^2 - x_{n+1} \cdot x_{n-1} \tag{1}$$

where x is the sample vector and n is the sequence index.

Signal windows were divided into 40 samples segments, as suggested by Herle [3]. For each segment, the following features were extracted: Mean Absolute Value - MAV, Mean Absolute Value Slope - MAVS, Zero Crossing - ZC, Slope Sign Changes - SSC and Waveform Length - WL [16].

MAV represents the mean absolute value of the analyzed segment. Equation 2 is used to calculate this value [16].

$$\bar{x_i} = \frac{1}{S}\sum_{m=1}^{S} |x_m|, \tag{2}$$

where i is the segment number, S is the number of samples per segment and x_m is the m-th sample in the segment i.

Mean absolute value slope (MAVS) consists of the difference between two adjacent segments MAV, and is calculated by the relation [16]:

$$\Delta\bar{x_i} = \bar{x}_i - \bar{x}_{i-1}, \tag{3}$$

where i and $i-1$ are two adjacent segments, $i = 2...I$ and I is the total number of segments for a given signal window.

Zero cross number (ZC) is a frequency measure that can be obtained by counting the number of times a waveform crosses the line $y = 0$. A threshold was included in order to ignore noise-induced zero cross. As proposed by Herle et al. [3], a threshold $\epsilon = 10^{-6}$ was used in this work. Zero cross counter is incremented each time the conditions

$$\begin{gathered} \{x_m > 0 \text{ and } x_{m+1} < 0\} \text{ or} \\ \{x_m < 0 \text{ and } x_{m+1} > 0\} \text{ and} \\ |x_m - x_{m+1}| \geq \epsilon \end{gathered} \tag{4}$$

are satisfied by two consecutive samples x_m and x_{m+1} [3].

Slope sign changes (SSC) provide another frequency content measurement. The same threshold of the ZC counter was used in the SSC counter, that is incremented when the condition 5 is satisfied for three consecutive samples x_{m-1}, x_m and x_{m+1} [3].

$$\begin{gathered} x_m > x_{m-1} \text{ and } x_m > x_{m+1} \text{ or} \\ x_m < x_{m-1} \text{ and } x_m < x_{m+1} \text{ and} \\ |x_m - x_{m+1}| \geq \epsilon \text{ or } |x_m - x_{m-1}| \geq \epsilon \end{gathered} \tag{5}$$

Waveform length (WL) is used to analyze waveform complexity in each segment. This parameter consists in the cumulative length of the waveform in the current segment. Equation 6 provides, in a single parameter, a measurement of the segment's amplitude, frequency and duration [3], [16]:

$$l = \sum_{m=1}^{S} |\Delta x_m|, \tag{6}$$

with $\Delta x_m = x_m - x_{m-1}$, x_m and x_{m-1} being two adjacent samples.

B. Network training

After feature extraction, some experiments were conducted in order to evaluate the influence of some configuration parameters in network training. Analyzed parameters were: number of output units, learning rate (α), tolerance and α decay rate.

In these experiments, training patterns were presented to the previously trained network. For each motion class, network efficiency was calculated as the ratio between correct classifications and total number of patterns [17]. Equation 7 presents efficiency calculation.

$$E = \frac{N_{correct}}{N_{total}} \tag{7}$$

C. Classification technique

In order to improve the classification performance of the network, a majority voting scheme based classification technique was used. Input vectors are divided into 40 samples segments, with no overlapping between segments. Each segment is then classified by the network. Finally, the network classifies the input vector as belonging to the same class as the majority of the classified segments. In case of a tie, the input vector is marked as unclassified by the network. Figure 2 presents an example of this classification strategy.

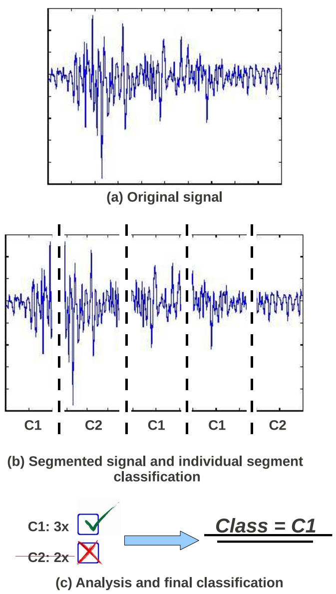

Fig. 2. Signal segmentation and classification.

In Figure 2, the entire sample set is presented in (a), whereas in (b), the signal is segmented and each of the segments is classified by the network. Finally, in (c), since the majority of the segments (3 of the 5 segments) were classified as belonging to the class 1, signal is classified as belonging to class 1 as well.

D. Training environment

In this work, a system prototype has been developed to provide neural network configuration and test. The network is then used to control a hand prosthesis, in a virtual environment. This prototype is presented in Figure 3.

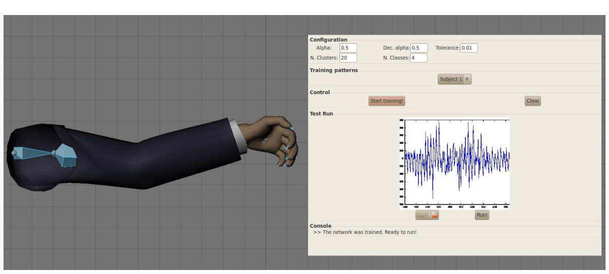

Fig. 3. Graphical user interface of proposed system.

The virtual arm used to represent the prosthesis in this work was adapted from the original model, developed by Kator and Legaz [18]. After the original model's segmentation, considering this work's requirements, a 22 bones armature was adapted to the virtual model, in order to provide the animation of the virtual hand. Considering the application of the model in a hand prosthesis training system, 4 movements (grasping, extension, flexion and pronation) were animated [19].

Patient's interaction with the virtual training environment is done through the EMG signal's classification interface. Four hand movements are executed in the virtual environment: hand extension, hand flexion, hand grasping and forearm pronation.

E. System architecture

Figure 4 shows the system architecture, which is composed by 3 main modules. In the data acquisition module, EMG signal is collected by the electromyograph and stored in data files. Then, in the processing module, feature extraction is conducted and resulting feature vectors are stored. The neural network provides signal classification from the stored feature vectors. Finally, using the obtained classification, the virtual prosthesis is animated.

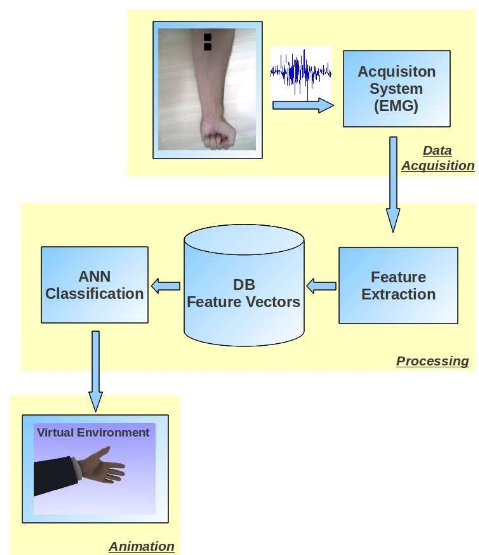

Fig. 4. Prototype's architecture.

In order to evaluate the prototype's performance in real-time applications, a real-time simulation module was developed. This module, presented in Figure 5, consists of a client-server application. In the client side, stored data is read from data files and sent by a stream socket to the server in a fixed rate. After collecting data, the server proceeds signal windowing, feature extraction and finally, segment classification.

III. Discussion

The developed prototype presented good performance in the classification of EMG signals. However, in this work, real-time signal processing was investigated using only the real-time simulation module. For real-time applications, the resulting response delay due to the signal acquisition devices

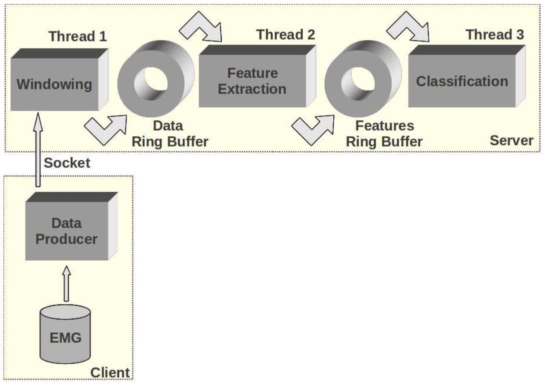

Fig. 5. Real-time simulation module architecture.

must be considered. In this experiment, this requirement did not affect overall network performance, since the real-time simulation data was read from stored data files.

Using the classification technique presented in Section II-C, the network correctly classified up to 19 of the 20 analyzed patterns, using 80 output units. This success rate corresponds to a 95% classification efficiency. Using 40 output units, a classification efficiency of around 80% (16 of the 20 patterns correctly classified) was obtained.

IV. Conclusion and future work

This paper presented artificial neural networks that were used to classify EMG signals, applied to hand prosthesis simulation and control within a Virtual Reality environment. The techniques used in signal's features extraction and classification enabled the network to achieve a 95% classification performance, which is similar to the classification performance reported by Herle [3] in off-line arm prosthesis control.

The proposed classification technique provided an increase in the classification system's efficiency (compared to the single segment classification approach). The time delay observed in real-time conducted tests (due to signal windowing and feature extraction in real-time) was not critical, since it corresponds to a slight increase in the overall response time. An evaluation of this response time by myoelectric prosthesis users consists in an interesting proposal for future works.

Virtual training environments used in myoelectric prosthesis simulation and control have large application in health areas, more specifically as assistive technologies in human post-amputation rehabilitation. Furthermore, these environments constitute an auxiliary monitoring and evaluation tool for potential users of this type of prosthesis. The possibility of integrating the presented prototype with a database system, in order to automatically generate training reports, is one of the main factors that suggests its applicability and use by health professionals.

More future work suggestions are: 1) the evaluation of other signal features' impact in the classification stage; 2) extension of the current system to other EMG signals (associated with other classes of movements); 3) statistical evaluation of different neural networks' performance in the analyzed signals' classification.

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References

[1] R. Costa and M. Ribeiro, *Aplicações de Realidade Virtual e Aumentada - Livro do pré-simpósio do SVR2009*. Porto Alegre: SBC, 2009.

[2] P. Weiss, D. Rand, N. Katz, and R. Kizony, "Video capture virtual reality as a flexible and effective rehabilitation tool," *Journal of NeuroEngineering and Rehabilitation*, vol. 1, no. 1, p. 12, 2004.

[3] S. Herle, P. Raica, G. Lazea, R. Robotin, C. Marcu, and L. Tamas, "Classification of surface electromyographic signals for control of upper limb virtual prosthesis using time-domain features," *Proceedings of the 2008 IEEE International Conference on Automation, Quality and Testing, Robotics*, pp. 160–165, 2008.

[4] F. Sebelius, M. Axelsson, N. Danielsen, J. Schouenborg, and T. Laurell, "Real-time control of a virtual hand," *Technology and Disability*, vol. 17, no. 3, pp. 131–141, 2005.

[5] A. Soares, A. Andrade, E. Lamounier, and R. Carrijo, "The development of a virtual myoelectric prosthesis controlled by an EMG pattern recognition system based on neural networks," *Journal of Intelligent Information Systems*, vol. 21, no. 2, pp. 127–141, 2003.

[6] E. Lamounier, K. Lopes, A. Cardoso, A. Andrade, and A. Soares, "On the use of Virtual and Augmented Reality for upper limb prostheses training and simulation," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*. IEEE, 2010, pp. 2451–2454.

[7] A. Andrade and A. Soares, "EMG Pattern Recognition for Prosthesis Control," in *Proceedings of 16th Brazilian Conference on Mechanical Engineering*, 2001.

[8] Y. Su, M. H. Fisher, A. Wolczowski, G. D. Bell, D. J. Burn, and R. X. Gao, "Towards an EMG-Controlled Prosthetic Hand Using a 3-D Electromagnetic Positioning System," *IEEE transactions on instrumentation and measurement*, pp. 178–186, 2007.

[9] D. Nishikawa, W. Yu, H. Yokoi, and Y. Kakazu, "On-Line Learning Method for EMG Prosthetic Hand Control," *Electronics and Communications in Japan*, pp. 1510–1519, 2001.

[10] J. Pons, R. Ceres, E. Rocon, S. Levin, I. Markovitz, B. Saro, D. Reynaerts, W. Van Moorleghem, and L. Bueno, "Virtual reality training and EMG control of the MANUS hand prosthesis," *Robotica*, vol. 23, no. 03, pp. 311–317, 2005.

[11] K. L. Nogueira, "O Uso de Técnicas de Realidade Virtual e Aumentada na Simulação de Prótese de Membros Superiores," Master's thesis, Universidade Federal de Uberlândia, Uberlândia, July 2007.

[12] K. Englehart, B. Hudgins, P. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Medical engineering & physics*, vol. 21, no. 6-7, pp. 431–438, 1999.

[13] M. Zecca, S. Micera, M. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Critical Reviews in Biomedical Engineering*, vol. 30, no. 4-6, p. 459, 2002.

[14] J. Kaiser, "Some useful properties of Teager's energy operators," in *Acoustics, Speech, and Signal Processing, 1993. ICASSP-93., 1993 IEEE International Conference on*, vol. 3. IEEE, 1993, pp. 149–152.

[15] I. S. Peretta, "A Speech Recognition System for Isolated Words With a Novel Word Boundaries Detector Based on Teager Energy Operator," Master's thesis, Universidade Federal de Uberlândia, Uberlândia, December 2010.

[16] B. Hudgins, P. Parker, and R. Scott, "A new strategy for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering*, vol. 40, no. 1, pp. 82–94, 1993.

[17] G. Li, A. Schultz, and T. Kuiken, "Quantifying Pattern Recognition-Based Myoelectric Control of Multifunctional Transradial Prostheses," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 18, no. 2, pp. 185–192, 2010.

[18] A. Kator and J. Legaz. (2010) 3d models - man in suit (armatured). [Online]. Available: http://www.katorlegaz.com/3d_models/

[19] P. Kyberd, C. Light, P. Chappell, J. Nightingale, D. Whatley, and M. Evans, "The design of anthropomorphic prosthetic hands: A study of the southampton hand," *Robotica*, vol. 19, no. 06, pp. 593–600, 2001.