Arm Orthosis/Prosthesis Control Based on Surface EMG Signal Extraction

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Abstract. The goal of this paper is to show EMG based system control applied to motorized orthoses. Through two biometrical sensors it captures biceps and triceps EMG signals, which are then filtered and processed by an acquisition system. Finally an output/control signal is produced and sent to the actuators, which will then perform the proper movement. The research goal is to predict the movement of the lower arm through the analysis of EMG signals, so that the movement can be reproduced by an arm orthosis, powered by two linear actuators.

Keywords: Orthosis, Prosthesis, Control, EMG, Power assistance.

1 Introduction

Due to different reasons, many people have disabilities in their body, and this causes difficulties in their life. Medical science has worked a lot on trying to solve these drawbacks, but sometimes it is impossible to achieve more improvements just with medical treatments. On this paper we have tried to develop an arm orthosis control, using EMG signals as input and creating a movement, as natural as possible, for a robotic arm.

At the University of Tsukuba the Hybrid Assisted Limb (HAL) was developed [1-3]. It is a battery-powered suit that detects muscle myoelectrical signals on the skin surface, below the hip and above the knee. Using these and other signals, such as gyroscopes, force sensors and potentiometers for measuring joint angles, it processes everything and each leg of HAL is powered in flexion/extension motion. The ankle includes passive degrees of freedom.

Yamamoto et al. [4, 5] have created an exoskeleton system for assisting nurses during patient handling. It includes pneumatic actuators for the flexion/extension of the hips and knees. User input is determined via force sensing resistors coupled to the wearer's skin, and the data used comes from those force sensing resistor and joint angles.

Pratt et al. developed a squatting assisting system that powered the knee movement [6]. The device is powered by a linear series-elastic actuator, and it uses a positive-feedback force controller to create an appropriate force for the actuator.

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Kong et al. developed a full lower-limb exoskeleton system that works with a powered walker [7]. The exoskeleton is lighter than others, because the electric actuators, the controller and the batteries are placed in the walker. The system's input is a set of pressure sensor that measure the force applied by the quadriceps on the knee.

Agrawal et al. have researched projects on statically balanced leg orthoses that reduce the effort during swing [8]. The device uses springs in order to cancel the gravity force associated with the device links and the person's leg. A substantial reduction of the required torque has been proved experimentally.

Just in the USA there is an estimate of 10,000 new upper extremity amputees every year. This can be caused by trauma, disease or due to congenital deficiencies. When a person loses control over a lower limb, there are several options that can be explored, taking into account several factors such as price, weight and performance. Passive prosthesis can be found among the most popular options. The most basic form, controlled by another limb, has limited possibilities but it is well designed esthetically and has low cost. Similarly, in mechanical ones the movement is controlled by another muscle and transferred by strings, with low cost. Voice controlled alternatives are not common, and have acceptable cost, but have limited control and background noise. EMG signals (electromyography), electrical power generated by remaining muscles of the harmed arm, have high cost and learning curve. Finally, options using AMG/MMG signals (acoustic/mechanical myographic), use the sound produced by contracting muscles, they cost less than EMG, they are not affected by electrical interference, background noise and difficulty of recording only the muscle sound.

2 EMG Signal Acquisition

The electromyography signals (EMG) detect the electrical potential generated by muscle fibers. When muscles are relaxes they generate no potential and when they are flexed to the maximum, the electrical potential takes also the peak value.

It is also important to notice that EMG signals are a combination of several Motor Unit Action Potentials (MUAP), as muscle fibers behave as motor units. The combination of those MUAPs is called Compound Muscle Action Potential (CMAP). Multiple MUAPs can be detected using one single electrode, and the EMG signal must be decomposed using some advanced techniques.

Typical EMG signal values are 50μV-30mV electrical potential and 7-20Hz frequency.

2.1 EMG Signals Capturing

Most common methods of capturing EMG signals are using surface, needle or fine-wire electrodes. Surface electrodes detect a larger number of motor units, while the two other methods allow focusing on single muscle fibers. Additionally, the correct placement of the electrodes affects the results of the EMG measuring.

Comparing surface electrodes, dry and wet ones can be differentiated. Needle electrodes are typically used in physiotherapy, and fine-wire electrodes can be surgically implanted into the muscle. In addition, when using surface electrodes, they can be mainly placed longitudinally, following the long axis of the muscle, ore transversally, perpendicular to the long axis.

2.2 EMG Signals Preparation

Once the EMG electrodes are placed, there are a few features to consider. First of all, voltage potential varies for each individual, so data normalization is very useful [9].

Principal sources of noise that must be avoided are: equipment noise (the higher the quality of the equipment is, the less the noise it generates), ambient noise (electromagnetic radiation caused by electronic devices around) and motion artifact (movement of the electrode cable or the electrode itself may produce irregularities in the data [10]).

Besides, some factors affect the EMG signals. One of the most important is causative factors, which can be extrinsic, like the structure or the placement of the electrodes, or intrinsic, like physiological or anatomical issues. There are also intermediate factors, such as physical and physiological phenomena influenced by causative factors. Finally some deterministic factors must be mentioned, because the number of active motor units and mechanical interaction between muscles are important too.

Extra attention is required by the crosstalk. It has to be taken into account very carefully because it affects the signals that will be processed later. Despite that EMG signals are dominated by the closest muscle, neighbor muscle signals may crosstalk with the desired muscle signals [11].

The effect of crosstalk can be minimized by choosing appropriate size of the electrode conductive area and appropriate inter-electrode distance. Crosstalk may also be further reduced by a proper location of the surface electrodes on the muscle [12]. Care should be taken to place the electrodes on the center of the muscle, away from the borders, although this is not always possible.

3 EMG Signal Processing

Once an EMG signal has been properly prepared and recorded, processing is required to extract as much data as possible. It is important to choose the best feature selection method before starting the signal classification.

3.1 Feature Selection

Depending on the type of data and its origin, different commonly used analysis techniques exist [13], as shown in Table 1.

The Principal Component Analysis (PCA) is interesting for pattern recognition because it reduces the number of coefficients needed for an effective feature representation by discarding the terms with small variances. Factor analysis is used to study the patterns of relationship among dependent variables, so you can discover something about the independent variable that affects them. The only variances that are analyzed are the ones that share variances, so the underlying structure of the variables can be identified [14-16].

Table 1. Selection chart for analysis

	Density estimation / model P(x) / probabilistic model	Define a subspace directly / reduce data / not probabilistic
Data assumed in a subspace	Factor analysis	PCA
Data assumed in groups	Mixture of Gaussians	K-means

K-means clustering assigns a set of samples into a subset called "cluster", in such a way that samples in the same cluster are alike in some way. It is considered a form of unsupervised learning and it is used in several fields among which can be found pattern recognition [17]. Finally, the mixture of Gaussians assumes that the data is produced by a mixture of N multivariate Gaussians. As Gaussians are to probability densities what sins and cosines are to periodic signals, in theory any distribution can be described as a combination of Gaussians [18-20].

It is also important to understand how the auto regressive model works. It is often used to predict and model various types of phenomena, and due to the stochastic nature of the EMG signals, it is a good solution for estimating signal samples as linear combinations of previous samples. But the reason why auto regressive model is important in our work is not the estimating aspect, but the vector with the AR-parameters that characterizes the data. And this vector is used as input for the classifier.

3.2 Signal Classification

Once the features of the EMG signals have been extracted and selected, the signals themselves have to be classified. The most popular methods for classification are based on artificial intelligence methods such as neural networks, fuzzy networks or neural-fuzzy networks.

Artificial neural networks (ANN) are, in essence, a simulation of how our brain works. They are structures of parallel processing based on the biological brain processing model [21]. It is formed by simple computation elements, which are partial or totally interconnected. Basically it is a network of nodes, in which each node is connected to each other by links. Additionally, each node has a weight value assigned. Artificial neural networks can have one or multiple layers: the more layers they have, the more complicated the problem they solve can be.

4 Practical Experiment

4.1 Setup

The surface electrode used is the Biometrics SX230. It contains all the necessary gain and filters so the biceps and triceps signals can be captured. Electrodes are connected to the Biometrics K800 base unit, and it also has a ground reference cable (R206) so the system has a good reference.

The K800 amplifier system being used has two main parts: the larger table mounted base unit and the small light weight subject unit. The sensors are connected to the subject unit, which has 8 instrumental amplifiers, and it converts all inputs to digital signals and samples the data. Then the data is transferred to the base unit, which converts the signals back to analogic for output to proprietary A/D systems.

The data acquisition board used is an AD622. It is used to connect PC compatible computers to real world signals. A PC with a numerical computing environment programming language is also needed.

In this experiment, the arm orthosis shown in Figure 1 is used. It is powered by two linear actuators which control the extension and flexion of the elbow. The actuators used are Firgelli Miniature Linear Motion Series L12.

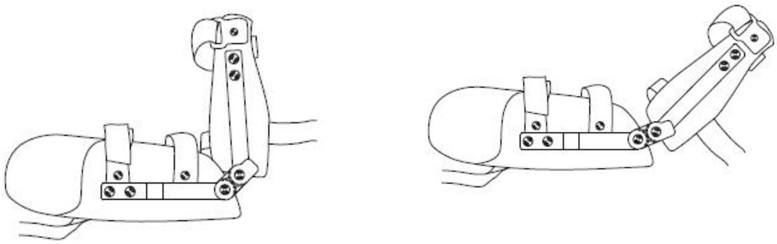

Fig. 1. Custom made arm orthosis

In Figure 2 we can see a general scheme of the tool used during the experiment.

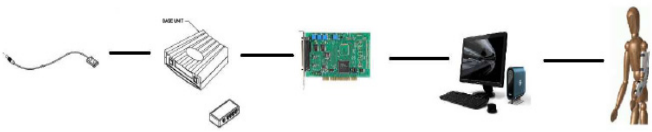

Fig. 2. Practical setup

4.2 Experiment Protocol

In the explained experiment, samples from two healthy male subjects (aged 23 and 25) are collected. The first electrode was positioned on the belly of the biceps brachii, and the second electrode is places on the triceps brachii opposed to the first electrode. Both electrodes are positioned longitudinally.

The movements that are recorded in this experiment are 10 elbow extensions and 10 flexions. The movements are performed under two different situations: while standing and holding an object of 1kg to apply a minimum level of force to ensure the registration of muscle activity during the movements (dataset A), and seated applying different levels of force varying between minimum and maximum voluntary contraction (dataset B).

The movement speed was varied due to 4 normal movement ranges, 3 fast and 3 slow. Each movement was sampled with a sample time of 1ms.

4.3 Binary Algorithm

The most basic solution is the binary algorithm, which only takes into account the amplitude of the signal. Once the biceps or triceps signal crosses a certain threshold, the orthosis will open or close.

After the signal is recorded, an average filter is applied, and then the signal is rectified and filtered again to accent peaks even more. Finally an envelope detector is used to smooth the final signal. This process is shown in Figure 3.

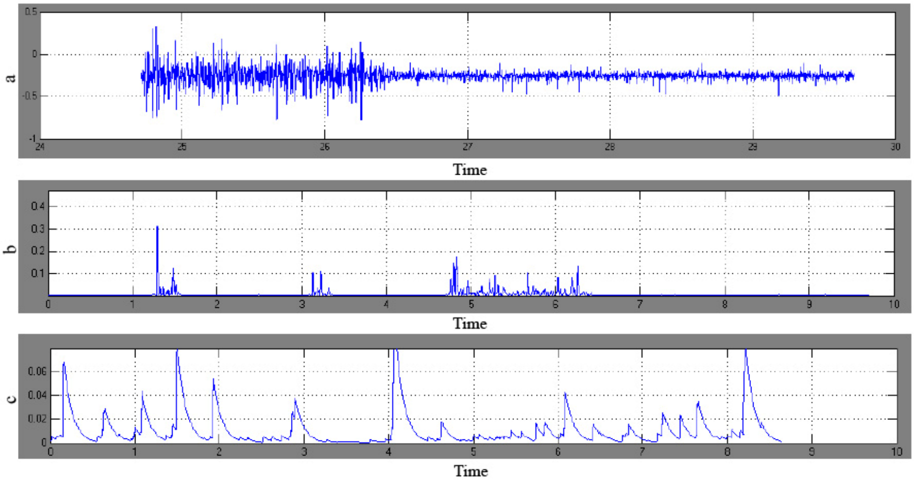

Fig. 3. a) EMG signal b) result of average filter c) result of envelope detector

As it is shown in Figure 4, depending on which threshold values the EMG signal crosses, the orthosis moves up or down.

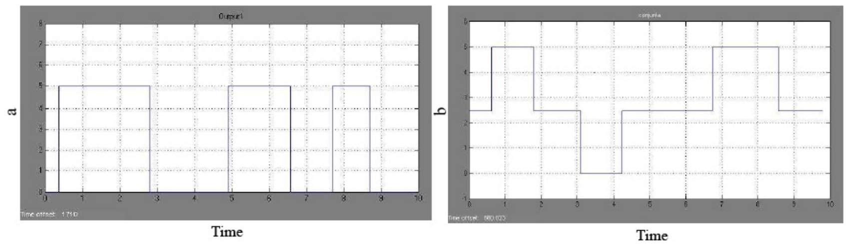

Fig. 4. a) One channel output b) Two channel output

4.4 Variable Algorithm

The variable algorithm uses the same filtering step as the binary algorithm, but it adds a series of threshold values to determine the speed of the movement. At the end the signal is sent through a first order transfer function to smooth the results. The values used in this variable algorithm are shown in Table 2.

Table 2. Variable speed algorithm

Input (X)	Output (Y)	Input (X)	Output (Y)
40≥X<50	Y = 100%	15≥X<20	Y = 50%
35≥X<40	Y = 90%	10≥X<15	Y = 40%
30≥X<35	Y = 80%	7.5≥X<10	Y = 30%
25≥X<30	Y = 70%	5≥X<7.5	Y = 20%
20≥X<25	Y = 60%	1.5≥X<5	Y = 10%

However, because of the high amount of force required to cross certain threshold amplitude, the system is difficult to control. In addition, the system needs practice and learning to control it properly. A typical output using the variable algorithm is shown in Figure 5.

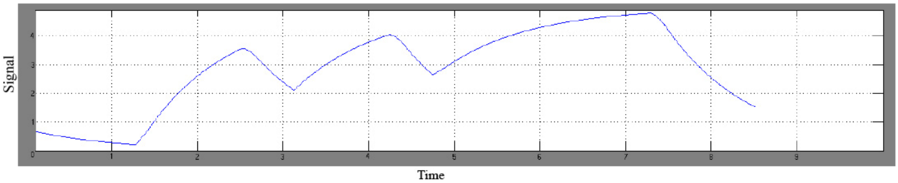

Fig. 5. One channel output

4.5 Autoregressive and Neural Networks

Another algorithm, a bit more complicated than the previous, is the one which uses autoregressive model and neural networks. In Figure 6 the performance of the neural network classifier is shown.

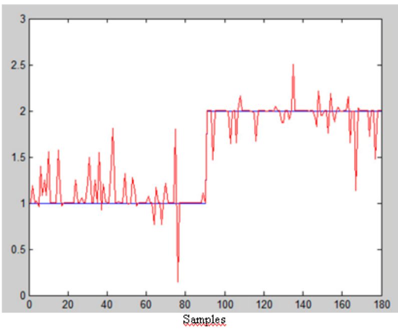

Fig. 6. Performance of the neural network classifier

First of all, after recording the data, the autoregressive coefficients are calculated. A length of 100ms is established for this experiment. Then the neural network is trained several times until the error rate stays below the established value. For the training phase a back propagation network with 15 neurons in the hidden layer is used, with a weight based learning function.

In the last step, the error of the system is calculated. The best performance achieved was a 94.34% accuracy using a sample block length of 100ms and an AR-model of order 15. These values returned from the dataset A.

When the values of dataset B were used, different results were returned. The best performance came from an AR-model of order 4 and block length of 100ms, getting an 80% in the best cases. In this case, lower AR-model order returns a better accuracy level. The results of this experiment are shown in Figure 7.

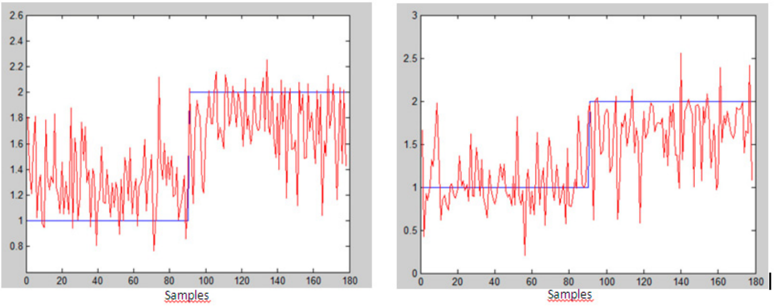

Fig. 7. Neural network response. a) AR order 10. b) AR order 4.

On this highly variance dataset, best results were obtained using an order 4 AR model and a 100ms block length. The network performed around 80% in best cases, being a 5%, on average, better the order 4 AR model rather than the order 10 AR model.

However, it was noticed that the signals toward the end of a movement performed better than the signals created at the beginning of the movement. The performance increased an 11%, getting a 91% of accuracy. In this case, the behavior of the system when the AR-model order is changed improves with higher order. AR-model of order 10 gives 5% more than AR-model of order 4. These results are shown in Figure 8.

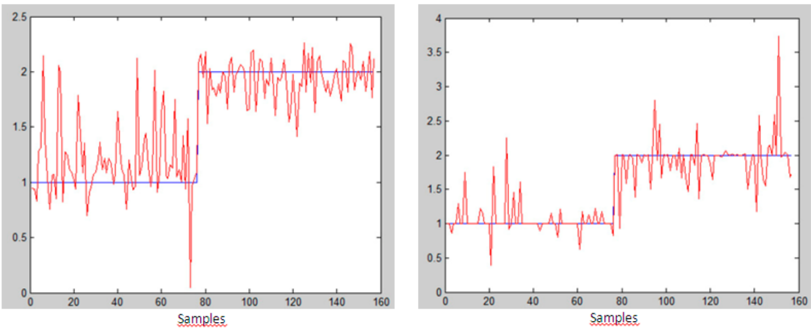

Fig. 8. Neural network response. a) AR order 10. b) AR order 4.

This change in performance can be explained by the fact that triceps signal is much clearer at the end of an elbow extension, and it is only in the later stages of the movement that triceps muscle gives a clear signal. Therefore, we can conclude that using a highly detailed AR-model only confuses the AR-algorithm when the signals have great variations within the same set. A highly detailed model should only be used when there is a high quality dataset.

5 Conclusions

The binary and variable algorithms are very basic time domain analysis solutions, with a low precision and they require the user to apply a significant amount of force, in order to have a clear detection. Furthermore, the system has to be calibrated for each individual. Despite these disadvantages, the system is very simple, which makes these methods easy to implement, requiring less computational power and a minimum amount of hardware.

The use of the autoregressive model combined with the artificial neural network allows a more precise detection of movement with a minimum amount of force to be applied by the user. It classifies the movement as an elbow flexion or extension, and gives back more accurate results than the previous algorithms.

In order to be suitable as a real life application, it is not only important to compare the accuracy of the classification, but also the response time and complexity of the system. It is also important to keep the system user friendly, in such a way that the training and calibration of the system should be kept to a minimum.

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