Fuzzy Control of a Robotic Arm using EMG Signals

M. Hidalgo*, G. Tene*, and A. Sánchez* *Member, IEEE*
*Departamento de Automatización y Control Industrial, Escuela Politécnica Nacional
Ladrón de Guevara E11-253, Quito Ecuador
Email: galoftene@mail.com

***Abstract*— This paper presents the control design of a robotic arm employing Fuzzy algorithms to interpret electromiographic (EMG) signals from the Flexor Carpi Radialis, Extensor Carpi Radialis and Biceps Brachii muscles. The control and aquisition systems is composed of a microprocessor, analog filtering, digital filtering and frequency analysis, and finally a fuzzy control system. The system has been implemented over a MICROCHIP PIC 16F876 and LabVIEW.**

I. Introduction

This paper presents the control design of a robotic arm employing Fuzzy algorithms to interpret electromyographic (EMG) signals from the Flexor Carpi Radialis, Extensor Carpi Radialis and Biceps Brachii muscles. The control and aquisition system is composed of a microprocessor, analog filtering, digital filtering and frequency analysis, and finally a fuzzy control system. The system has been implemented over a MICROCHIP PIC 16F876 and LabVIEW.

The processing of EMG signals has been discussed in several works as from de Luca [1], where the author gives an extensive explanation on how these signals are generated, and how they can be modelled. The difficulty to acquire the EMG signals have led to research in the use optimal estimation for this purpose. Work in this area is extensive, as for example the work of Hogan and Mann [2], [3]. The correlation between myographic signals and motion has been investigated by several researchers as for example the works presented in [4], [5], [6]. How to acquire the signal via surface eletrodes is extensively presented by de Luca in [7], [8].

The use of these signals for several applications have also been reported by several authors. Rodríguez [9] employs a computer simulation to investigate if a proesthetic limb can be adapted to a particular person before this device is acquired or constructed. This software employs pre-processed signals acquired using a device developed by de la Rosa [10]. Zahedi [11] for example employs these signals to simulate the motion control of a full complex hand, while in [12], a similar device is implemented and experimental results are presented.

The work presented in this paper employs EMG signals acquired using surface Ag/AgCl disposable electrodes. The signals are then amplified with a 46 dB instrumentation amplifier implemented using a driven-right-leg circuit to enhance the CMRR. After the amplification phase, the signals are then passed through high-pass filter to eliminate bias and a second amplification stage. Prior to the analog to digital conversion the signals are passed through an anti-aliasing filter. The conversion is performed employing a MICROCHIP PIC 16F876 AD interface. Sampling is performed at 10 kHz with a 19.5 mV resolution and 8 bit quantification.

Once the signals have been acquired, they are transmitted to a computer runnig LabVIEW via RS-232 at 115.2 Kbps. The software implemented in LabVIEW performs additional filtering to eliminate low frequencies residual componentes (60 Hz), and all fuzzy algorithms to generate control signals which are later transmitted back to the microprocessor to drive the robotic arm.

The paper is organized in the following way: the theory behind the EMG signals produced by the muscles is presented in section 2. Subsequently the signal processing, is presented in section 3. The fuzzy controllers implementations are presented in section 4, and finally at the end of the paper, conclusions are drawn.

II. Electromyographic Signals

This section introduces the nature of the EMG signals and their correlation with motion. The section is based on the work of de Luca [7].

A. Nature of the EMG Signals

In the human body, the signal required to move a muscle is generated in the spine. This signal is transmitted through neurones. The neurone that is joined to

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the muscle is called a motoneurone. Each motoneurone activates muscular fibers. The set of the motoneurone and activated fibers is called an active motor unit. The voltage generated from the contraction of these fibers is called motor unit action potential (MUAP).

The EMG signal, acquired using surface electrodes, measures the potential from some motor units. The magnitude of the MUAPs is directly related to the contraction of the muscles. The biological explanation for the generation of these potentials is called Sodium-Potassium bomb.

When the motoneurone stimulates the contraction of the fiber, the membrane of this fiber changes its potential. This stimulus is transmitted across the membrane. The speed of transmission of this stimulus is called conduction speed.

The magnitude of the signal acquired using surface electrodes is from 0.1 to 5 mV peak to peak. The frequency content is in a range from 2 to 10 kHz, but the most relevant information concerning the movement is below 500 Hz. However, the range of the magnitude and of the bandwidth of the EMG signal can change depending on the physiological, anatomical and bio-chemical characteristics of the muscle and the electrode configuration and location.

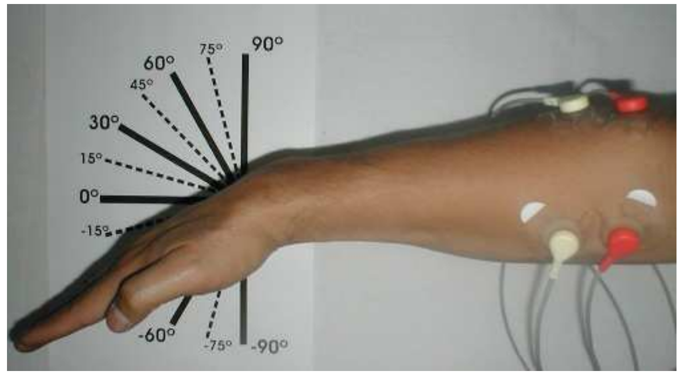


Fig. 1. Electrode placement

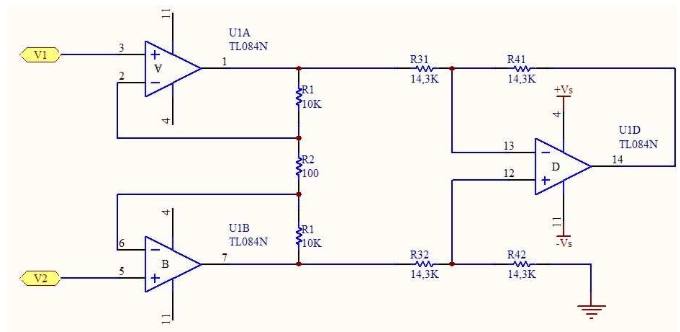


Fig. 2. Instrumentation Amplifier

III. EMG Signal Processing

This section describes how the EMG signals are acquired employing surface Ag/AgCl electrodes, the processing of these signals so they can be used to generate control signals via a Fuzzy Inference Engine.

A. Placement and Electrode Configuration

The device acquires the EMG signal from two electrodes per muscle, for a differential measurement, and an additional electrode for reference as shown in Figure (1).

The device measures the EMG signal from three muscles: Flexor Carpi Radialis, Extensor Carpi Radialis and Biceps Brachii, using the same reference for the three of them. The distance between the electrodes is about 1 cm. This avoids that the acquired signals will have interference from other muscles which are not of interest. Besides, since the conduction speed is about 4 m/s ([9]), the 400 Hz signals will be in phase after 1 cm, and the common mode rejection will cancel both signals. Further, if the distance between the electrodes is longer, other frequency components below 500 Hz range will also be cancelled.

The measurement electrodes should be placed along the longitudinal midline of the muscle on the area with more muscular mass. The reference electrode is placed over a bony prominence like the elbow. The wires that connect the electrodes with the analog circuit should be shielded in order to minimize the electromagnetic interference.

B. Analog Circuit

The analog circuit should condition the EMG signal to obtain a suitable signal in a range from 0 to 5 volts, in order to use the analog to digital converter of the microcontroller. The analog circuit has two main stages: amplifying and filtering.

The main noise source is generated by the power lines. This is a common mode noise, so it is important the circuit has a good CMRR level to reject this contamination. To obtain a high CMRR, an instrumentation amplifier with a 46 dB gain is implemented, as presented in Figure (2). The circuit is composed of a driven right leg (DRL) configuration that feedbacks the common mode voltage into the human body, in order to raise the CMRR, as shown in Figure (3).

A high pass filter is used to eliminate bias from the

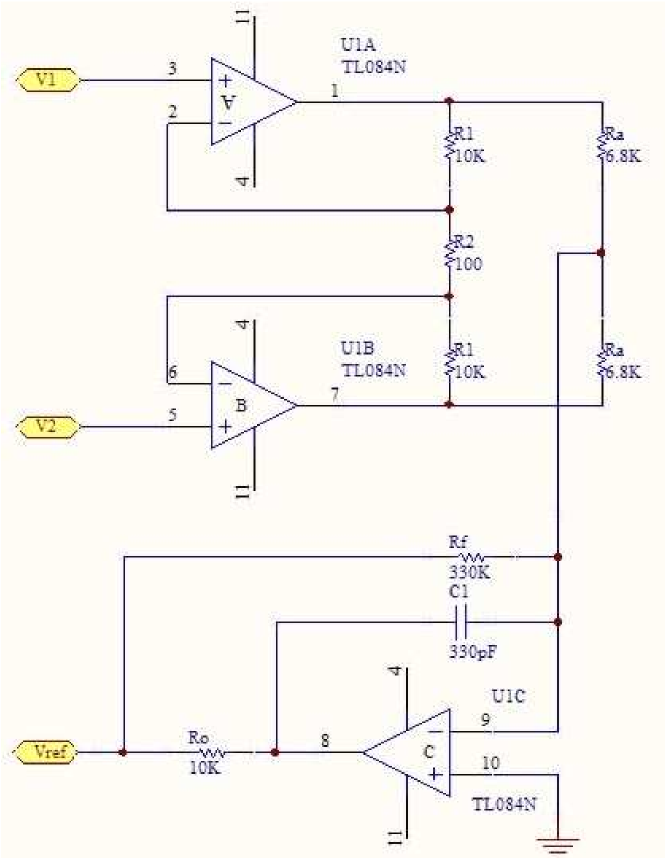
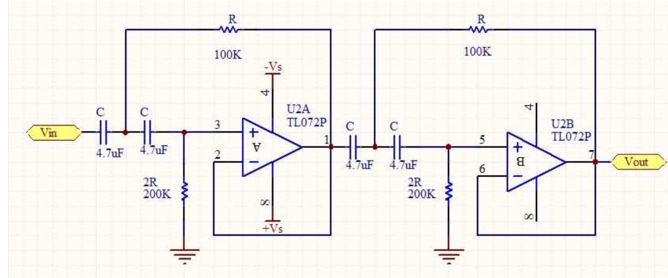
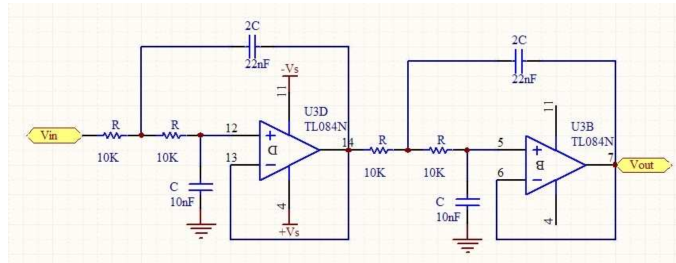


Fig. 3. Driven Right Leg circuit



(a) Highpass filter



(b) Lowpass filter

Fig. 4. Filter configurations

EMG signal. A low pass filter is used to eliminated the high frequencies over 1 kHz in order to avoid the aliasing effect. A Linkwitz configuration is used for both filters. This configuration has similar characteristics of the Butterworth filter and has the advantage that it is easy to implement because of a simple relationship between the elements values. Figures (4(a)) and (4(b)) show the highpass and lowpass implemented filters respectively. An additional amplifier stage is included to obtain a final voltage range between 0 and 5 V. This final stage includes an offset correction and protection circuits to guarantee a 5.1 V input to the microcontroller AD channel. The amplifying and filtering stages are implemented using a TL074 that has JFET input to assure a high input impedance for the circuit.

The A/D conversion is performed by a MICROCHIP PIC17F876 controller. A total of three channels are employed, one for each EMG signal from the three muscles: Flexor Carpi Radialis, Extensor Carpi Radialis and Biceps Brachii. The sampling frequency is set at 10 kHz. This frequency is 10 times greater than 1 kHz, which is the maximum frequency of the analogue signal out of the anti-aliasing filter.

The conversion has a 19.5 mV resolution with an 8 bit quantification. This voltage resolution and quantification has demonstrated to be sufficient to provide accurate measurements of the EMG signals. After the AD conversion, the signals are transmitted to the computer via RS-232. The baudrate is set at 115,2 Kbps. The time required for the transmission of a byte (10 bits) is 86,8 μs and can be performed within a sampling rate (100 μs).

The amplification, filtering and conversion stages provide a sufficiently high CMRR; however, the tolerance of the elements (1%) cannot completly reject the 60 Hz component from the power line. To improve the elimination of this noise, a stopband digital filter is implemented in the computer.

C. Computer EMG Signal Processing

The EMG signal processing in the computer is implemented using LabVIEW7.1. This platform offers many mathematical tools to analyze the characteristic of the EMG signals. The software program developed in LabVIEW, provides and additional filtering stage to eliminate the 60 Hz components using a Butterworth configuration, carries an spectral analysis, calculates RMS and the variance of the signals and finally executes the fuzzy control algorithm. The control signals generated by the fuzzy controller are then transmitted back to the microcontroller to drive the servomotors that move the robotic arm.

The software operates with a data block of 2000 samples per channel. After the passing through the stop band filter, the EMG signals are automatically analyzed in the frequency-domain performing a power spectrum decomposition using an FFT algorithm, which delivers the EMG spectral content between DC and 5 kHz.

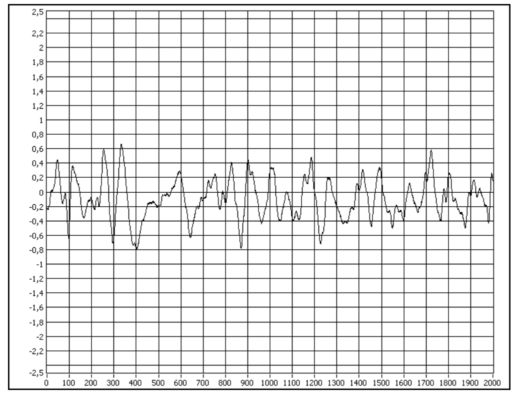
Employing the power spectrum, the less representative frequency components are eliminated, so only the most significant information concerning the muscle contraction is left. Components under 20 Hz are discarded because they are correlated with the electrodes movements in the skin surface[13]. This noise is commonly called *motion artifacts*.

According to some biomedical research the most representative information about limb position is contained in the frequency range under 500Hz [14]. The recovered frequency content is employed to calculate an average RMS value of the EMG, mainly due to the non-stationary properties of the EMG. Thus, to improve the reliability of the measurement, the mean of a set of ten measurements is employed. Therefore the control system will actually employ an estimation of the expected value of the EMG signal. The equation to calculate the expected value is presented in Equation (1).

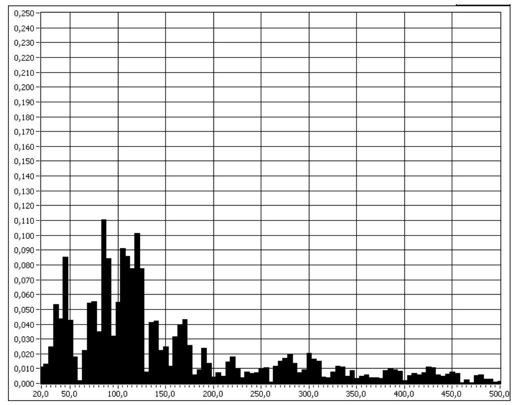
$$
\begin{aligned}
V_{RMS} &= E\left\{V_{rms}\right\} \qquad (1)\\
&= \frac{1}{10}\sum_{i}^{10} V_{rms_i}
\end{aligned}
$$

The expected RMS value has a relatively lineal relationship with the analyzed muscle contraction. This lineal relationship was obtained performing several experiments, in which the EMG signal was correlated with the muscle motion and position. To determinate the position of the wrist, the muscles Extensor Carpi Radialis and the Flexor Carpi Radialis were analyzed. Considering that when the Extensor Carpi is contracted, it produces the wrist extension, whereas the contraction of the Flexor Carpi does not produce relevant information. Similarly, when the Flexor Carpi Radialis is contracted, it produces the wrist flexion, and the contraction of Extensor Carpi Radialis does not produce relevant information.

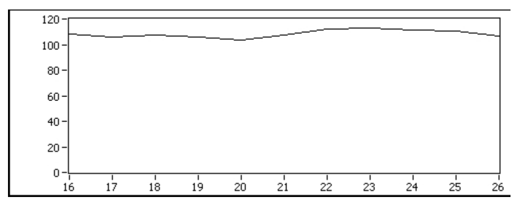
The fuzzy controller is designed using the relationship between the values of the average RMS obtained per muscle (Flexor Carpi Radialis and Extensor Carpi Radialis) and the wrist position obtained via experimentation. Figure (5) shows the EMG signal, its Frequency content, and the calculated expected RMS values for the Flexor Carpi Radialis muscle.



(a) Time Series



(b) Power Spectrum



(c) RMS value

Fig. 5. Flexor Carpi Radialis Analysis

The information provided by both EMGs are also employed to control the opening and closing of the robotic-arm gripper. The exact position of the gripper cannot be controlled, because this will require the use of the EMG signals from additional muscles which have not been considered in this work. The controller is designed to open the gripper when the hand is totally relaxed and close the gripper when the hand is closed.

To determine the control signal for the elbow position, the only muscle analyzed is the Biceps Brachii. However, experimental and theoretical results [9] indicate that to improve the position estimation and thus the control of the elbow of the robotic arm, not only the expected RMS value is necessary but also the variance.

The variance calculation significantly improves the estimation of a change in position (motion) of the muscle. If the variance has a low value (<150), the fuzzy controller provides a stable position for the robotic arm. Thus the robotic arm will not follow the motion of the muscle in each instant, but when the muscle has reached a final position.The position calculated by the fuzzy controller is then transmitted to the microcontroller to drive the arm to the required position.

IV. Fuzzy Controllers

The controller is composed of two fuzzy control systems for the movement of the wrist and the elbow, and an ON/OFF controller for the gripper.

The fuzzy controller for the wrist receives the RMS expected values of the Flexor Carpi Radialis and the Extensor Carpi Radialis. This controller is configured in the following way: (i) singleton fuzzyfication, (ii) 5 triangular membership functions, (iii) COG defuzzification, and (iv) Mamdami inference engine usign the Max-Min{} operators. The controller output is the calculated position. The Fuzzy Associative Memory for this controller is presented in Table (I). In this table the following convention of symbols have been used: (i) L for Low (ii) LL for Very Low (iii) H for High (iv) HH Very High (v) M for Medium (vi) I for Left (vii) D for Right (viii) C for Centre.

For the elbow the input is the expected rms value and the variance of the Biceps Brachii. The controller is configured in a similar way as for the wrist. The Fuzzy Associative Memory for this controller is presented in Table (II). In this table the following convention of symbols have been used: (i) B for Low (ii) BB for Very Low (iii) A for High (iv) AA Very High (v) M for Medium.

Figure (6) shows a picture of the robotic arm employed, and Figure (7) shows the complete system.

V. Conclusions and Further Work

The analysis of EMG signals applied to robotics control are a field of quick development in the last years. The treatment of these signals is complex. This work has presented an application of the use of EMG signals for the control of a robotic arm, employing fuzzy algorithms. Even though the system works in an acceptable way, there is however room for several improvements. The robotic arm moves accordingly to the movements of the three muscles, however, the processing time is quite

TABLE I
Fuzzy Associative Memory for Wrist Control

No.	FCR	ECR	Inference
1	PLL	PLL	PC
2	PLL	PL	PC
3	PLL	PM	PD
4	PLL	PH	PDD
5	PLL	PHH	PDDD
6	PL	PLL	PI
7	PL	PL	NONE
8	PL	PM	PD
9	PL	PH	PDDD
10	PL	PHH	PDDD
11	PM	PLL	PII
12	PM	PL	PII
13	PM	PM	PC
14	PM	PH	PDD
15	PM	PHH	PDDD
16	PH	PLL	PII
17	PH	PL	PIII
18	PH	PM	PIII
19	PH	PH	NONE
20	PH	PHH	NONE
21	PHH	PLL	PIII
22	PHH	PL	PIII
23	PHH	PM	PIII
24	PHH	PH	PIII
25	PHH	PHH	NONE

TABLE II
Fuzzy Associative Memory for Elbow Control

No.	RMS	Variance	Inference
1	BB	B	PBB
2	BB	M	PBB
3	BB	A	PBB
4	B	B	PB
5	B	M	PB
6	B	A	PB
7	M	B	PM
8	M	M	PM
9	M	A	PM
10	A	B	PA
11	A	M	PA
12	A	A	PA
13	AA	B	PAA
14	AA	M	PAA
15	AA	A	PAA

Fig. 6. Robotic Arm

Fig. 7. Robotic Arm System

significative. Also the arm presents several oscilations around the stable point. This could be due to strain of the muscles or electrode placement.

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