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MYOELECTRIC CONTROL OF MANIPULATOR BY FUSION WITH VISION INFORMATION

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Abstract. *The purpose of this paper is to present an interface to generate "movement signals" to a manipulator. A new strategy has been created to control manipulators in a natural fashion, by fusion of data generated by two subsystems: an electromyographic subsystem and a visual subsystem. The main object of such a system is to mimic the behavior of a human being in object manipulation, who doesn't need to look at the target object before her/his hand is near it. Until then, it's sufficient to move her/his arm in a "not-so-precise" trajectory. With a camera installed on the manipulator in a hand-eye configuration, it's possible to implement such control, by adding vision to it, allowing a more precise movement as it approximates the target object. This paper presents some characteristics and the viability of this type of control, the researches on this field and its results.*

Keywords*: manipulator control, computer vision, data fusion, myoelectric control, fuzzy logic*

1. INTRODUCTION

There is no doubt about robot application on industry. Many processes apply manipulators in substitution of human operators, in order to protect human life or just for productivity reasons. Executive summary published by International Federation of Robotics (IFR, 2007) reports a growth of 30% of world-wide robotic sales on 2005 (126.700 units).

Although there are many programming languages for robot control (Fu *et al.,* 1987), there may be some kind of natural (intuitive) way to determine the manipulator's action. From a point of view that a great part of activities executed by manipulators are human action repetitions, it's possible to think a way to mimic human behavior in object manipulation.

Researches can be found on computer vision field, where a human operator's image is taken from a virtual workspace and his/her movements are monitored and processed, defining the trajectory to be followed. This approach has the problem of demanding an overall charged power of processing, besides the issue of eventual occlusion of important images of workspace.

Another source of command signals naturally generated is the monitoring of myoelectric signals from the operators body. Myoelectric signal (MES) is an electric signal generated by muscle fibers when they contract to perform a member movement (e.g., arms, legs). It's possible, for example, to infer the arm movement of an operator by reading MES from her/his biceps. However an issue about MES must be observed: captured on the surface of skin, this signal is weak and noisy, besides the cross-talk phenomena (reading of signals of adjacent fibers, not used in the specific movement being observed).

Even so the two technologies mentioned above are experimenting a great development, in order to achieve higher levels of movement classification, it's not possible yet for just one of them to ideally control a manipulator in real-time. This paper proposes an interface to generate "movement signal" to a manipulator. A new strategy has been created to control manipulator in a natural fashion, by fusion of data generated by two subsystems: electromyographic subsystem and visual subsystem. The main objective of such a system is to mimic the behavior of a human being in object manipulation, who doesn't need to look at the target object before her/his hand is near it. Until then, it's sufficient to move her/his arm in a "not-so-precise" trajectory. With a camera installed on manipulator in a *hand-eye* configuration, it's possible to implement such control, by adding vision to it, allowing a more precise movement as it approximates the target object.

Based on this assumption, MES is defined as the *command* signal, and vision subsystem is defined as a *control* signal. These two information must be fused in one (the "movement signal"), to be sent to manipulator, on this basis: while vision subsystem doesn't "see" the target object, the only way to reach it is through myoelectric signal (although it can be somewhat imprecise); from the point vision the subsystem can identify a target object, the two signals are considered by the fusion module in processing of the right movement to be executed by manipulator. From this point on, myoelectric signal defines the action to take place (i.e., the movement to be executed) as a course control, and vision subsystem produces information to be used as a fine control, as it can have more detailed information of target object's pose. So, on a mimetic approach of human action, MES represents the intention of movement, while vision subsystem represents the vision feedback of a person. Fusion module represents the human's decision making.

This paper presents some characteristics and the viability of this type of control, the researches on this field and its results.

2. CONCEPTUAL INTRODUTION

2.1. The Myoelectric Signal

Muscle activity has been studied for a long time: in Renascence, Leonardo da Vinci dedicated part of his research to muscle functions. In 1666 Francesco Redi suspected for the first time about the relation of muscle activity and electricity, observing electric fishes; Du Bois-Reymond demonstrated this relationship through voluntary generation of an electric signal with his muscles. In 1912 surface electrodes were developed by Piper (1912), as a small metallic plate. On last century many advances took place on electronics and biological interfaces to instrumentation, enabling the application of myoelectric signals (MES) mainly on prostheses to amputees. In order to use myoelectric signals for control, it is necessary understand how they are generated and know it's characteristics.

Contraction of a muscle initiates through synaptic transmission of **action potential**, conducted by nervous neurons associated with movement (motoneurons) until the muscle fibers. Action potential is an electrochemical reaction caused by fast changing of elements concentration (K^+ and Na^+) around motoneuron membrane, generating a difference of potential of units of milivolts around the membrane. Each motoneuron carries the action potential to fiber muscle, and it occurs in different times due to ramification differences in neurons and stochastic nature of ionic discharges. The set of elements described just above is named **motor unit (**DeLuca and Basmajian, 1986), depicted in Fig. 1.

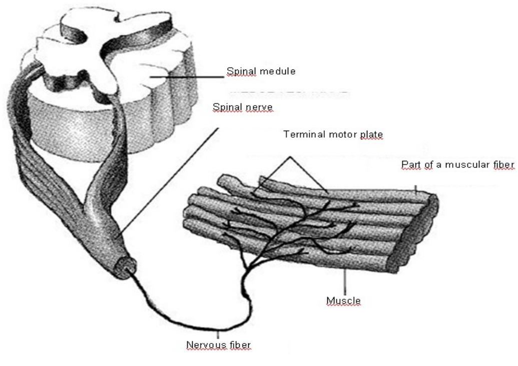


Figure 1. Motor unit

Each fiber of muscle contributes to the generation of MES, which is the summation of fiber signals of that muscle. Figure 2 shows a representation of this composition. One can note that, by the way signal is generated, the myoelectric signal can be considered stochastic.

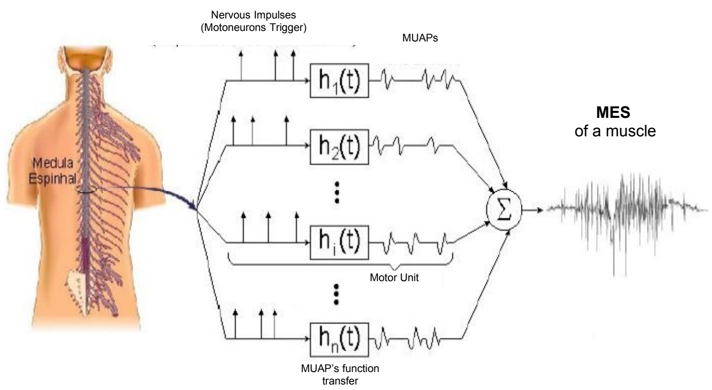


Figure 2. Schematic representation of MES composition

The frequency range of MES goes from 10Hz to 500Hz, being the range 20-150Hz responsible for the most part of signal power. Signal amplitude can vary from tens of microvolts (µV) to units of milivolts (mV), depending on monitored muscle.

For control applications MES is acquired through superficial electrodes, more comfortable than needles used on clinical applications.

Due to the weakness of myoelectric signal, some care is needed during acquisition, as described by De Luca (1986 and 2002). At the very first stage it's necessary a pre-amplification as near as possible to electrodes, by instrumentation amplifiers, that has high common mode rejection ratio (CMRR). This minimizes amplification of ambient and artifact noise. After pre-amplification, additional circuits must filter unusable frequencies, to provide a pre-processed signal to the system.

Many researches have dedicated their work to processing of myoelectric signals, mainly on clinical applications. Command applications are restricted to active prostheses controlled by MES. This signal was not yet explored as a natural human-robot interface, neither as a command signal nor as a programming tool.

Strategies for classifying myoelectric signal include neural networks (Kelly *et al.*, 1990), wavelets (Norris *et al.*, 2001 and Englehart *et al.*, 1999), statistical theories (Micera *et al.*, 1999), and time-frequency analysis (Englehart *et al.*, 1999a). However, the real-time requirements of control systems restrict application of complex techniques that are process intensive. It´s necessary to create new strategies, or to adapt techniques already created, to be used in real-time applications. Englehart and Hudgins (2003) proposed utilization of time parameters already applied on statistical classification of myoelectric signal in a fast (real-time) classification approach. This work uses one of these parameters, called *waveform* length, detailed on section 3.1.

2.2. Computer Vision

Image processing can be used to extract information like object identification, it´s position, orientation or dimensional data. Computational vision systems have been used by industry in inspection, localization, counting, measurement and robot control (Fu *et al.*, 1987).

An image can be represented by vector $\{p_{yx},\ y = 1, ..., A;\ x = 1, ..., L\}$, where each element p_{yx} is called pixel (picture cell or picture element). The y data correspond to lines of image and x correspond to the columns, the two forming an inverted coordinate system, with origin located at upper left corner of image. Element x increases to the right while y increases to down, as depicted on Fig. 3, where H is height, that is, the number of rows, and W is width (number of columns). The resolution of an image is expressed by these two dimensions. As resolution increases, more detail can be observed (processed) on image.

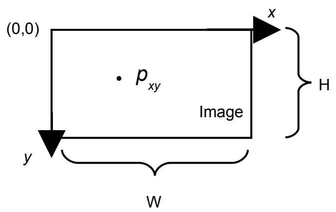


Figure 3. Conventions on coordinate system of images

The bright resolution of a pixel is the number of values it can assume. For example, if $0 \leq p_{yx} \leq 63$, one can say the image has 64 bright levels (2^6) or a resolution of 6 bits. If the image has a bright resolution of 1 bit, it is referred as a *binary image*.

This work is interested in recognition and classification possibilities of this type of system. In this task the system must determine if a part of image correspond to one of various alternatives, or neither one. Normally the system is fed with geometric characteristics of target object, in order to classify an unknown object by comparison with known templates. These characteristics are numeric quantities, independents from object's pose.

2.3. Data Fusion

Data fusion identifies the technique of combining data from multiple sources to produce an even more confident output that just one source alone can't produce (Hall and McMulen, 2004). The term *data* includes information from sensors, signal processing, statistical estimation, pattern recognition, artificial intelligence, and others.

Applications of data fusion include military use, intercontinental missile trajectory control, vegetable composition determination, underground mineral localization, industrial machine control, and more (Hall and Llinas, 1997).

Hall (2001) makes analogy to human capacity of using multiple feelings in determination of more precise information about environment where he/she lives in. For example, to know if a fruit is edible, one apply not only the vision, but touch and taste. The result of all this feelings is more accurate than of each one isolated.

Many approaches to data fusion have being implemented, including (Saziadeck, 2002) probabilistic modeling, mainly Bayesian models (Djafari, 1997), minimum-quadratic techniques, where Kalman Filter is the best example, and intelligent fusion techniques, using fuzzy logic (Lee and Qian, 1998), (Chen and Huang, 2000), (Aplacharla *et al.*, 1999), (Gibson *et al.*, 1994), and neural networks (Fincher and Mix, 1990), (Cires *et al.*, 1995), (Savia and Koivo, 2004). This paper presents the utilization of fuzzy logic in data fusion process.

3. SYSTEM IMPLEMENTATION

The system is composed of three complementary modules, as can be seen in Fig. 4. Myoelectric signals are acquired and analyzed by *Myoelectric Module*, generating information about operator's intention on moving. At same time, a video camera positioned on robotic manipulator, in a configuration called *hand-eye*, monitors environment. The *Computer Vision Module* continuously analyses the environment image captured just to find objects that can be elected as a *target-object,* or simply *target*.

The data generated by the two modules just described above are fed into *Data Fusion Module*, that processes them and generates control signal to the machine being controlled (the manipulator). It is required that all this process be executed in real-time.

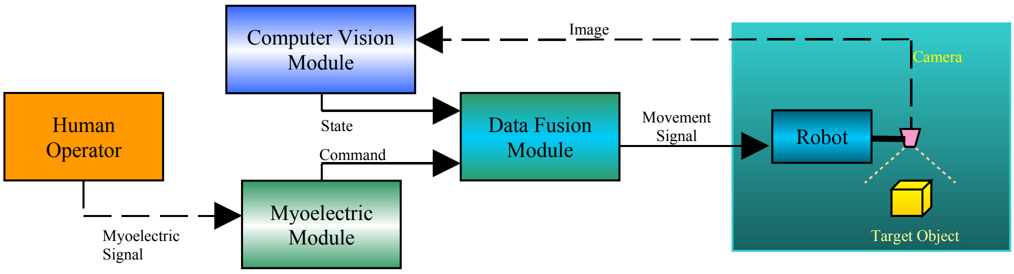


Figure 4. Schematic representation of proposed system

3.1. Myoelectric Module (Single Joint Command)

A mechanical manipulator can be modeled as an open-loop articulated chain with several rigid bodies (links) connected in series by either revolute or prismatic joints driven by actuators (this paper will consider revolute joints). In most robotic applications, one is interested in the spatial description of the end-effector of manipulator as a relative movement composition of its links (through joints), and with respect to a fixed reference coordinate system (Fu *et al.*, 1987). By other side it is desired to move manipulator's joints in a controlled way, and commanded by an intelligent agent (computer or human).

It's required, then, to identify the relationship between command signal and movement to be developed by joints in order to take manipulator to the desired position in space. If each joint on manipulator is associated to myoelectric signal captured from muscles associated to the convenient human joints (elbow, shoulder or wrist), it can be possible to command manipulator by natural gestures.

For a joint U_m of manipulator, it can be associated to a myoelectric signal MES_h generated by muscles associated to human joint U_h (Fig. 5), so it produces angle θ_m on joint U_m. It's desired to determinate the relation expressed by Eq. 1.

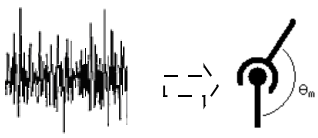


Figure 5. MES defines joint angle

$$\theta_m = f(MES_h) \tag{1}$$

It was used *waveform length (wfl)* as parameter to indicate movement intention. This characteristic of myoelectric signal supply information of frequency, amplitude and complexity, in one numeric value, and is rapidly obtained, wich is fundamental in real-time command systems. For a frame with N samples, *wfl* is obtained through Eq. 2, where x_k indicates k^{th} sample and x_{k-1} is one sample before.

$$wfl = \sum_{k=1}^{N} |\Delta x_k| \qquad \text{onde: } \Delta x_k = x_k - x_{k-1} \tag{2}$$

So, Eq. 1 can be reformulated as θ_m being dependent of *wfl* (Eq. 3).

$$\theta_m = f(wfl) \tag{3}$$

In capturing of myoelectric signal it was used a computer with CPU Athlon 1.2GHz, a 16 bits of resolution A/D (analog to digital converter) and sample rate of 1000 samples/second. Signal was captured by Ag/AgCl superficial electrodes, and firstly applied to instrumentation amplifier, near electrodes (to minimize noise and parasitic capacitances influence). The pre-amplified signal was filtered by notch filter to remove 60Hz component and amplified once more to produce a signal capable to be read by computer. It was defined frames of 256ms, with 256 samples per frame (Fig. 6), in capturing and analysis of MES, which provides a command update rate of approximately 3 commands per second (included time processing of the other two modules), considered sufficient in real-time command applications (Englehart and Hudgins, 2003).

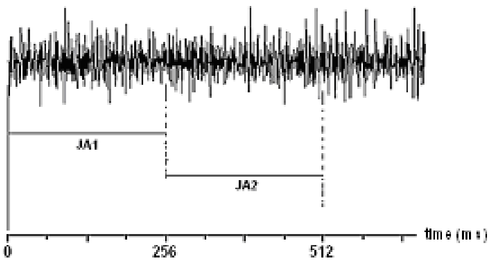
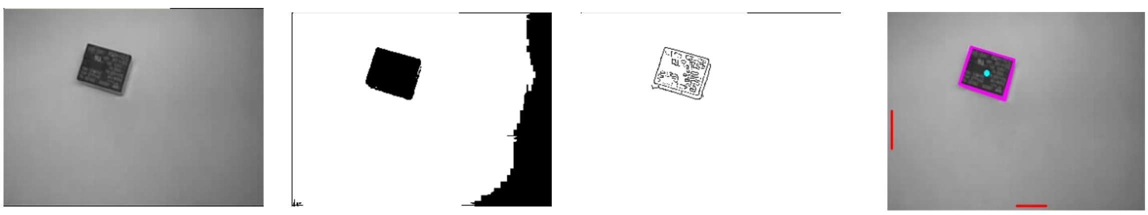


Figure 6. Frames of MES acquisition

3.2 Computer Vision

It was defined a rectangular object to be the target-object, that is, the object to be manipulated by robot. Computer Vision Module identifies in captured image the target's position and it's relative velocity (relative because actually who's moving is manipulator). These information are sent to Data Fusion Module. The choice of a simple objetc's geometric characteristic is due to the fact of this work be mainly occupied with mimetic method of human behavior in manipulation of objects.



(a) (b) (c) (d)

Figure 7. Steps to identifying rectangles

Figure 7 shows some steps to identify rectangles executed by Computer Vision Module: (a) presents original image, captured by camera and stored in computer memory; (b) shows image after binarization process. After that, border identification is processed (by Canny algorithm); (c) shows result of contour determination (from border information). After that, angle measuring identifies which of them are rectangles; (d) shows identified rectangle and *target-point,* overlapped to original image.

3.3 Data Fusion Module

This work explores fuzzy logic (Zadeh, 1965) in data fusion processing. One can observe that data to be fused here are not of the same nature (two positional information, for example), but of different types (as it is in human world). It's supposed to be analyzed **command** data, represented by myoelectric signal (through its *wfl* characteristic), and **state** data, represented by target position relative to manipulator's coordinate system (through Computer Vision Module), as it is in human world, where he/she supply energy to muscles in order to move a member till target object, helped by vision, to get the best position of his/her "manipulator" (arm/hand subsystem).

It was developed a Fuzzy Logic System (FLS), that has flexibility to process a variable quantity of inputs, with a Rule Table easily configurable too. It was chosen four input variables, as described below:

- CMD : correspondent value to operator's movement intention of a member, through *wfl* parameter;
- dCMD : CMD variation in time;
- POS : correspondent value to target's position, relative to the center of vision area (in captured image);
- dPOS : POS variation in time (target's relative velocity).

It was defined tree linguistic values to each input variable, and than defined membership-functions to each one, with triangular shape and base's configuration determined experimentally (Fig. 8). Input values were normalized in the range 0-100 (as can be seen in Tab. 1), for time optimization of FLS processing.

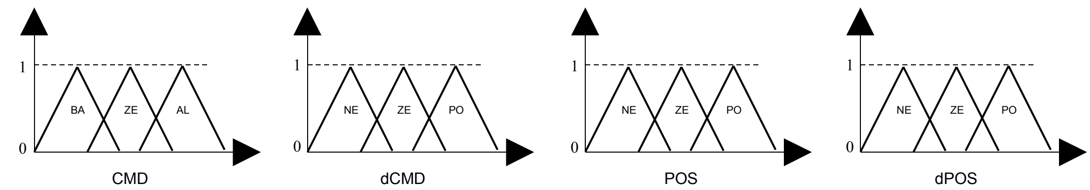


Figure 8. Input member-functions, with its linguistic values

A fuzzy logic system receive numeric values as input, transform then in linguistic values according to associated membership-functions (fuzzyfication), process inference mechanism (through predefined Rule Table), generating a set of linguistic values, which must be composed in membership-function of output linguistic variable.

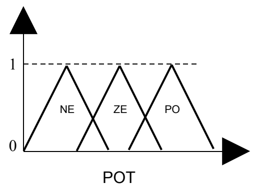


Figure 9. Output member-functions, with its linguistic values

This composition generates the numeric output value (defuzzification) (Mendel, 1995), (Kasabov, 1998), through processing of contribution of each output membership-function (Fig. 9). The Rule Table has 81 rules, associating to each composition of the four linguistic input variables, a linguistic value of output variable.

Table 1. Normalization of input and output variables

Variable	I/O	Value / Value Range	Meaning
CMD	I	0	Muscle in rest
		50	Muscle at middle of contraction
		100	Muscle at full contraction
dCMD	I	0 < dCMD < 50	CMD decreasing (muscle relaxing)
		50	Zero (CMD without changing)
		50 < dCMD < 100	CMD increasing (muscle contracting)
POS	I	0	Target out of vision (not identified on image)
		0 < POS < 50	Target at left of center image
		50	Target at center image
		50 < POS < 100	Target at right of center image
dPOS	I	0 < dPOS < 50	POS decreasing (target decelerating)
		50	Zero (target stopped)
		50 < dPOS < 100	POS increasing (target accelerating)
POT	O	0	Maximun "negative" power (inverse rotation)
		50	Zero (motor stopped)
		100	Maximun "positive" power (direct rotation)

After processed by FLS, numeric output signal is applied to a low-pass filter (as defined in Eq. 4), to eliminate abrupt transitions of power supplied to actuator. (Fig. 10).

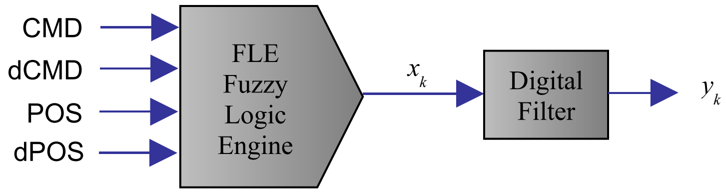


Figure 10. Diagrammatic representation of smoothing process of output signal

$$y_k = (\bar{x} + x_k)/2 \qquad \text{and} \quad \bar{x} = (x_{k-1} + x_{k-2})/2 \qquad (4)$$

where: y_k is the output value in time k;
x_k is FLS processing result for input values, in time k (last sample);
x_{k-i} is FLS processing result for input values, in time i samples before the last one

4. RESULTS AND DISCUSSION

Input values were simulated, from identification of various critical situations where system could be involved in. For each variable (input and output), normalization followed criteria listed in Tab. 1.

Simulated data was inputted in FLS and output numeric value (power signal to manipulator's joint motor) was plotted for each situation, as described below.

Figure 11 shows FLS's behavior where manipulator gets near to target object (i.e., an object appears in system's image area) and reaches target position. In this situation (indicated by ellipse in Fig. 11) the output signal remains stable in zero (according to criteria defined in normalization), that is, joint motor remains stopped, even there is some (normal) variation in CMD value, which is desired, because myoelectric signal is stochastic in nature and it's not possible to get a stable command signal just from it.

It was observed that, even with removing of target object, command signal was not affected significantly, following CMD signal, which remained stable between steps 25 and 32.

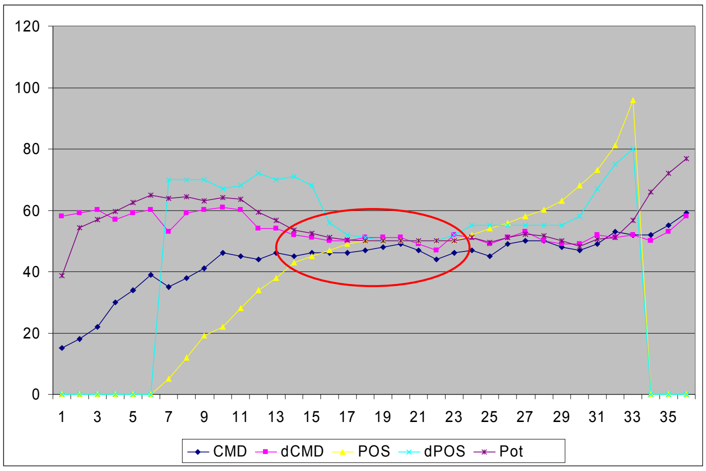


Figure 11. Manipulator stabilization on target's position

Figure 12 shows FLS's behavior where manipulator is at target position and must decide if operator intention is to leave object to go to another place (ellipse in figure), which is observed in step 11. From this point on, output signal follows CMD signal.

Figure 13 shows FLS's behavior where "target object" (really, a potential target object) is identified in vision field and is approaching, but operator doesn't want to stop over that object (ellipse in figure). In this case, system must not stop over object, but continue to follow "instructions" of myoelectric command (CMD signal).

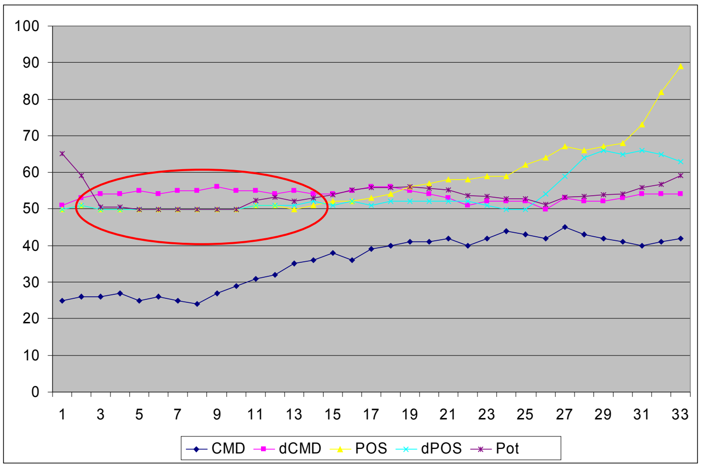


Figura 12. Stability on target position and pursue of command signal

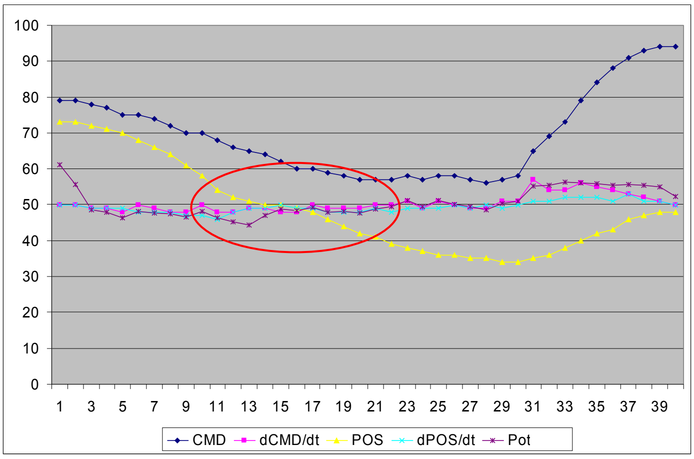


Figure 13. Decision of NOT to stop over "target-object"

4.1 FLS performance

During FLS data processing, it was registered inference process time of each step. The result was plotted and is presented in Fig. 14.

The average processing time of FLS was 20,34 microseconds (µs), for input and rules configuration adopted. For average calculation it was not computed zeroed values (which indicates object was out of system's vision field) and initial value (step 9), which high value is attributed to time of charging routines in memory.

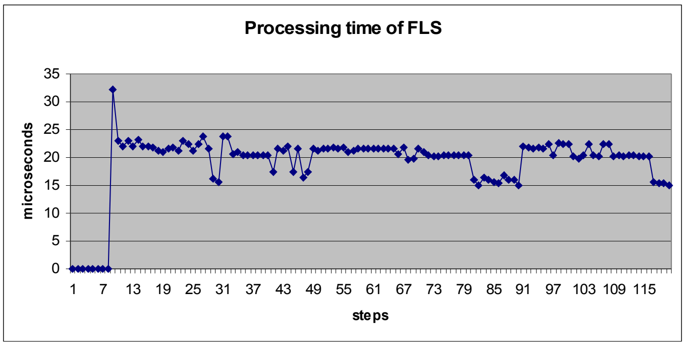


Figure 14. Processing time of SLN

5. CONCLUSION

This paper presented a new approach to robotic control, based in mimic of human behavior in object manipulation. This mimic was implemented through data fusion of myoelectric and position information. Intelligent fusion was applied in fusion process, through a Fuzzy Logic System (FLS), developed for this research. The obtained results show the viability of this approach.

FLS's performance was measured, due to real-time necessities. The average time for each inference was 20,34μs. For applications where myoelectric and positional (via computer vision) information are processed, and input data update rate is around 300ms, the inference process time measured is acceptable for timing requirements of the system FLS is inserted in.

5.1 Future Works

Data presented in this work are result of simulated information for 1 DOF (degree of freedom) mechanism, that is, one joint. The ongoing work includes extrapolation and test of results to 3 DOF mechanisms, where myoelectric information will be captured from shoulder, elbow and wrist.

Another research thread is utilization of neural network and probabilistic theory on data fusion implementation, in order to compare the various strategies of fusion, identifying the most adequate one for this type of application.

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