Managing EMG signals for control strategies for a Multi-Functional Interface for Patients with Severe Motor Disabilities

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***Abstract*— A hybrid multi-source, multi-functional assistive interface system was conceived with the intention of addressing the needs of a diverse group of patients with congenital, chronic, permanent or temporary motor disabilities for local and/or remote actuator control and/or task accessing, through the processing of source signals acquired from the disabled patient. The inherit differences present on patient's cases makes it difficult to manufacture assistive mechanisms that can be broadly distributed; therefore, adaptability was a main requirement. An FPGA board was incorporated into the main hardware design in order to offer increased flexibility when determining signal acquisition and processing strategies, in this way expanding the different types of possible source signal and output control signals. EMG and EOG signals, obtained through non-invasive electrodes, are of special interest due to their importance when interfacing with patient with limited muscular control (quadriplegics, cerebral palsy, etc.). Also, this paper presents an adaptive EMG signal processing scheme with pattern differentiation for actuator control, which can be separated in two main algorithms: a detection algorithm and an interpretation algorithm. The detection algorithm senses activation/deactivation of muscular activity through noise rejection and activity detection based on wavelet filtering and self-adjustable thresholds. The interpretation algorithm associates an input vector (formed by source signals events) with a particular control task, through comparison with a tree-structured database. A training mode allows the formation of the mentioned database of "to be recognized" patterns. Although the design is still in a prototype stage, a limited number of trials have been performed, upgrades to the system are being added continuously and the information gathered up to now shows promising results.**

Keywords – Assistive Technology, Interface, EMG, muscular activation

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I. Introduction

THE Human-Computer Interface (HCI) has been the centre of attention within the Assistive Technology (AT) research groups. New advances in adaptive technology and the reduced cost of some high level programmable hardware (CPLD, DSP, and FPGA) has in a way allowed the departure from HCI to a more general approach; the Human-Machine Interface (HMI or Human Device Interface, HDI). Within rehabilitation engineering, especially in the area of technological aids for disabled patients with significant motor compromise in one or more limbs, the need for HMI is becoming more apparent. By obtaining information from sources were the patient still has control, such as bio-signals, (especially electromyography (EMG) and electrooculography (EOG)), a limited limb movement, voice, etc., these interfaces could be used for controlling/performing a wide number of functional tasks [1]. A wide variety of devices and actuators have been developed for expanding the capacities of a disabled individual, such devices or "assistive devices" include: mobility devices, remote controls, robotic arms [2], domestic devices (instrumented home appliances, switches, doors, etc.) and many others. These devices allow an individual to perform many functional tasks, therefore restoring some sense of self-sufficiency by allowing him/her to interact with his/her environment and social surroundings.

A broad study (conducted in several rehabilitation centers, orthopaedic hospitals, and augmentative communication centers, among others) revealed a lack of sufficient commercially available assistive technology devices in Venezuela's metropolitan area, especially when referring to low cost versions [1]. It would appear that the particular details present in each patient's case make it inconvenient or to expensive for industry to manufacture low-cost assistive mechanisms that could be broadly distributed. Even for patients with the same illness, factors such as age, sex, height, weight, etc., can make it highly improbable for them to benefit from a common assistive mechanism.

The prohibitely high cost of most electronic assistive technology motivated the Center for Assistive Technology (CETA), at Venezuela's Simon Bolivar University, to undertake among their main objectives the mission of designing and developing low-cost alternative solutions within assistive technology [1,2,3]. This paper describes the algorithms being developed using EMG signals as an input source for the hybrid multi-source, multi-functional assistive system [4,5] (see Figure 1) that could benefit a wide variety of patients with motor and other types of disabilities.

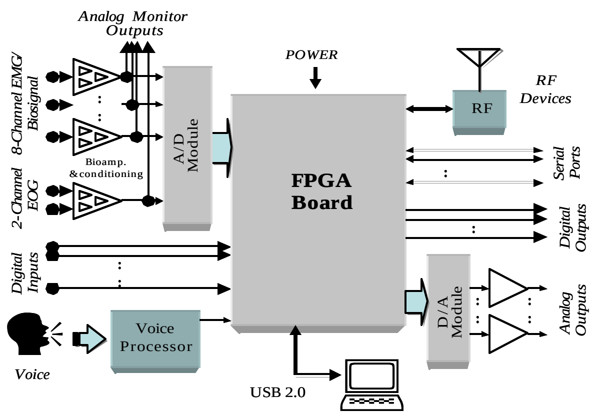


Figure 1. FPGA based model of universal interface

II. METHODOLOGY

A. Preliminary Research and Algorithm Development

In order to better understand EMG signals a preliminary study of an EMG signals database was performed [4]. The signals were collected at the Children Orthopedic Hospital at Caracas, Venezuela, with surface electrodes connected to a MA-200 EMG System (Motion Labs Inc.). The database contains a significant number of EMG data from lower limbs, collected during gait analysis studies. The patients vary in their condition, but most present some level of motor compromise. Due to the nature of the signals, the data presents a variety of signal features (biopotential activation, interferences, noise, artifacts, baseline wandering, etc) needed for a study seeking muscular activation detection for a real multi-patient case scenario. Based on that database, signal processing algorithms were selected and 'tuned'. A draw back of the data was the lack of proper determination of intentional muscular activation sequences, but since the database represents only a starting point it was not considered an obstacle. Professional assistance was use to determine sequences of intentional muscular activation versus non-intentional or false-positive scenarios due to muscular compromise or other factors.

An extra group of data was acquired with voluntary muscular contractions synchronized with on-off timing. The voluntary muscle activation signals set, was collected through the same EMG recording protocol (surface electrodes, MA-200 EMG System), triggering a timed contraction of wrist pronator (pronator tere), wrist supinator and esternoclidomastoid muscles. Three subjects were asked to start, maintain, and end a group of ten contractions, in isometric, increasing and decreasing tension contractions. The start-maintain-end time windows were recorded in an extra channel. Twenty random maintain-time-windows were asked, time between windows was random too. This dataset is intended to be used as a 'detector tuning' reference signal.

An in depth characterization of the EMG signals seemed not to be necessary for an algorithm seeking to recognize muscle activation. Traditionally, spectral and amplitude analysis are the approach when studying EMG signals, and numerous techniques exist for such purpose. Since the objective is to extract information from the EMG signal in real time or dynamic scenarios, many techniques that depend on post-processing of the signal were be readily discarded. Pattern recognition techniques based on Support Vector Machines (SVM), Neural Networks (NN), Independent Component Analysis (ICA), Matching Pursuits, and Wavelets Decomposition (WD), each has unique benefits and drawbacks, but due to the inherent calculation simplicity and of mapping a WD based algorithm into discrete electronic components, WD was chosen as a starting point. WD also provided the added benefit that although related to spectral components extraction it is a real-time technique that does not force the static analysis of signals, and could therefore be modified to the serve the main purposes.

WD of the signals reveal a number of interesting phenomena, some which initiated separate studies within the research group and the findings will be presented in future articles. An important consequence of WD's separation of spectral components was the resulting "cleaning" of the EMG signal from noise and other factors, as it can be seen on Figure 2. After observation of a large number of data, the third decomposition (D3, third from the bottom on Figure 2) was determined to offer the benefits of having fewer high frequency elements (noise, etc.) while still maintaining a strong correlation with the original signal. This filtering represented a first step in the developed of a simple muscle activation detection algorithm.

A crude scheme to transform the EMG signals into a binary signal was then developed. The binary signal would represent muscle activation with a high state and no muscle activation with a low state. In the past this type of strategy has utilized threshold based schemes to establish the binary representation of a signal. Background noise, crosstalk, and fatigue, among others, are responsible for complicating the use of thresholds for muscle activation detection. Not only a common threshold among multiple patients would be unpractical, a single patient's patterns change during relatively short periods of time, requiring constant tuning for proper performance. Being that EMG signals cannot be considered consistent, then the algorithm would have to count with a self-adjusting threshold.

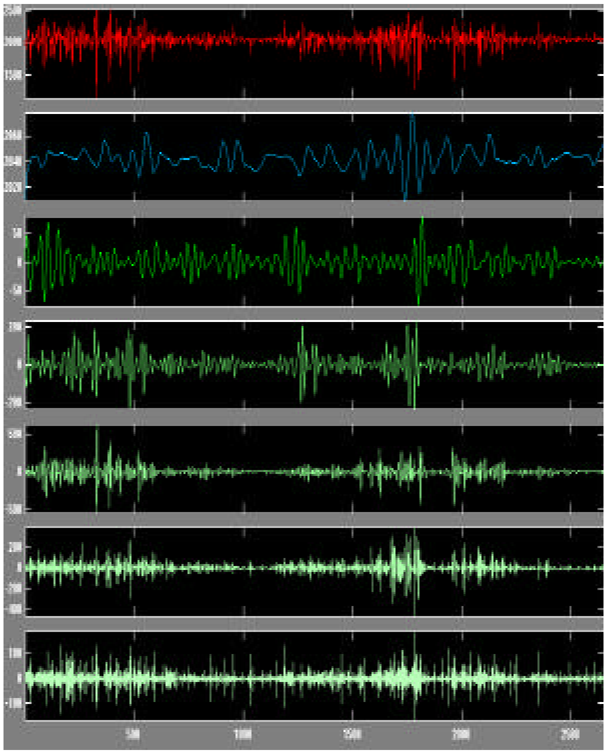


Figure 2. Wavelet Decomposition in five levels using wavelet DB4. Original signal in red.

As previously mentioned, the output signal of a D3 WD with a wavelet DB4 (factor used for WD), was chosen through observation to be an adequate candidate for further processing. This signal was then rectified for simplification and smoothed with a window averaging effect, in order to reduce the number of peaks and disruptions present in the signal. The pseudo-code for such averaging procedure is as follows:

```
buffer = [0..n]
position = 0
initialize = false
For each signal's sample
  do
    buffer[position] = sample
    if (initialize == true)
      sample = averaging_function(buffer)
    fi

    position = position+ 1
    if (position == n)
      position = 0
      initialize = true
    fi
  od
```

The actual threshold level was determined by another signal averaging algorithm, which continuously averaged the incoming data with past data. In order to avoid sharp changes in the signals average, the algorithm considered a weight factor to compensate. The signals average function pseudo code is as follows:

```
num_buffers = B
size_buffer = T
array_buffers = [0..num_buffers]
array_average = [0..num_buffers]
actual_buffer = 0
position = 0
average = 0
For each sample
  do
    buffer = array_buffers[actual_buffer]
    buffer[position] = sample
    position = position + 1
    if (position == size_buffer)
      array_average[buffer_actual]=
averaging_function(buffer)
      average= averaging_fu nction(array_average)
      position= 0
      actual_buffer = actual_buffer + 1
      if( actual_buffer == num_buffers)
        actual_buffer = 0
      fi
    fi
  od
```

The threshold was then established as the signal's average adjusted by a factor of 1.75, obtained through trial and error and observation. Finally, in order to compensate noise effect in the signals amplitude a simple noise level routine was implemented by applying averaging to a small window of data, in this way taking into consideration the changes of the signal; the consequent noise level was utilized to adjust the signal level. The algorithm then compares de difference between the signal and noise level with the threshold, in order to determine muscle activation.

It should be noted that the need for developing a dynamic algorithm, i.e. an algorithm that could process incoming real time signals, was a strong motivator for algorithm and calculations simplicity. Further observation and experimental trials with the database signals and voluntary muscle activation signals, revealed the need to compensate for false-positive and positive-negative scenarios, specially in the presence of rapid muscle activation scenarios or tremors (such as in Parkinson's disease patients). The algorithm compensates for such scenarios through the use of adjustable "grace" periods and the beginning and end of recognized muscle activation. Other compensation strategies currently being tested are using a double threshold one with a smaller factor, for situation when the muscle activation has already been detected. These last strategies represent adjustment to the main algorithm in order to increase the robustness for unforeseen scenarios. The following section shows the complete algorithm:

B. Single Channel Muscle Activation Detection

The algorithm presented before, was designed as to be completely implemented in hardware, in such way maximizing its processing speed capacity. The wavelet based preprocessing and filtering was substitute and simulated

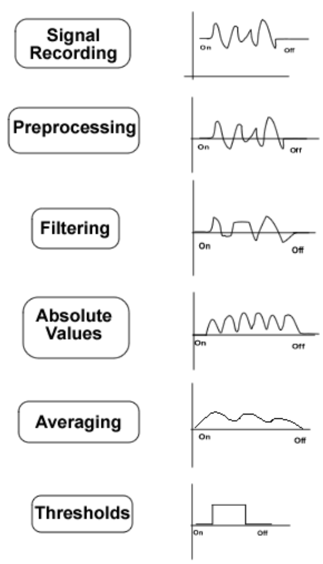
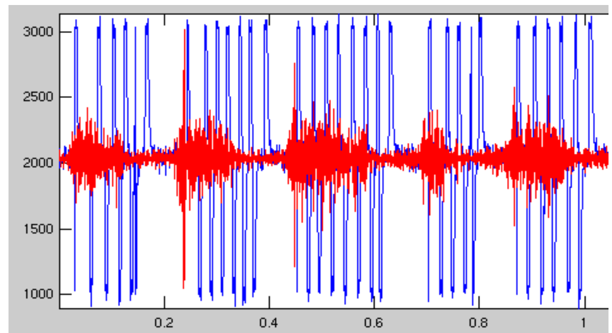


Figure 3. Single Channel Muscle Activation Detection

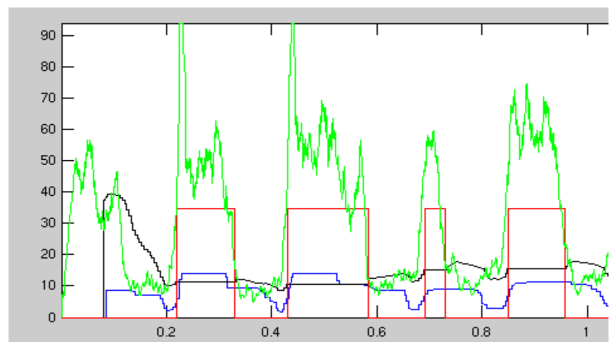
with hardware equivalent filters. When combined with an FPGA based hardware structure, parallelism can be incorporated in order to process multi-channel inputs efficiently [4]. The final algorithm can be seen in Figure 3, while a sample input signal (with reference trigger signal) can be observed in figure 4 (a). In Figure 4 (b) we can observe the signals of the different stages of the algorithm, including: the processed EMG signal, the noise level, the threshold and the resulting digitalizes output.

C. Multi-channel Detection

The multi-channel detection was based on a vector formation scheme [4], where the digitalized outputs of the multiple channels where combined in one input vector. This strategy limits the user control through EMG to one task per sequence, since the multiple channels' outputs are being combined. While this seems very limiting, this scenario is only being considered for the initial stages of the hybrid interface. Future developments will consider independent multi-channel analysis, providing patients with a more flexible control scheme.



(a)



(b)

Figure 4. (a) Input EMG signal in red and pulsing trigger in blue. (b) Processed EMG signal in green, noise level in black, adjustable threshold in blue, recognized muscle activation in red.

D. Training Algorithm

In order to recognize an input pattern, so as to be used for control purposes, it is necessary to consider a manner for comparing such patterns. The direct configuration of the patterns, although not a multiple patient adaptable method, provides the interface with an adequate hardware testing method. This early stage of algorithm testing required a simple training algorithm, which was conceived with the application of "majority rules" and undefined or "don't care" conditions [4]. The training algorithm compares the input vector sequences and in the case of clearmajority cases (per each channel) sets the pattern cells to such results. In the cases where a clear majority case can not be establish the specific cell is set as a “don’t care” or undefined. This approach increases the flexibility of input vector sequences, allowing input channels that are not directly involve in the control command not to be involve. This training approach represents an initial step for a research that seeks a true patient adaptable self-training algorithm.

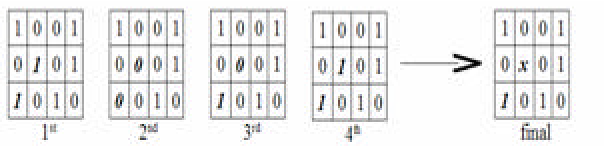


Figure 5. Input vector sequences and resulting training algorithm result

E. Pattern Detection Algorithm

A tree based scheme was implemented for comparing input vectors with pre-determined vector sequence patterns[4]. This method, used for optimizing search sequences, is known to reduce the matching speed; avoiding exponential searches. This also represents an initial step of a more developed pattern detection algorithm, which is adaptable for parallel input channel pattern detection.

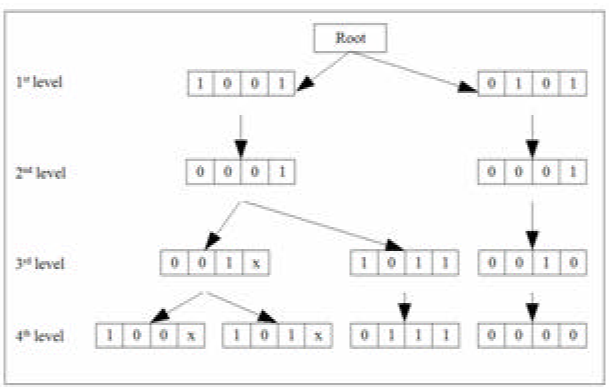


Figure 6. Pattern detection algorithm sample

III. RESULTS AND DISCUSSION

The registers of the EMG database from the Orthopedic Children Hospital contained data from normal subjects and patients with different types of Spastic Hemiplegia (SH), among other conditions; which where used to define and adjust the filters and parameters of the algorithm.

Once the algorithm was established, data from voluntary muscle activation signals were collected and used for testing. Twenty repetitions for six distinct voluntary isometric contraction modes were registered; each repetition was synchronized with luminic stimuli for three subjects with no motor compromise. The contraction modes were: short (1 sec. contraction and 2 sec. of rest), long (4 sec. contraction and 5 sec. of rest), crescendo (4 sec. of continuous increase of tension, 5 sec. of rest), spasmodic (twiches each 2 sec.), and random (the subject was given freedom to contract and rest at his/her discretion). The event detection algorithm was adjusted in order to obtain the best sensibilities and specificities, Table 1 contains the results:

Table 1
Sensitivity and Specificity of the event detection algorithm for different contraction modes

	Muscle					
	Wrist supinator		Wrist pronator		Esternocleido mastoid	
Contraction Modes	S	SP	S	SP	S	SP
Short	1	1	0,79	1	1	1
Long	1	1	1	1	1	1
Crescendo	0	1	1	0,66	0,75	1
Spasmodic	1	1	0,95	1	1	1
Random	0,88	1	0,79	1	1	1

S = Sensitivity, SP = Specificity

Table 1 reveals a very high specificity (except for the crescendo for the wrist) for the event detection algorithm, not the case for the sensitivity which ranges from 0,75 to 1. For a detection signal to be considered as successful a small delay limit (of approximate 100 milliseconds) from the reference signal was establish. This is to say that, the detection signal was considered a true positive if and only if it was within the delay limit for both on/off voluntary muscle activation edges. This maximum delay limit was established experimentally through the considerations of many factors, such as: the perception delay of the visual stimuli, the condition of patients who are going to use the interface, the ‘slow’ nature of task to be done, etc. Additional efforts are being focused on minimizing the delays inherits from event detection algorithms, in this way allowing for faster tasks and/or faster learning of the user.

Another aspect that requires improvement is the response of the detection algorithm to smooth signal increase/decrease, as observed by the 0 sensitivity for wrist supinator. This scenario could be caused by the threshold self-adjustability which evidences the need for future revisions. The introduction of a gradient detection scheme in future version could correct this shortfall.

IV. CONCLUSION

There exists a need for low cost assistive technology alternatives, especially in less developed countries, requiring ad-hoc solutions for each patient. This design is intended to provide an adaptable, low cost interface for disabled people who let the patient expand him/her capability to accomplish functional tasks and life expectations. The algorithms presented in this work seek to utilize EMG signals as an input source, allowing patients with severe motor compromise an alternative when interacting with their surroundings. This project although in an initial stage of hardware and algorithms developed shows some promising results. Future revisions, testing and new advancement are in progress.

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