A VERSATILE ROBOTIC WHEELCHAIR COMMANDED BY BRAIN SIGNALS OR EYE BLINKS

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Abstract: A system allowing a person with severe neuromotor disfunction to choose symbols in a Personal Digital Assistent (PDA) using electroencephalography (EEG) or electromyography (EMG) is implemented onboard an electrical wheelchair. Through this system the user is able to elicit personal needs or states, like sleep, thirst or hunger; to write texts using an alpha-numeric keyboard and to command a robotic wheelchair. The EEG patterns used are event-related synchronization and de-synchronization (ERS and ERD, respectively) occurring in the alpha band of the signal spectrum captured in the occipital region of the head, while the EMG patterns are eye-blinks. The results so far obtained with the system developed, in indoor and outdoor environments, are quite satisfactory. This paper describes the system so far implemented and shows some experimental results associated to it.

1 INTRODUCTION

The use of biological signals intentionally generated by impaired people can contribute to improve their life-quality, providing augmentative communication capabilities and autonomy of movement (Wolpaw et al., 2002; Millán et al., 2003). The development of a Human Machine Interface (HMI) that considers myoelectric (EMG) or electroencephalographic (EEG) signals is here described. Such an HMI acquires the myoelectric or electroencephalographic signals of an impaired individual in order to recognize a short set of easily voluntarily generated patterns, which are associated to a group of previously defined tasks. Such an interface has been used in connection to robotic devices (Ferreira et al., 2006; Frizera-Neto et al., 2006), and is currently being used to allow an individual to control a robotic wheelchair and to communicate with other people, as it is shown hereinafter.

To the extent of the authors' knowledge, just two works using EEG to command a wheelchair have been published so far (Tanaka et al., 2005; Rebsamen et al., 2007). In (Tanaka et al., 2005) the processing unit is off board the wheelchair, a high number of EEG electrodes (thirteen) is used, and the recognition rate associated to the brain signal may be as low as 20%. In (Rebsamen et al., 2007) the focus is the navigation of the wheelchair (no communication support is included), and a high number of electrodes (fifteen) is used. The system here developed, by its turn, uses only three EEG electrodes, is quite easy to use, presents a high recognition rate, and is more versatile, since it allows selecting between two communication channels (EEG or EMG). Besides allowing commanding the wheelchair, the system here described provides other useful functions, as it is shown in Section 4. It was tested in indoor and outdoor environments, with quite satisfactory results.
The current structure of the proposed HMI and the way it interacts with the impaired individual and the wheelchair are shown in Figure 1. The signal acquired by the electrodes connected to the face/head of the impaired individual are conditioned and quantized through a high-resolution A/D converter. After being read by a computer, such a signal is filtered through a bandpass digital filter whose pass band spans from 1 to 30 Hz, when using the EMG option, or from 8 to 13 Hz, when acquiring EEG signal (the alpha band). Features of interest extracted from such signals are then delivered to a classifier that identifies if the impaired individual wishes or not to select a symbol shown on the screen of the Personal Digital Assistant (PDA) as illustrated in Figure 1. If yes, the communication interface shown in the figure asks the PDA for the information necessary and sends it to the next module, which is responsible for generat-

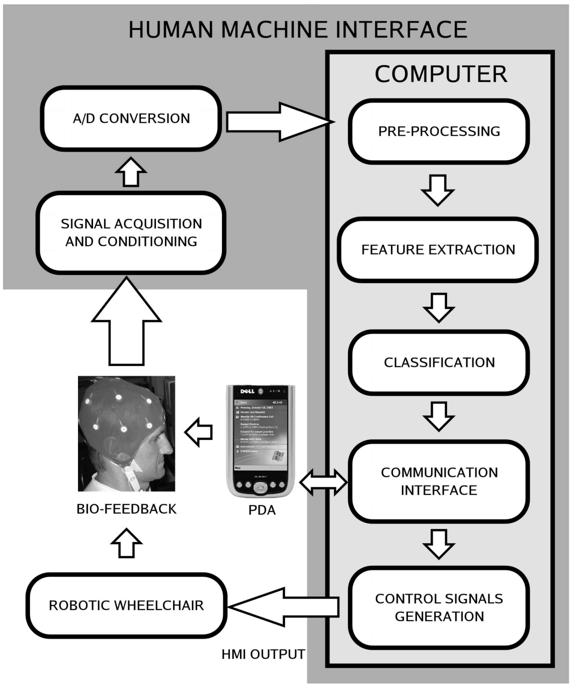

Figure 1: The structure of the proposed HMI.

ing the necessary control actions so that the robotic wheelchair executes the task the impaired individual has chosen. The feedback is closed through the operator (bio-feedback), as shown in the figure.

The description of the system so far implemented is completed in Section 2. The data acquisition system and the techniques used in the EMG and EEG processing module are presented in Section 3. In the sequel, a description of the functionalities included in the graphic interface programmed in the PDA is presented in Section 4. The experimental results are presented in Section 5 and are discussed in Section 6, which highlights the conclusions of the work as well.

2 HARDWARE STRUCTURE

Figure 2 illustrates the hardware embedded on the wheelchair. Encoders and ultrasonic sensors are functional, while the others are under development. The motors are controlled by a low-level controller programmed on a MSP430 microcontroller (Texas Instruments, Inc.), which receives commands of angular and linear velocities from a mini-PC onboard the wheelchair. The signal acquisition system and the PDA are connected to the PC through a parallel and a serial port, respectively.

Two electronic boards, a signal conditioning one and a quantization one, compound the signal-acquisition system. The signal acquisition board has two input channels and a third electrode used as the reference for the signal amplifier. A high-pass filter with cutoff frequency of 0.1 Hz avoids the saturation of the amplifiers due to the continuous voltage caused by the coupling between the electrodes and the skin. A fourth order low-pass Butterworth filter with cutoff frequency of 32 Hz limits the spectrum of the acquired signal and attenuates 60 Hz artifacts (electromagnetic induction), some contaminating noise and disturbances generated by muscles movements, electrodes displacement, etc. Such a board also embeds a Body Driver circuit to reduce 60 Hz artifacts (Webster, 1998).

The second part of the acquisition system is a quantization board based on the AD7716 analog to digital converter. The main features of such a chip are a resolution correspondent to 22 bits, four A/D channels, and a low-pass digital filter with a cutoff frequency selectable among 36.5 Hz, 73 Hz, 146 Hz, 292 Hz and 584 Hz. The sampling rate used for the EEG signal is 140 Hz, so that the cutoff frequency of such a low-pass filter has been set to 36.5 Hz. The digital signal thus obtained is then sent to the high level hardware.

After receiving the acquired data delivered by the data acquisition board, the onboard CPU (mini-ITX) is responsible for pre-processing them, extracting the desired features, classifying them and generating the control signals associated to the recognized pattern. Figure 2 illustrates how the hardware pieces are connected.

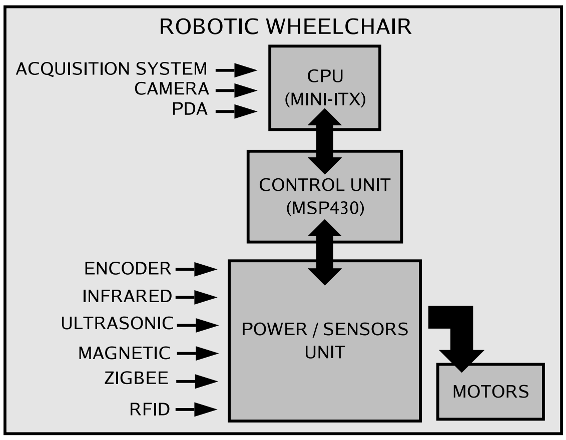

Figure 2: The hardware structure of the system developed.

3 RECOGNIZING SIGNAL PATTERNS

3.1 Through Processing EEG

Event-related Synchronization and De-synchronization (ERS and ERD, respectively) are the EEG patterns searched for in this work. They are characterized by meaningful changes in the signal energy in specific frequency bands. An energy increase is associated to an ERS, while an energy decrease is associated to an ERD (Pfurtscheller and da Silva, 1999). The frequency band used to detect these patterns is the alpha band (8-13 Hz) and, thus, the digitized signal is filtered by a FIR filter with such a pass band.

The EEG signal is acquired in the occipital region of the user's head, with electrodes in the positions O_1 and O_2 (regarding the 10-20 International System of Figure 3) and the reference in the right ear.

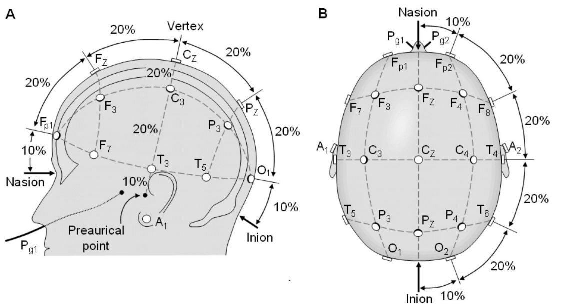

Figure 3: The 10-20 International System.

A user whose eyes are open (under visual stimulus or concentrated) keeps the alpha rhythm in a low energy level. When he/she closes the eyes (with no visual stimulus or relaxed), there is a great energy increase in the alpha rhythm, characterizing an ERS. The variance of the filtered EEG signal allows detecting these energy changes, as observed in Figure 4.

The second graphic in Figure 4 is generated regarding a moving window filled with $N = 280$ samples (N is empirically determined) of the filtered EEG signal (x_k), for which the mean value and the variance are, respectively, $\mu = \frac{1}{N}\sum_{k=1}^{N} x_k$ and $\sigma^2 = \frac{1}{N}\sum_{k=1}^{N}(x_k - \mu)^2$.

The variance thus obtained is the input of a threshold-based classifier, whose function is to detect if the user wishes or not to select a symbol presented in the PDA screen. Case yes, a request is sent to the PDA through a serial line, and it informs which symbol has been selected. Knowing that, the mini-ITX calculates the necessary control signals to accomplish

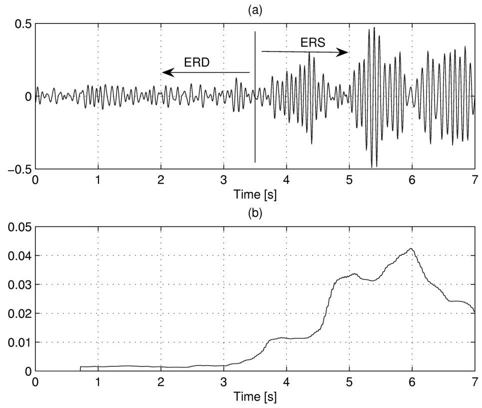

Figure 4: (a) Filtered EEG signal with ERD and ERS. (b) Variance increase during an ERS.

the chosen task and sends it to the actuation module (MSP430).

3.2 Through Processing EMG

The objective here is to recognize the presence of an eye-blink (Figure 5) in the Myoelectrical signal (MES) acquired on the user's face, for selecting symbols presented in the PDA screen.

The samples of a given MES can be considered as a random variable, whose variance represents an averaged measure of the variability or activity of the signal about its mean (Rangaraj, 2002), as shown in Figure 6. Such indicator of signal activity was used to control the robotic wheelchair with good results, as it is indicated in Table 1. Four individuals tested the capability of choosing an icon in the PDA screen through the variance associated to the MES signal. They should blink an eye to select an icon they were asked to select. As shown in Table 1, the accuracy obtained by using the MES variance as the indicator of activity was very high, thus justifying to use

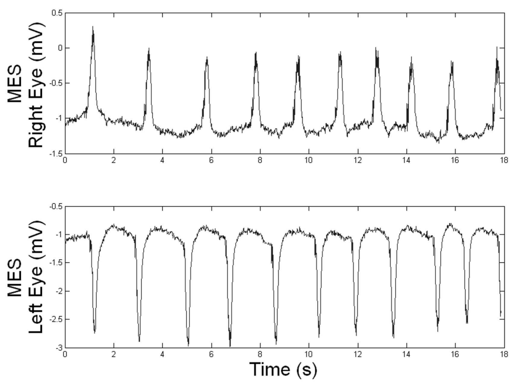

Figure 5: Myoelectrical signal associated to eye-blinks.

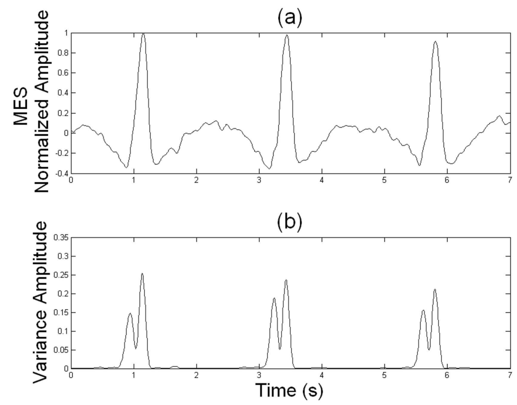

Figure 6: (a) MES of an ordinary individual (male, 25 years). (b) Signal variance.

such an indicator. Each individual was asked to select 15 icons, each one associated to a movement of the wheelchair. The calculation of the variance of the MES is performed in the same way used for the EEG signal (Subsection 3.1), after normalizing the signal amplitude. A threshold-based classifier was used again.

However, according to (Kreifeldt, 1974) the myoelectrical signal is better described as a stochastic random process, for its average and variance vary along time. Thus, it is necessary to use more robust systems to process MES, to take into account its stochastic behavior. In (Hudgins et al., 1993) it is shown that such signal presents a deterministic characteristic in the first 200 ms after a muscular contraction. Due to the nature of the MES, it is reasonable to expect meaningful changes in the value of the parameter describing a particular pattern from one individual to other. Other aspects, like changes in the position of the electrodes and body-weight fluctuations, will produce changes in the signal patterns along time (Hudgins et al., 1993). Thus, a classifier based on an artificial neural network (ANN) was trained to accommodate the expected individual differences and, as well, to accept slow variations in the values associated to the patterns to be recognized.

The neural network is trained using three backpropagation algorithms: Bayesian Regularization (BR), Resilient Back-propagation (RP) and Scaled Conjugate Gradient (SCG) (MathWorks, 2000). A total of 210 pre-processed sequences of facial MES correspondent to right-eye blinks, 210 pre-processed samples of facial MES correspondent to left-eye blinks, and 210 sequences of random noise, resulting in 630 sequences of signal samples, were used for training and validating the neural networks tested. For each one of these three sets of samples, fifty percent were used for training and fifty percent were used for validation. The results are shown in Table 2. A hidden layer with 4 to 10 neurons resulted in a very good accuracy in classifying the three patterns of interest, knowing left-eye blink, right-eye blink and noise (no blink). The error presented in Table 2 is the sum of the errors during training and validation.

The ANN configurations showing the best performances in Table 2 were tested, now regarding 252 new test signals, from which 84 corresponds to left-eye blinks, 84 corresponds to right-eye blinks and 84 corresponds to noise sequences (no blinks). The results obtained when classifying them are presented in Table 3, and show that the use of the artificial neural network as a classifier for the patterns searched for in the MES resulted in a high rate of rightness. In particular, the classifier currently implemented in the system here addressed is an artificial neural network having 20 neurons in the input layer, 4 neurons in the hidden layer and 3 neurons in the output layer, whose training algorithm is the Resilient Back-propagation.

Table 1: Results for controlling the wheelchair with basis on the indicator of activity.

Individual	# of Tests	# of Errors	Rightness
A	15	0	100 %
B	15	0	100 %
C	15	1	93.3 %
D	15	0	100 %

Table 2: The ANN's implemented and the training algorithms.

Training Algorithm	Input Layer	Hidden Layer	Output Layer	Error (%)
BR	20	4	3	0.6
BR	20	6	3	0.5
BR	20	8	3	0.6
BR	20	10	3	0.6
RP	20	4	3	0.3
RP	20	6	3	0.6
RP	20	8	3	0.3
RP	20	10	3	0.5
SCG	20	4	3	0.8
SCG	20	6	3	0.5
SCG	20	8	3	0.3
SCG	20	10	3	0.3

Table 3: Results of testing the best ANN's in Table 2.

Training Algorithm	# of Neurons in the Hidden Layer	Success Rate (%)
BR	6	98.4
RP	4	99.6
SCG	10	98.4

4 SELECTING AN OPTION ON THE PDA SCREEN

The PDA (Figure 1) is installed onboard the wheelchair in such a way that it is always visible for the impaired individual seated on it. It provides a graphic interface containing the possible options for the operator, including the pre-programmed movements of the wheelchair, a virtual keyboard for text edition, and symbols to express some basic needs or feelings of the impaired individual, such as to sleep, drink, eat, feel cold, heat, etc. For all these cases, a specific option is selected using a procedure to scan the rows and columns in which the icons are distributed on the PDA screen (once the desired screen is presented). A voice player confirms the option chosen, providing a feedback to the user and allowing the communication with people around as well, either through EMG or through EEG signals.

The operator selects symbols presented on the PDA screen, which are distributed in a form that resembles a matrix, assisted by an automatic scanning system. Each row of the matrix of symbols remains pre-selected for a while, until the operator confirms the choice. After selecting the row, the process is repeated, now regarding the columns of that row. For tasks like controlling the wheelchair or asking for specific external help, this scanning system is quite suitable.

Figure 7 illustrates the `STATE` and `TEXT` screens. The first one is designed to support interpersonal communication. It presents options to the operator in order to elicit emotions, personal states or some basic needs. Although the options of this screen can be expressed by using the `TEXT` screen, this mode is much faster, mainly in emergencies, such as to complain about pain. The `TEXT` mode provides a communication channel to the operator, allowing the selection of letters and numbers through a virtual keyboard, whose sounds are echoed to speakers. Although being a low bit-rate communication process, it provides a way to elicit words via artificial voice when the patient does not have this capacity anymore.

The screen `MOVEMENT` provides to the operator a set of symbols corresponding to movements of the robotic wheelchair. The options are shown in Figure 8, and represents actions sent directly to the wheelchair motors. The first command starts the movement of the wheelchair and the next one, it does not mind where the automatic scan is, stops the wheelchair. For safety, only successive short back-displacements are allowed, because of the null visibility in such a movement. Through the screen `CONTROLLER`, option currently being developed, the user will be able to choose a place in a structured environment, and the wheelchair will be guided to that place by an automatic control system. This screen is shown in Figure 8.

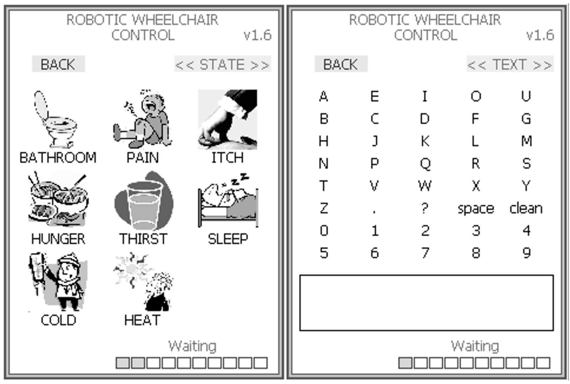

Figure 7: Software `RWCC`: `STATE.` and `TEXT` screens.

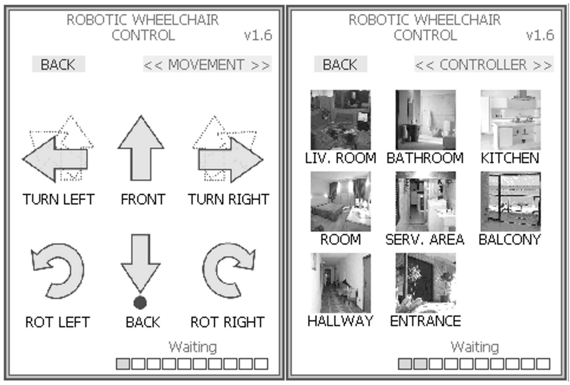

Figure 8: Software `RWCC`: `MOVEMENT.` and `CONTROLLER` screens.

5 EXPERIMENTS

A user testing the wheelchair in an indoor environment (left) and in an outdoor environment (right), using the EEG signal option of the developed HMI, is presented in Figure 9. The preparation of the user to operate the system consists of cleaning the regions where the electrodes should be connected (the O_1 and O_2 positions in the head and the right earlobe) and, then, a special gel is applied between the electrode and the user's skin, for impedance-matching.

A meaningful group of users tested their capability of using the system, and the result was that all of them were capable to command the wheelchair and to communicate with people around it.

The analysis of the EEG signal in the alpha band, and of its variance as well, shows very clearly when

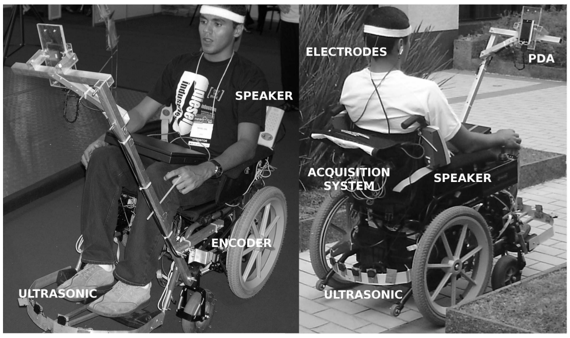

Figure 9: Testing the system prototype.

the user closes his/her eyes, generating an ERS (the signal variance exhibits a great increase, as shown in Figure 4). This indicates that the user wishes to select the option currently highlighted in the PDA screen. An important aspect, regarding the detection of the changes in the signal variance, is that an adjustable hysteresis-zone is included in the threshold-based classifier in order to increase the system robustness, thus avoiding false ERS/ERD detection.

6 CONCLUSIONS

The HMI so far developed was tested in indoor and outdoor environments, with quite satisfactory results, according to the statements of the users who operated the prototype during the tests.

The acquisition system allied to the PDA has proven to be quite efficient for choosing commands to the wheelchair using EMG or EEG signals. A minimum knowledge about the HMI and a very quick training is required to operate the whole system.

However, it is worthy to mention that so far the developed HMI has not been tested by people with severe neuromotor disabilities, which is the next step of this work.

The ANN used in the analysis of MES has demonstrated a very good capability to find the desired patterns in such signals. The feedforward topology with back-propagation training algorithm, having two active and one hidden layers, allowed a satisfactory rate of classification rightness.

The easiness of electrode-placing (for both EMG and EEG options), the simplicity of the graphical interface running in the PDA and the easiness to adapt the system to a commercial electrical wheelchair are the major advantages of the HMI here developed, when taking into account the final users of this assistive technology.

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