Peripheral Control Using EEG Signals and Facial Artifacts

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Abstract— **As an attempt in providing a contribution to the endeavor of improving the quality of life of physically disabled persons, this study concerned itself with the development of a brain-computer interface application that enhanced device control and mobility. In particular, the NeuroSky MindWave headset was used to detect and measure electrical activity from the user's forehead and then send it as data, wirelessly, to a computer for processing. A detection algorithm within the computer detected the user's intended commands for the device at hand. After which, the computer sent appropriate control signals such that the said device executed the user's commands. In order to establish a basis for the detection algorithm, the group gathered data from both impaired and non-impaired persons. The non-impaired persons came from healthy students of the Loyola Schools community. For impaired persons, the group coordinated with several members of Tahanang Walang Hagdan. Both impaired and non-impaired persons underwent the same data gathering procedure: both were tasked to perform several facial gestures and mental actions, as data was recorded. Data revealed that blinks were the best choice as commands for device control. It was found out that blinks elicited a sudden spiking in the electrical activities detected by the MindWave headset and registered a substantial increase in the 2.5 Hz region in the frequency domain. The group developed a brain-computer interface application which detected the user's eye blinks based from the data sent by the headset. Based from the detected eye blinks, the computer sent the proper signals to control any device connected to it. The group made two implementations: an appliance controller which controls an array of appliances; and a wheelchair controller, which controls a wheelchair in all four directions.**

Keywords-PWDs;brain-computer interface; wheelchair; EEG artifacts;

I. INTRODUCTION

It is the group's firm belief that everyone deserves equal opportunities without prejudice to physical attributes and what better way to achieve this than to provide the physically challenged with the necessary tools that will aid them in their day-to-day activities. Thus, in this study, the group hopes to be able to provide avenues for assisting the physically challenged in terms of mobility and performing activities such as travelling and appliance control. As such, this study also aims to empower paralyzed patients in a hospital setting by enabling them to perform simple tasks such as turning on the lights, the television and other appliances in the room without the need to ask for any assistance.

Data from the neuroheadset was accessed through the API of NeuroSky Inc. for the MindWave headset. Data was then plotted in real-time using a Processing-based program. Recorded data came from 20 subjects (10 non-impaired and 10 impaired). All subjects were tasked to perform facial gestures and mental activities, namely: opened eyes (Idle State), closed eyes, alternating opened and closed eyes, blink, hard blink, smile, frown, attention/focus and meditation/relax. Data was recorded as the subjects performed these actions.

Data was then analyzed both in the time and frequency domains. Time-domain analysis involved looking at the signal plot in synch with video of the subject performing the facial gesture/mental activity. In this way, signal variations can be seen together with the subject's corresponding actions. On the other hand, frequency-domain analysis was done by computing for the FFT and Power Spectral Density (PSD) of the signal.

Using results of the analyses, the group developed an application program that enabled users to control devices without the use of limbs. This was made possible by interfacing the laptop, which collects data from the neuroheadset, with a microcontroller board that controls the device at hand. In particular, the group made two implementations: an appliance controller and a wheelchair controller.

II. THEORETICAL BACKGROUND

An electroencephalogram (EEG) is a test that measures and records the electrical activity of the brain. Special sensors (electrodes) are attached to the head and hooked by wires to a computer. The computer records the brain's electrical activity and displays the graph on the screen or on paper. The brain's electrical charge is maintained by billions of neurons. Neurons are electrically charged (or "polarized") by membrane transport proteins that pump ions across their membranes [1].

Generally, brainwaves are categorized in 5 categories: Alpha, Beta, Theta, Delta and Gamma. Alpha (8 – 12 Hz) pattern appears in wakefulness where there is a relaxed and effortless alertness wherein persons are tranquil but remains conscious. Beta (12 – 30 Hz) is often associated with thinking, awareness of self and surroundings and alertness. Theta (4 – 7 Hz) is associated with creativity, dreams and imaginary perception. Delta (0.1 – 3 Hz) is associated with deep sleep. This brainwave pattern is most evident during non-REM and dreamless sleep [1]. Last are the Gamma (30 – 100 Hz) rhythms which are associated with information-rich task processing and high-level information processing [3]. They show relation with linking of stimulus features into common perceptual information [4].

The EEG signals contain artifacts in practice. Artifacts are considered unwanted signals or interference in a signal [10]. Different types of artifacts can be divided to external and internal artifacts [10]. External artifacts are caused by outer actions and internal artifacts are associated with the actions made by subject itself [10]. This project focuses on the characteristics of internal artifacts especially the artifacts associated with facial gestures.

With the introduction of EEG digital recordings, Fourier Transform became a solution for the difficult task of studying and separating different EEG rhythms which occur simultaneously [9]. The spectral analysis based on the Fourier Transform is by far the most used quantitative method for the analysis of EEG signals [9]. The fast Fourier transform (FFT) is a discrete Fourier transform algorithm which reduces the number of computations needed for N2 points from 2N2 to2N lg N, where lg is the base-2 logarithm [5]. If the function to be transformed is not harmonically related to the sampling frequency, the response of an FFT looks like a sinc function (although the integrated power is still correct) [5]. The equation is given as follows

$$\sum_{n=0}^{N-1} a_n e^{-2\pi i n k/N} = \sum_{n=0}^{\frac{N}{2}-1} a_n^{even} e^{-2\pi i n k/(\frac{N}{2})} + e^{-2\pi i n k/N} \sum_{n=0}^{\frac{N}{2}-1} a_n^{odd} e^{-2\pi i n k/(\frac{N}{2})}. \quad (1)$$

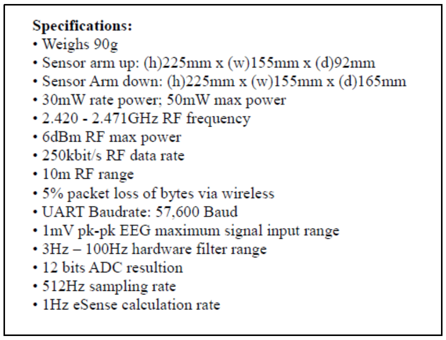
FFTs were first discussed by Cooley and Tukey (1965), although Gauss had actually described the critical factorization step as early as 1805 (Bergland 1969, Strang 1993) [5]. An efficient real Fourier transform algorithm or a fast Hartley transform (Bracewell 1999) gives a further increase in speed by approximately a factor of two [5].

Fast Fourier transform algorithms generally fall into two classes: decimation in time, and decimation in frequency [5]. The Cooley-Tukey FFT algorithm first rearranges the input elements in bit-reversed order, and then builds the output transform (decimation in time) [5]. The basic idea is to break up a transform of length N into two transforms of length N/2 using the identity as in (1) [5].

III. METHODOLOGY

A. *Utilized Resources: Hardware*

The main hardware used for this study was the NeuroSky MindWave headset which was used for obtaining the EEG signals. The NeuroSky MindWave is a commercially available EEG neuroheadset primarily designed to measure brainwave signals and use that to monitor attention and meditation levels [8]. The headset's sensor is located on the left side of the forehead, along the FP1 position in accordance with the 10-20 System of Electrode Placement [4]. Signals from this sensor is referenced via a reference electrode located on the left ear lobe. Data is then obtained and sampled at a rate of 512 Hz with each sample having 16-bit full ADC resolution [8]. Additional details regarding the neuroheadset's specifications can be seen in Fig. 1 below.



Specifications:
- Weighs 90g
- Sensor arm up: (h)225mm x (w)155mm x (d)92mm
- Sensor Arm down: (h)225mm x (w)155mm x (d)165mm
- 30mW rate power; 50mW max power
- 2.420 - 2.471GHz RF frequency
- 6dBm RF max power
- 250kbit/s RF data rate
- 10m RF range
- 5% packet loss of bytes via wireless
- UART Baudrate: 57,600 Baud
- 1mV pk-pk EEG maximum signal input range
- 3Hz – 100Hz hardware filter range
- 12 bits ADC resultion
- 512Hz sampling rate
- 1Hz eSense calculation rate

Figure 1. The NeuroSky MindWave Headset Specifications [21]

The group also used the GizDuino, a microcontroller board by e-Gizmo, is based on the Arduino Diecimilia [6]. The GizDuino board is an open source computing platform based on simple input/output board and standard programming language [6]. It is compatible and can be programmed using the Arduino IDE (Integrated Development Environment) [6]. Simpler compared to other platforms, the GizDuino can be programmed through a USB cable and is compatible with Windows, Macintosh and Linux [6]. This board was connected to solid state relays (for the appliance controller) and to H-bridges (for the wheelchair controller).

B. *Utilized Resources: Software*

Interfacing with the neuroheadset was done through the Mindset Development Tools. It is a guide directing users to files and code samples needed to develop BCI-enabled applications using the NeuroSky MindSet/MindWave for any platform, from PCs to microprocessors [2]. These tools provide developers with various levels of interfaces for communicating with the MindSet/MindWave headsets.

Signal processing and data analysis was done using MATLAB, a computing language by MathWorks designed for data analysis, computation, and visualization [11]. MATLAB specializes in 2D and 3D visualizations of data, and Digital Signal Processing (DSP) [11]. Two DSP methods (Fast Fourier Transform and Welch's method for computing Power Spectral Density), under the signal processing toolbox of MATLAB, were utilized to analyze Electroencephalography (EEG) signals yielded by facial artifacts in both time and frequency domain.

The application program developed by the group was based from MindSetBTViewer which was a program developed and written in the Processing environment by Dr. Sean Montgomery [7]. The MindSetBTViewer enables users to read, plot and log data available from the NeuroSky MindWave [7]. These can be plotted in real time while data is being streamed from the MindWave via Bluetooth connection [7].

C. *Data Gathering*

The group collected data from 10 non-impaired people and 10 impaired people – making for a total of 20 subjects. For the non-impaired subjects, the group collected data from 10 healthy volunteers from the Loyola Schools community. On the other hand, for the impaired subjects, the group coordinated with Tahanang Walang Hagdan – an organization for persons with disabilities (PWDs). In conjunction with the ECCE Department and Mr. Carlos M. Oppus, the group's faculty adviser for this research, the group wrote a letter to the organization asking for their consent to conduct data gathering with some of its members. After approval, the group was debriefed about Tahanang Walang Hagdan's policy regarding research being conducted with its members and within its premises. After which, data was then collected from 10 members of the organization.

The data gathered and processed for the project were EEG signals and facial artifacts derived from facial gestures and mental activities. For the data to be consistent and reliable, a certain protocol was implemented for all 20 subjects. These subjects performed seven facial sequences (idle, blink, hard blink, smile, frown, closed eyes, and alternating close-open eyes) and two mental activities (concentration/attention and meditation/relaxation) under a protocol established by the group.

D. *System Architecture and Setup*

Shown in the chart below was the general process flow and system setup employed in this project.

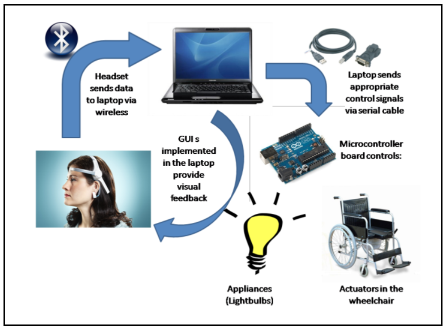


Figure 2. General System Architecture and Process Flow

As illustrated, the process started off with the neuroheadset which acquired data from the user and sent it to a laptop via wireless means. GUI's implemented in the laptop provided visual feedback to the user. The laptop then processed data received from the neuroheadset and, depending on the detected gesture, sent appropriate control signals to a microcontroller board via serial cable. In turn, the microcontroller board controlled the devices connected to it. For an appliance control application, devices could be in the form of several appliances. On the other hand, for a wheelchair control application, the microcontroller controlled the motors or actuators in the wheelchair.

IV. Results and Discussion

Although data from a total of 7 gestures and 2 mental activities were obtained from 10 non-impaired and 10 impaired subjects that participated in the study, for brevity's sake, only data for the Opened Eyes, Blink, Hard Blink, Attention and Meditation were explicitly elaborated in this paper. The reason behind was that these were the ones used in the application prototypes developed by the group namely the: Appliance Controller and the Wheelchair Controller. The Opened Eyes sequence, now to be referred to as the Idle State, was made as the reference for the analysis of the other facial gesture sequences and mental activities. Thus, shown in blue is the plot for the sequence at hand and shown in red is the Idle State in comparison. The graphs shown below consist of the time-domain plots and magnitude spectrums for each gesture. The PSD estimate for each was also computed; although the graphs are not shown.

A. *Idle (Opened Eyes)*

The time-domain plots of the Idle recording (without blinking) in the time domain as averaged from 10 non-impaired subjects and 10 impaired subjects are shown below.

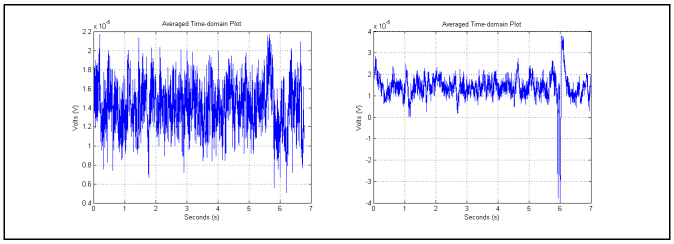


Figure 3. Averaged Time-Domain Plots of the Idle State for 10 Non-Impaired Subjects (Left) and 10 Impaired Subjects (Right)

Data for the non-impaired subjects showed that values ranged from 5.054 µV to 21.71 µV. On the other hand, data from impaired subjects revealed that magnitudes ranged from -0.1099 µV to 28.43 µV before the 6-second mark. At the 6-second mark, there was a large spiking observed in the signal with magnitudes ranging from -39.4 µV to 37.97 µV. This may have been caused by the neuroheadset sensor losing contact with one of the subject's forehead or other unforeseen anomalies.

The frequency domain plots of these time-domain plots are shown below.

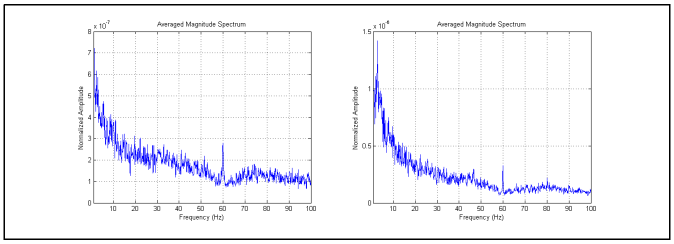


Figure 4. Averaged Magnitude Spectrums of the Idle State for 10 Non-Impaired Subjects (Left) and 10 Impaired Subjects (Right)

The magnitude spectrum for the non-impaired subjects had significant increase for frequencies below 10 Hz, with a maximum value of 0.72 µV. The magnitude spectrum for the impaired subjects showed the same. It was found out that there was also significant increase for frequencies below 10 Hz, with a peak value of 1.4 µV. The PSD estimates also pointed out that there was a significant increase for frequencies below 10 Hz. Peak values were -112 dB/Hz (for non-impaired subjects) and -103 dB/Hz (for impaired subjects).

B. Blink

The averaged time-domain plots for the blink gesture of impaired and non-impaired subjects are shown below.

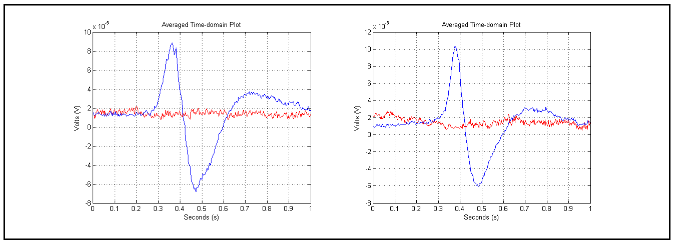


Figure 5. Averaged Time Domain Plot of the EEG Signals for the Blink Gesture of Non-Impaired (Left) and Impaired (Right) Subjects

It can be seen from the time-domain plots shown that, in comparison with the Idle State, the blink gesture elicited signal spiking for both impaired and non-impaired subjects. It was found for non-impaired subjects that signal spiking on the order of 80 µV and -68 µV, with time between peaks on the order of 109 ms were present. Similar results were also found out for impaired subjects with signal spiking on the order of 100 µV and -60 µV; and time between peaks on the order of 107 ms.

The magnitude spectrums of the blink gesture are also shown below.

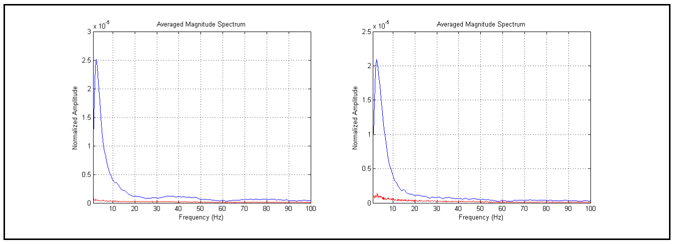


Figure 6. Averaged Magnitude Spectrums of the Blink Gesture for 10 Non-Impaired Subjects (Left) and 10 Impaired Subjects (Right)

The magnitude spectrums revealed that there was significant increase for frequencies below 10 Hz in comparison with the Idle State for both impaired and non-impaired subjects. Spectrum peaks occurred at 2.5 Hz with magnitudes of 25 µV (for non-impaired subjects) and 21 µV (for impaired subjects). The PSD estimates also gave the same results. They revealed that the blink gesture spectra had great increases along the 2.5 Hz region with peak values of -95 dB/Hz and -96 dB/Hz for non-impaired and impaired subjects respectively.

C. Hard Blink

Shown below were the averaged time-domain plots for the hard blink gesture as obtained from both impaired and non-impaired subjects.

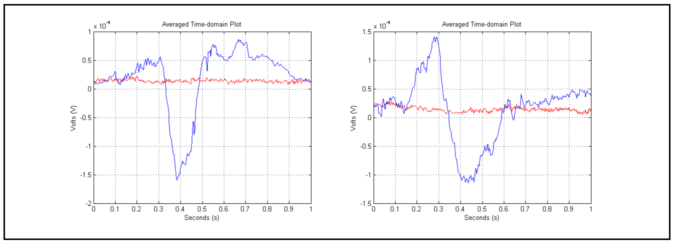


Figure 7. Averaged Time Domain Plot of the EEG Signals for the Hard Blink Gesture of Non-Impaired (Left) and Impaired (Right) Subjects

Time-domain plots for the hard blink gesture have shown large signal spiking in both cases. Data for non-impaired subjects had signal fluctuations with peaks around -160 µV and 87 µV; and 280 ms time between peaks. Data for impaired subjects, in comparison, had peak values around 141 µV and -114 µV; with time between peaks of 146.5 ms.

Shown below are the magnitude spectrums of the hard blink gesture.

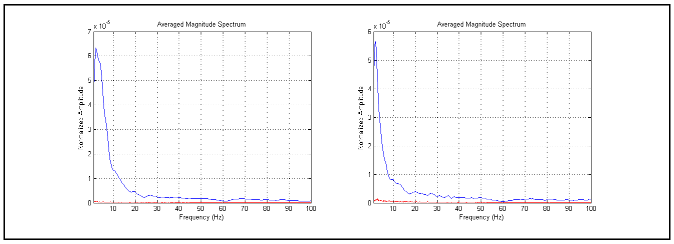


Figure 8. Averaged Magnitude Spectrums of the Hard Blink Gesture for 10 Non-Impaired Subjects (Left) and 10 Impaired Subjects (Right)

It can be seen from the magnitude spectrums that, like for the blink gesture, the greatest increase was for frequencies below 10 Hz. In particular, it was found out that the spectrums peaked at 2 Hz with values 63 µV (non-impaired) and 57 µV (impaired). The PSD estimates pointed out that there was, in fact, a wideband increase due to the hard blink gesture. However, still, the greatest increase was at the 2 Hz region: -86 dB/Hz for non-impaired subjects and -87 dB/Hz for impaired subjects.

D. Attention/Concentration

The time-domain plots for the mental activity, attention or concentration are shown below.

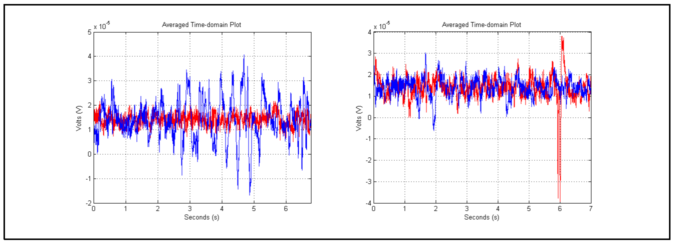


Figure 9. Averaged Time Domain Plot of the EEG Signals for Attention/Concentration of Non-Impaired (Left) and Impaired (Right) Subjects

For non-impaired subjects, it was observed that there was an increase in amplitude relative to the Idle State. Furthermore, there were several signal spiking present in the time-domain plot. The time-domain plot for impaired subjects showed that there was almost no change in amplitude due to the attention/concentration mental activity. However, a large signal spike was observed near the end of the trial.

Shown in the charts below are the frequency domain representations for the attention/concentration mental activity.

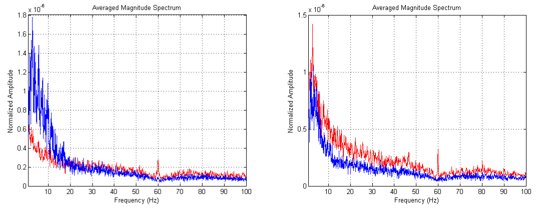


Figure 10. Averaged Magnitude Spectrums for Attention/Concentration of 10 Non-Impaired Subjects (Left) and 10 Impaired Subjects (Right)

For non-impaired subjects, it was observed that there was an increase in the 1 – 20 Hz region with respect to the Idle State. Other frequencies demonstrated a decrease in comparison with the Idle State. On the other hand, for impaired subjects, it was found out that there was a decrease in all frequency bands during the attention/concentration mental activity.

The PSD estimate for non-impaired subjects displayed a high power increase in the 1 – 20 Hz band relative to the Idle State, slight increase at the 20 – 60 Hz band and almost no change in the 70 – 100 Hz region. On the other hand, the PSD estimate for impaired subjects showed a decrease in power relative to Idle State in the 1 – 60 Hz band and almost no change in the 70 – 100 Hz region.

E. Meditation/Relaxation

Shown below are the time-domain plots obtained from 10 non-impaired subjects and 10 impaired subjects for the meditation/relaxation mental activity.

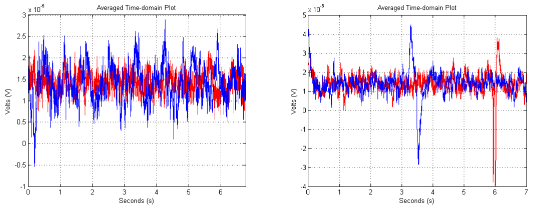


Figure 11. Averaged Time Domain Plot of the EEG Signals for Meditation/Relaxation of Non-Impaired (Left) and Impaired (Right) Subjects

The plots pointed out that there was an increase in amplitude of about 5.3 μV relative to the Idle State for non-impaired subjects; and negligible increase or decrease in amplitude relative to the Idle State for impaired subjects.

Shown below are the corresponding magnitude spectrums for the meditation/relaxation mental activity.

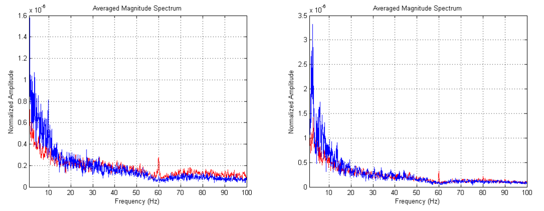


Figure 12. Averaged Magnitude Spectrums for Meditation/Relaxation of 10 Non-Impaired Subjects (Left) and 10 Impaired Subjects (Right)

For both impaired and non-impaired subjects, it was observed that there was an increase in magnitude at the 1 – 10 Hz band and a decrease in the 20 – 30 Hz bands. For non-impaired subjects, the remaining bands demonstrated a decrease in magnitude; whereas, data for impaired subjects displayed almost no change at the remaining bands.

The PSD estimate for non-impaired subjects displayed an increase in the 1 – 50 Hz frequency band, a decrease at the 60 Hz region and no noticeable change in the 70 – 100 Hz band relative to the Idle State. In comparison, the PSD estimate for impaired subjects experienced a wideband increase for all frequencies relative to the Idle State.

F. Appliance Controller

Using results from the preceding analyses, the group developed a system that enabled users to control an array of appliances. For purposes of demonstration, two light bulbs connected to solid state relays were used. However, any appliance can be used by also connecting them to solid state relays. In this application, the blink and hard blink gestures were used as the command signals since they can be voluntarily and easily invoked by the user. Incoming signals were filtered in order to further eliminate unwanted noise and in order to provide for a more reliable blink or hard blink detection scheme.

However, actually the Attention and Meditation levels can also be used as the command signals. In one particular setup, specific ranges of values for the Attention and Meditation levels were used as a threshold for the light bulbs to turn on and off.

G. Wheelchair Controller

In addition to the appliance controller application, the group also developed an application for wheelchair control. In this implementation, the group converted a standard design wheelchair into a motorized version using two wiper motors and a 12 V battery for power supply. In this system, the blink and hard blink gestures were also used for reasons mentioned previously. Also, like for the appliance controller, the Attention and Meditation levels can also be used for wheelchair control by setting ranges of values as thresholds for selection and execution of a desired action. However, using Attention and

Meditation levels as command signals only enabled for control in, at most, only two directions.

Thus, a combination of blink and hard blink gestures was then used for direction selection and execution. In order to provide for smoother and better controllability, signals were filtered so as to further emphasize those corresponding to a blink or hard blink gesture. This, in effect, enabled for a more reliable detection and better control of the wheelchair.

In addition to these, GUIs implemented in the application program provided users with additional controls and necessary visual feedback for better and smoother control over the wheelchair's actions. Calibration controls were also included in the GUI in order to adjust the system to their own individual response; and thus, provide for maximum reliability.

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