Low Cost Point of Care Testing for Cognitive Motor Aspects Using Electroencephalography*

Rishabh Sehgal, Anirban Dutta, *Member, IEEE*, David Guiraud, *Member, IEEE*

***Abstract*—A low-cost point of care testing system for assessing cognitive motor aspects of neuromotor disorders was developed from basic components for systematic understanding and effective diagnosis of psychomotor symptoms of various neuromotor disorders, like depressions. The Data Acquisition part of this system was implemented with the help of custom made electrodes and off-the-shelf low-cost data acquisition system (National Instrument's DAQ USB 6008). LabVIEW visual programing language was used for creating the graphical user interface (GUI) and for implementing online processing of the acquired signal. The acquired data was displayed to the user in real time in the GUI. For cognition testing and postural feedback from human during functional-reach tasks, Wii Balance Board was integrated to the system. The system was thoroughly jitter-tested to quantify its robustness and minimal loss of data samples was achieved. Furthermore, simple electroencephalogram (EEG) acquisition was performed on a healthy human using the 2-channel low-cost device during eyes-open and eyes-closed conditions both when the subject was sitting and when the subject was standing. A classifier (threshold detector) was fitted to discriminate the signals between the two states (eyes-open and eyes-closed) and called Brain Switch.**

I. Introduction

The World Health Organization (WHO) estimated that major depression is the fourth significant cause of disability for people aged >65 years [1], where depression is a major contributor to the healthcare costs associated with the elderly population. Depression is a major health issue for elders, yet late-life depression often goes undiagnosed [2]. Psychomotor symptoms of depression may contribute to falls among elderly and an associated fear of falling [4]. Kumar et al from the Dharma Foundation of India investigated psychomotor aspects of depression with a large sample-size and found negative correlation Berg Balance Scale (BBS) score and Geriatric Depression Scale (GDS) score. Both scores increases with age leading to poorer balance and depression. Moreover, in depressed elderly, the Quantitative Electroencephalography (QEEG) markers of depression correlated negatively with the maximum lean-line excursion of Center of Mass-Center of Pressure (CoM-CoP)-a quantitative measure of standing balance during the functional reach test. Therefore point-of-care-testing (POCT) of psychomotor symptoms of depression is urgently needed in order to screen community dwelling elderly at risk as well as to monitor the course of treatment [2]. The integration of multiple devices (Fig.1) acquiring multitudes of data is required for successful reflection of these psychomotor symptoms of depression [3].

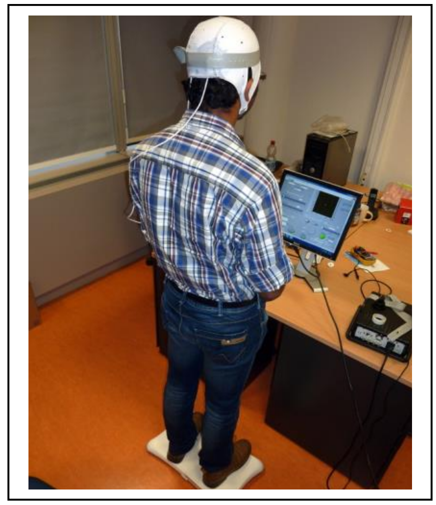


Fig. 1 Bench-testing setup created

For acquiring the QEEG markers, Brain Computer Interface (BCI) was employed which provides direct method of communication and control from the Brain Function of the user, even independent of any motor function. Despite the relatively poor spatial sensitivity of EEG, it possesses multiple advantages over other neuroimaging modalities such as fine temporal resolutions, ease of use, portability and significantly lower hardware and setup costs [5]. Methods exist for minimizing, and even eliminating movement artefacts in EEG data, making it relatively tolerant to subject movement.

Hence, the main objectives of our current study were to develop a Low-Cost Point of Care Testing (POCT) system that is reliable, portable and usable and to develop the GUI and online signal processing which was neither DAQ specific nor electrode specific, giving more freedom to operators and clinicians. Moreover, we wanted to develop a system which acquired EEG data in real time, preprocesses and processes the acquired epochs of data also in real time which could be stored systematically using the help of GUI itself, and which integrated postural data acquired through Wii Balance Board (WiiBB) having diverse applications in the areas of neurofeedback and rehabilitation (Fig.1). The focal point of our study, WiiBB feedback data, needed to be displayed as it gives the motor aspects related to cognition and hence it also helps in detecting any postural anomalies which could be associated to cognitive symptoms of depression.

*Research supported by grants from INRIA, Campus France and Dharma Foundation of India (DFI).

R. Sehgal is a graduate student at University of Minnesota, USA (e-mail: sehgal.rish25@gmail.com). This work was done while the author was an intern at Team DEMAR, LIRMM-INRIA, Montpellier, France.

A. Dutta is with INRIA, France (email:anirban.dutta@inria.fr).

D. Guiraud is Senior Research scientist at LIRMM and head of team DEMAR, LIRMM INRIA, University of Montpellier, 161 Rue Ada, 34095. Montpellier Cedex 5, France. 2 (e-mail: guiraud@lirmm.fr).

II. Methodology

The Data acquisition unit used in the present work is NI DAQ USB-6008. The NI USB-6008/6009 provides connection to eight analog input (AI) channels, two analog output (AO) channels, 12 digital input/output (DIO) channels, and a 32-bit counter with a full-speed USB interface. It has 12 bits for differential operation and 11 bits for single ended operation. The maximum sampling rate of the device is 10 kS/s. This device was chosen because of its low cost, high reliability and high portability. It has a fairly large number of Input channels (both analog and digital). Also for system design and algorithmic implementation LabVIEW was used. The EEG data is read in epochs of time [7]. There is a window length of data read from the electrodes that is processed and displayed every time in the graphs. So ascertaining an appropriate length of epoch was very vital.

A. *Basic Parts of Acquisition System*

There are two parts to this Data Acquisition challenge. The first part is generally concerned with the actual data reading done by the DAQ. Here the "sampling frequency" is specified as the rate of gathering the digital samples from the incoming analog values at the electrodes which is external to the LabVIEW program and it only concerns itself with the speed of data sampling and digital samples gathering. There is a FIFO buffer inside the DAQ which can hold 512 bytes; 256 samples [8] and which stores the digitized samples before they are read by the program. If sampling rate is high the buffer fills up fairly quickly and it overflows which can cause the loss of samples resulting in the loss of information. The LabVIEW program then reads this buffer according to the time interval between the two iterations of the while loop. All the processing was done in this loop after an interval of ΔT. The EEG signal (which is rather noisy) could not be predicted and the loss of samples could not be detected. Hence an external function generator was used to simulate a sinusoid on the input channel of DAQ before displaying the acquired data, thus realizing the loss of samples.

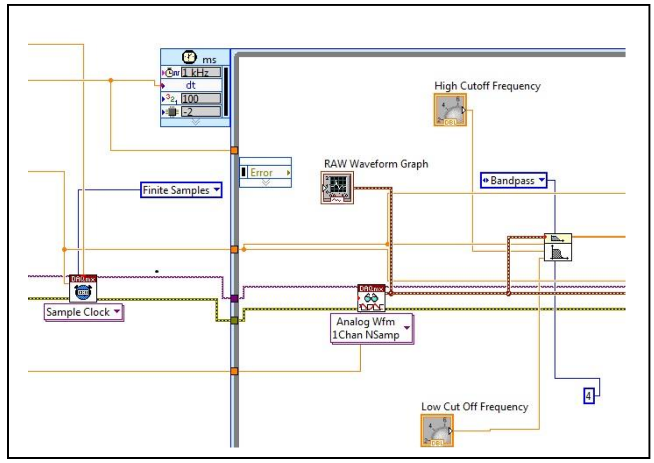
B. *Preprocessing Using Timed Loop*

A timed loop function was created in which the incoming signal was processed and filtered using two Butterworth 4th order filters, one acting as a high pass and other acting as a band pass filter. Raw data and filtered data were read and displayed every time. The timed loop was imperative in defining the various customizable time interval between the two iterations which were related with the sampling frequency and buffer size. Three main parameters of DAQ namely (a) Sampling Frequency (Fs), (b) Buffer Size (N) and (c) Time interval of execution of timed loop (ΔT) are inherently interrelated. The Time interval can be obtained by dividing the total number of samples set by the sampling rate.

i.e. $$\Delta T = N/F_s \qquad (1)$$

Hence eqn. (1) was used in the program for finding out the third parameter i.e. Time interval of execution of timed loop (ΔT) when the other two parameters Fs and N were specified by the user through GUI. The channels and timing function were placed outside the loop as they had to remain functioning throughout but the DAQmx Read function, the two Butterworth filters were placed inside the timed loop this time acquiring the data from buffer and processing it after an interval of (ΔT). Considerable care was taken to reduce the unnecessary delays within the processing of loop. The LabVIEW program showing the implemented timed loop snippet is also shown in Fig. 2.

Fig. 2 Timed Loop implementation.



C. *Feature Extraction*

In the context of objectives of this project, features used for EEG trial classification mainly result from the time, frequency, and time-frequency analysis. The goal here was to do the spectral analysis of the preprocessed data that was obtained from the acquired raw data, to detect any periodicities in the data by observing peaks at the frequencies corresponding to these periodicities. FFT Power Spectrum and PSD are preferred over Lomb-Scargle periodograms because the observational data in biomedical signals often contain fractions of non-Gaussian noise or may consist of periodic signals with non-sinusoidal shapes and Lomb-Scargle method can be sensitive to discordant data points such as isolated large amplitude outliers caused by instrument failures or disturbances in the test environment. Using the FFT Power Spectrum and Power Spectrum Density VI we had the flexibility to process the signal by specifying a whole variety of windows applied to the time domain signal e.g. Rectangle, Hanning and Hamming etc. We could specify the averaging parameters, when to restart averaging and number of averages completed in the GUI. The LabVIEW program showing FFT PSD VI is shown in Fig. 3.

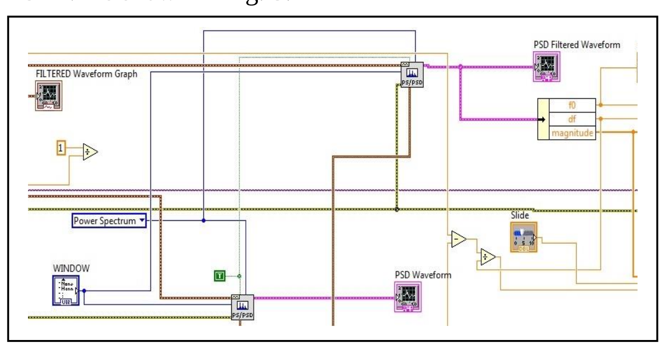


Fig. 3 Snapshot of program showing the FFT PSD VI and its clustered output.

Furthermore the PSD was implemented on both the raw data and the filtered data. For identifying the frequency present in the input signal having the highest amplitude an "Extract

Single Tone VI" was implemented after the Filtered Raw Data. This was very useful for the testing purposes also, as we could cross check the obtained frequency and amplitude value with the values that we specify of the sinusoidal signal on the function generator that provides input to the DAQ setup.

D. Datasets saving module and other additions

A data saving module was programmed in the same LabVIEW VI which could save the recorded raw EEG data coming directly from the DAQ in a .txt file. The "Test Features" that were obtained through the "Extract Single Tone VI" were also stored. The data saving module has assistive file naming system which automatically appends the important test parameters as Sampling Frequency, Buffer Size and type of data (Raw, Test Features or Jitter) in the filename thereby reducing considerable time and error by users in manual saving of test results. The GUI only asks the user about the "Directory" into which the test results files should be saved. Moreover, a switch is provided in GUI which when pressed ON starts the data saving feature. The switch can be pressed again to for OFF state so that the data saving stops but acquisition, preprocessing and displaying keeps going on. The file saving module is a sub-module of whole program and it can be kept OFF without affecting the functionality of the whole program.

E. Implementing Threshold Detector

Since it was now possible to process the data, extract its features and save them in real time, implementing a classifier was the next logical step. In this project, a simple peak detector was used to give a basic discriminating function to the datasets. A threshold voltage value could be set manually by the user through the GUI and the number of frequencies corresponding to which the voltage is greater than the threshold voltage are detected as the signal peaks. For these signal peaks, amplitudes and frequencies are displayed and a "Brain Switch" LED was turned ON when the number of such peaks exceeded zero. This was generally used for testing purpose and for getting a neurofeedback output.

III. JITTER TESTING, RESULTS AND DISCUSSIONS

As mentioned earlier, several provisions were made in the algorithm to help in data collection at various stages so as to effectively test the algorithm against any sample losses and jitter. All the testing data were acquired by giving the DAQ a sinusoidal input from a function generator. Data with different input frequencies were collected. Although the jitter test results do not depend on the input signal details; but for the following jitter test results the frequency was 30Hz and the voltage value was equal to approximately 5.00 Volts. The jitter test values were stored in an .xlx file using the assisted naming implemented by the algorithm and they were obtained by getting the difference between the peak values detected from the Peak Detector VI after FFT Periodogram and the Test Features extracted from filtered raw data. The datasets were acquired with different acquisition parameter values.

(A) Firstly the Buffer Size (N) was kept constant at 500 and the Sampling Frequency (F_s) was varied from 500Hz to 1500Hz with an interval of 100 Hz. This data was analyzed by taking the mean and standard deviation of 20 acquired samples for both frequency and amplitude and was plotted as shown in the Fig. 4.

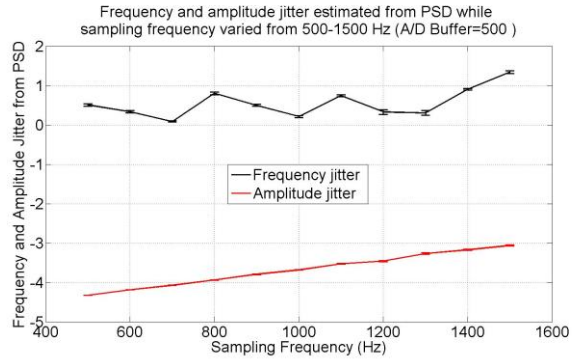


Fig. 4 Jitter data when Buffer Size (N) = 500 and Fs is varying

From Fig.4 it could be noticed that the amplitude jitter, which is induced in the system due to timing uncertainty (clock jitter or clock phase noise), decreases as we increase the 'Fs' as this amounts to more number of samples for a particular segment of the signal. The standard deviation increases although very marginally as we increase the sampling frequency. The frequency jitter mean is seen to be decreasing for some repeated periodic intervals because of the windowing effect and to some extent it depends on the input frequency of the signal. Here the input signal inherently contains a single tone of 30Hz frequency.

(B) Secondly the Sampling Frequency (Fs) was kept constant at 1000Hz and the Buffer Size (N) was varied from 350 to 1550 with an interval of 100 units. This data was analyzed by taking the mean and standard deviation of 35 acquired samples of for both frequency and amplitude. Plot of these results is given in Fig. 5.

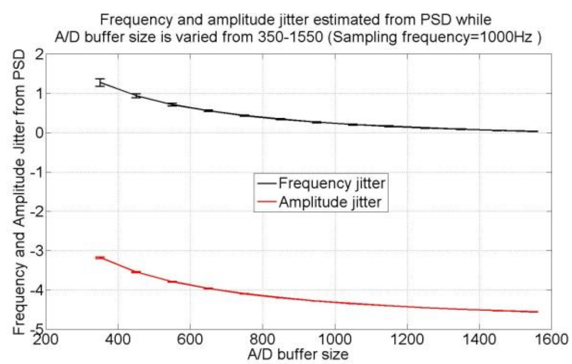


Fig. 5 Jitter data at Fs=1000Hz and with buffer size (N) varying from 350-1550

From the Fig. 5 it could be seen that here the standard deviation of the frequency jitter values is constantly decreasing as the 'N' is increased. This is because with the increased buffer size, more data samples will be acquired and processed in one iteration by the program thereby decreasing the spread of data values across the mean. The mean of frequency jitter is decreasing as the number of samples increase (due to increase in N) because the jitter values are decreasing to the point of being nearly zero. Also, the standard deviation for the amplitude jitter is decreasing as the N increases because of less spread of jitter due to increase in analyzed sample values. However, the mean of amplitude jitter is constantly decreasing as opposed to the mean of frequency jitter as the gap between the two amplitude values is increasing.

IV. THRESHOLD CLASSIFIER (EYES OPEN/EYES CLOSE)

It was imperative to check the system that was developed, for the robustness and the accuracy of the results. This could be tested best with the simple eyes open/close experiment where the EEG readings coming in the frequency band of 4-12 Hz are taken from the visual cortex region in the occipital lobe. The EEG reading were first taken in a sitting task for eyes open and eyes close only. Afterwards the EEG readings were also acquired in a quiet standing task, while balancing over Wii Balance Board, both when the eyes were open and eyes were closed. A threshold classifier was implemented for eyes open/eyes close by taking the voltage readings from electrodes placed at the both Cz-O1 and O1-O2 regions while sitting. During the course of our experiments the best data can be obtained from O1-O2 region and hence that region only was taken into consideration both for standing and sitting data acquisition. Further the two types of configuration to acquire eyes open/close data were used. The first objective was to acquire the eyes open/close data, while sitting, in a differential mode of operation of electrodes. The second was to acquire data in a single electrode mode of acquisition where the ground electrode was placed over the elbow bone. So this gave us 4 combinations for data acquisition.

The first graph (Fig. 6) shows the distribution of Eyes open/ eyes closed data points while the acquisition was done in differential mode. As we can clearly visualize that the data points here are bit overlapped near the frequency region 6-8Hz. Due to lack of proper distinction between Eyes open/closed data we can say that a high order NN classifier may be used to discriminate between the two states.

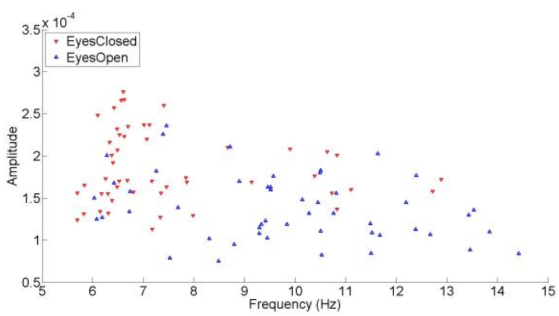


Fig. 6 Plot for Eyes Close/Open data values for differential electrode mode

The second graph (Fig. 7) shows the distribution of Eyes open/ eyes closed data points while the acquisition was done in single mode. As we can clearly visualize that the data points here are distinctly located for both Eyes Close and Eyes Open values. Moreover the spread of data points here is very exact and is located between the bands of 6.374-6.378 Hz. Hence LDA classifier can be fitted very easily here with a discriminating voltage value of 0.1687 Volts. Anything above this voltage value can be fairly characterized as eyes closed signal and anything below that would be eyes open signal.

V. CONCLUSIONS

The setup is utilizing the basic classifier for eyes open/close task of one subject but is perfectly capable of being augmented with a higher order classifiers for more complex tasks like Motor Imagery, extension-flexion of finger and actual movement tasks.

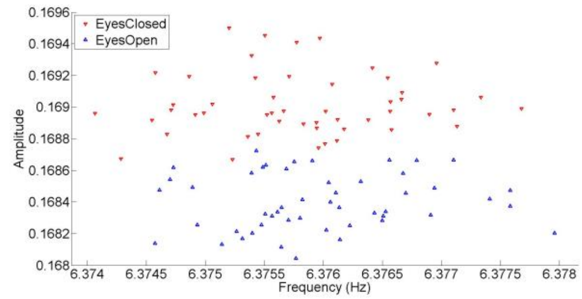


Fig. 7 Plot for Eyes Close/Open data values for single electrode mode

Moreover, it was also determined from the results that O1-O2 site is better than Cz-O1 for collection of visual data. Further, we noted that better results were obtained when electrodes were in single ended mode rather than differential mode. The GUI was tailor made for research purposes and can also be customized according to the needs for the different kind of cognitive training tasks. Moreover this system can provide a platform for collecting neurological data for the elderly subjects and also the differently abled subjects so that appropriate neurological feedback be given to them after being analyzed by the concerned experts.

ACKNOWLEDGEMENT

The internship grant received from National Institute for Research in Computer Science and Control (INRIA) is acknowledged and R. Sehgal is thankful to Dr. Guiraud for recommendation for this scholarship and particularly acknowledges guidance provided by Dr. Dutta at every step. R. Sehgal was the recipient of Charpak Scholarship provided by Campus France. Campus France's help for this great opportunity and all the arrangements made by them are thoroughly acknowledged. The help received from Dr. A. Banerjee of DFI, Ms. A. Aliaga (INRIA), Mr. F. Saadoun and Ms. A. Kelkar (both from Campus France) for all the administrative works required regarding the internship mobility from India to France, is deeply acknowledged.

REFERENCES

[1] Pollock B, Reynolds C. "Depression late in life," Harvard Mental Health Letter 2000; 17, pp. 3–5.

[2] Lebowitz B, et al. "Diagnosis and treatment of depression in late life," Journal of the American Medical Association 1997; 278, pp. 1186–1190.

[3] Rishabh Sehgal and Anirban Dutta, "Real time integration in Low-cost visual postural feedback with Wii balance board and Microsoft Kinect"; published in the proceedings of 'Indo-German Workshop on Neurobionics in Clinical Neurology', JIPMER Pondicherry, India on 15th-17th February, 2013.

[4] Zijlstra AR, et al. "Prevalence and correlates of fear of falling, and associated avoidance of activity in the general population of community-living older people," Age and Ageing 2007, 36, pp. 304–309

[5] W.-K. Chen, *Linear Networks and Systems* (Book style). Belmont, CA: Wadsworth, 1993, pp. 123–135.

[6] Ozols, K.; Greitans, M.; Shavelis, R., "EEG data acquisition system based on asynchronous sigma-delta modulator," Electronics Conference (BEC), 2012 13th Biennial Baltic , vol., no., pp.183, 186, 3-5 Oct. 2012

[7] Eoin Thomas, Joan Fruitet, Maureen Clerc, Combining ERD and ERS features to create a system-paced BCI, Journal of Neuroscience Methods, Volume 216, Issue 2, 15 June 2013, pp. 96-103, ISSN 0165-0270, http://dx.doi.org/10.1016/j.jneumeth.2013.03.026.

[8] http://sine.ni.com/nips/cds/view/p/lang/en/nid/201986.