Self-Tracking via Brain-Mobile-Cloud Interface

Garima Bajwa[†], **Ram Dantu**[†], **Mohamed Fazeen**[†] and **Rajiv M. Joseph**[§]
[†]Department of Computer Science and Engineering, University of North Texas, Denton, Texas, 76203, USA
[§]Associate Professor, Department of Neurology, University of Texas Southwestern Medical Center, Dallas, Texas, 75390

Abstract

Abnormalities in the brain are one of the leading causes of disability amongst people. There is a significant delay between monitoring the onset of these disorders and their treatments. This paper presents a brain-mobile-cloud interface (BMCI) to integrate the mobile platform, cloud computing technology and existing brain monitoring systems to remotely monitor the brain signals of an individual using their electroencephalograms (EEGs) in unconventional environments. Further, we discuss the potential of our proposed framework in applications like tracking mental activities, identifying distracted driving behavior and their corresponding changes in cerebral blood flow (CBF).

Introduction

The use of Electroencephalography (EEG) to analyze brain activity has existed since 1924 after its invention by a German Scientist Hans Berger (Haas 2003). EEG measures the potential difference across the scalp as a result of ionic current flows, when the neurons in the brain communicate with each other. Previously, it was not a fully developed diagnostic tool but has now become viable in diagnosing and treating neurological disorders especially epilepsy, seizures, brain tumors, sleep disorders, coma and brain death.

One of the initial attempts to provide real-time remote EEG monitoring (Chen and Lee 2008) was developed as an internet based EEG information system using the wireless local area network (WLAN) and a WLAN compliant EEG sensor node named pEEG. In another work, (Gad 2011) proposes architecture based on Cloud Computing and MapReduce for Ubiquitous Learning systems. However, in his scheme only generated EEG data sets and virtual users were used. (Ericson, Pallickara, and Anderson 2010) also offer the use of cloud runtime to allow training of neural networks for EEG classification of different mental tasks from multiple users to use their intended actions for keyboard input or control motion of wheel chair. Their results were based on only pseudo generated EEG streams and a static data set.

The main motivation of our brain-mobile-cloud interface for EEG monitoring is to bridge the enormous gap between diagnosis and treatment of mental disorders. Also, a constraint EEG recording environment cannot accurately determine the onset or presence of many of the complex neural disabilities. As more and more people have access to smart phones, adding mobility in EEG data collection provides unrestrained, remote monitoring of people for more accurate, up-to-date patient data readily available to the doctors. This helps to deliver patient centric care and prioritize the resources of hospitals towards acute patients. It will prevent unnecessary visits to healthcare centres thereby cutting overall costs involved in mental healthcare. In the following sections we discuss the proposed infrastructure of the BMCI design, application interface, relevance of our work in applications of self-tracking behavior and finally, some challenges and future work.

Application Interface Prototype

The system design as shown in Figure 1 is a detailed overview of the proposed architecture for brain-mobile-cloud interface. The EEG brain signals are captured using a headband called Mindband (Neurosky). The Bluetooth interface i.e. brain-mobile interface obtains data on the smart phone and the android API displays the collected data from the EEG sensor on the mobile phone. The phone has a 1 GHz processor with 512 MB internal storage. Light weight on board processing can be performed in the smart phone itself for preliminary data analysis. The expected urgent results are displayed using the existing API; otherwise the data is sent to the cloud network via the mobile-cloud interface.

Brain-Mobile Interface

In our system we use the headband as the brain-mobile interface to obtain the EEG data of the user. The headband contains a single sensor dry electrode with an ear clip reference to record signals from the scalp. It is comfortable and convenient to wear. Additionally, it does some preprocessing of EEG data and provides bluetooth connection for transfer of data to peripheral devices.

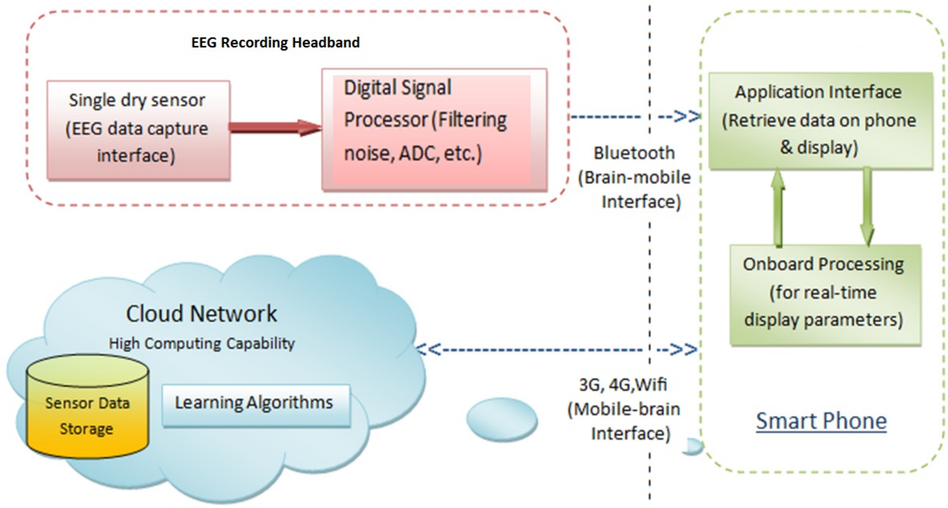

Figure 1: System design for the Brain-Mobile-Cloud Interface

Mobile-Cloud Interface

To realize the mobile-cloud interface, we have used the NSL server (Network Security Lab at UNT) to test the upload of raw EEG data file onto the server from the mobile phone. For this process, we used the available Intents from the AndFTP application to perform the upload, download and browsing process. AndFTP is a FTP, SFTP, SCP, FTPS client for android devices (Lysesoft). To use these Intents in our current brain-mobile API, the AndFTP application needs to be already installed in the mobile system (Android). The file transfer is performed over a secured SSH connection using Wi-Fi and the authentication process is carried out by verifying a username and password.

Applications

The idea behind development of the BMCI design is to provide a platform for monitoring the brain health of an individual, in parallel to the emerging health trends for quantified self. We explore the relationship between EEG signals and Cerebral Blood Flow (CBF) estimates in two scenarios; performing mental activities and distracted driving behavior.

Tracking Mental Activities

Significant work has been done by (Buxton et al. 2004) to show neurovascular coupling between EEG signals and CBF. The estimated CBF from EEG signal in case of performing mental tasks such as finding a word in a reading passage and doing a simple multiplication in mind, co-insides with the theory of neuronal activation and vascular coupling (Freeman 2008). Figure 2 shows the baseline CBF of an individual for an EEG signal recorded when the eyes are closed. Figures 3 and 4 show the increase in CBF while performing mental activities compared to the baseline CBF. Amplitude coupling appears to be linear as observed in our experiment in healthy individuals. Thus, we observe that the neural responses evoke CBF response, though CBF values are not calibrated here, only nature of change is studied. The CBF response as computed from the SPM canonical HRF function is in agreement with the literature which shows a delay by 1-2 seconds following the neural activation with peaks around 4- 6 seconds after neural response (SPM). The actual mechanism of rise and fall of CBF values within a mental activity may be related to bursts of neuronal activation while executing that task.

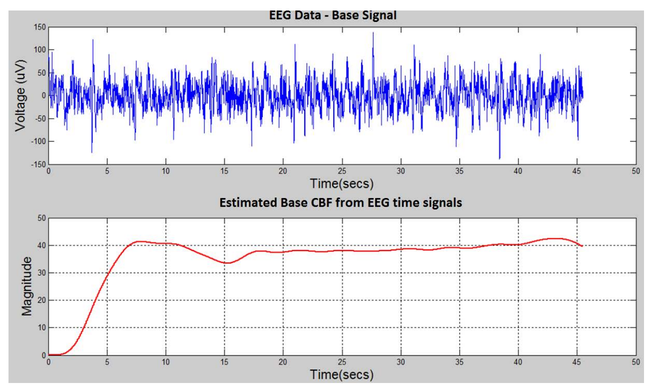

Figure 2: EEG signal (top) and estimated CBF for an individual in resting state and eyes closed

Driver Distraction

Another potential application of our BMCI design is observation of distracted driving behavior in a real world scenario. The distracted driving experiment is conducted to differentiate between a texting event and a normal driving event. We found that channel-4 (FC5) shows little activity in the base profile, but sudden bursts of change in frequency of EEG signals emerge while texting compared to other electrodes as shown in Figure 5. It is very interesting to note that other researchers also found similar regions of scalp active in de-

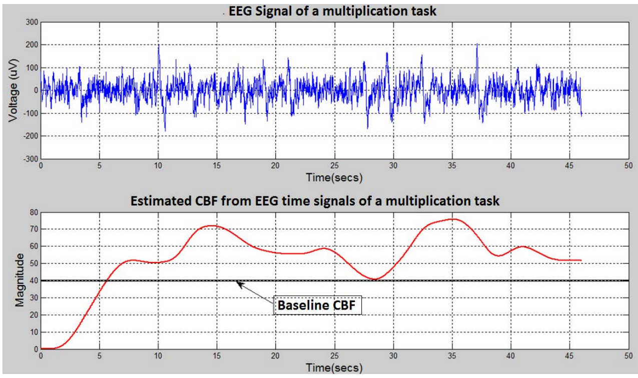

Figure 3: EEG signal (top) and estimated CBF in case of multiplication task

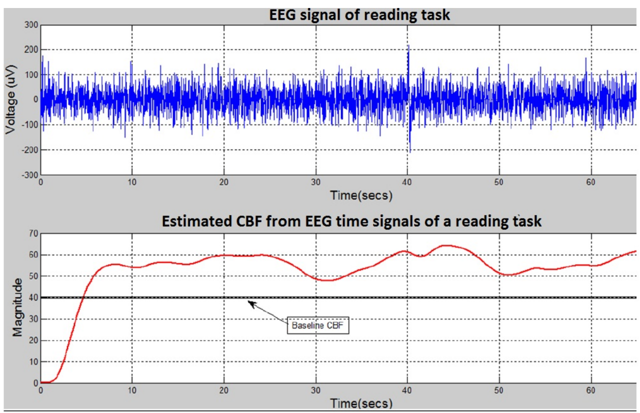

Figure 4: EEG signal (top) and estimated CBF in case of reading task

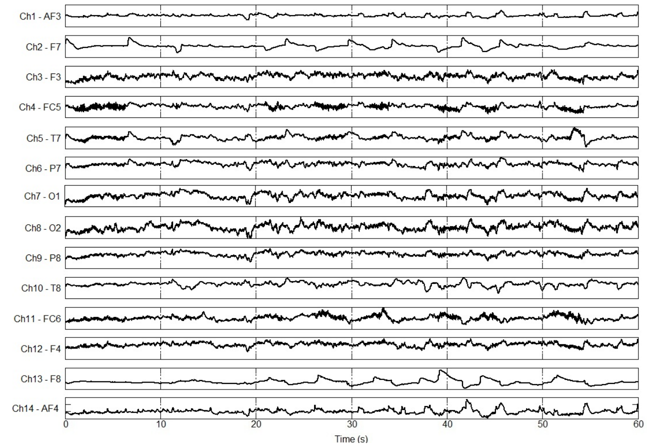

Figure 5: EEG recording of texting experiment while driving from 14 channel headset

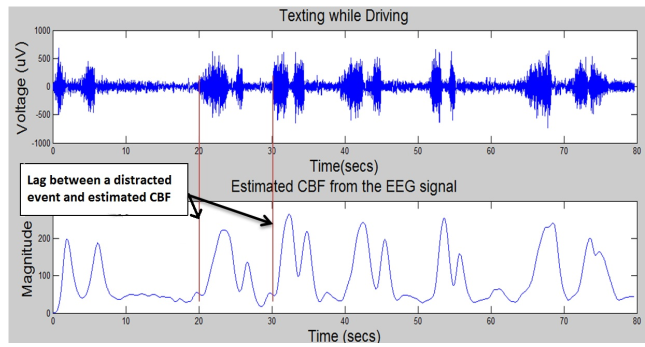

Figure 6: EEG signal of a texting event while driving (top)and corresponding changes in estimated CBF

tecting driver distraction (Lin et al. 2008) (Faro, Giordano, and Spampinato 2006).

In order to quantify the behavior of distracted driving, we need to devise a system in the smart phone that can detect the changes in the frequency bands of EEG signal to characterize such distraction events successfully.We also observed changes in CBF corresponding to EEG signals recorded in distracted driving events. To our surprise, significant variation is observed in estimated CBF values corresponding to the texting events while driving as shown in Figure 6. The other electrodes did not show much activity which indicates the potential of characterizing spatial CBF responses as well (provided we have more electrodes recording data simultaneously). Figure 7 shows the comparison of CBF values in the case of texting while driving and not driving.

Discussion

The observed results in our experimental measurements capture the features that have been reported in the model framework of neurovascular coupling in literature and are in accordance with the underlying assumptions. It highlights the potential use of portable EEG monitoring devices to be used for real time self-tracking of an individuals cerebral blood flow in absence of fMRI, NIRS techniques (assuming the state of the art techniques existing in EEG capturing devices will expand to offer more miniaturized, reliable and cost effective devices). Numerical validation of the measures has to be carried out to provide a better estimate of such measures for clinical relevance and personal health monitoring. Though EEG signals qualitatively characterize the CBF behavior, all the ideas motivating the model may not be correct as neurovascular coupling still remains a subject of debate with researchers and no consensus has been established on exactly which aspect of neural activity drives the hemodynamic response.

Further, we have shown that EEG signals from one channel may be sufficient to detect the intense thinking that can be used to quantize drivers distraction index. Frequency bands can be used for peak detection algorithms to quantify any variations. Such algorithms involve less intensive computation in low resource devices like mobile phones as compared to detecting bursts in time domain. Thus, a mobile implementation of these applications would be a major improvement in ensuring the health and safety of an individual.

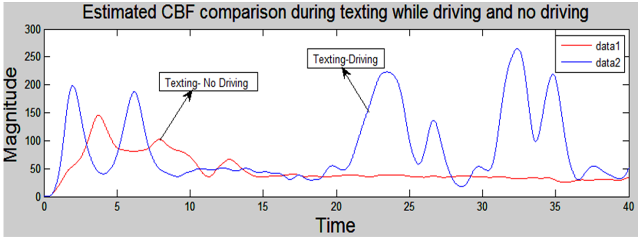

Figure 7: CBF Comparison in events of texting while driving and not driving

Table 1: Performance Metrics for Data Transfer between the two Interfaces

	Brain-Mobile-Interface	Mobile-Cloud-Interface	
Metrics	EEG Data Transfer to mobile phone	Upload Process	Download Process
Transfer Size	Streaming (raw data at 512 Hz)	2,644 KB	2,644 KB
Transfer Rate	250 kbits/sec (RF data rate)	344.08 KB/s	293.22KB/s

Performance Metrics

We used some metrics to evaluate the data transfer speeds of our interfaces, namely; Bluetooth data transfer from headband to mobile phone and upload, download processes for mobile-server-interface. The results of our trials are shown in Table I. We used the same file to perform the upload and download for the mobile-cloud interface to compare the metrics. The impact of transfer rates between the different interfaces is more significant for real-time alerts compared to the diagnosis and processing of data at the health providers side.

The EEG recording of 1 minute from single electrode amounts up to nearly 1.12 Mb of data. As the number of electrodes and the duration of EEG recording increases, the data storage requirement will be enormous. The mobile-cloud interface will be a feasible solution to handle such large data collections.Presently, upload of the EEG data file to server and collection of the raw EEG data from the headband is not supported simultaneous in our application. However, transfer speed of 344 KB/sec during upload is sufficient to allow the data recording and relaying being done simultaneously.

Conclusion and Future Work

The BMCI design described in this paper put forwards the idea to carry a wearable headband that is easily connected to the smartphone, which acts as a medium to transfer data to the cloud network for analyses. It provides the ability to use EEG signals with BMCI application as a means to equip individuals with a self-tracking tool for monitoring their brain signals for symptoms of developing any brain injury. This self-knowledge about ones brain health leads to timely acknowledgment of abnormalities, improved patient centric treatments leading to an overall change in behavioral response of both patients and doctors.

Further use of this application can be extended in driver distraction detection which will lead to safe driving scenarios with timely distracted alerts. More work is in progress to study the relationship of our observations in the EEG data of diseased patients. Also, we need to investigate what kind of risk models can be developed for brain abnormalities/distracted driving based on long-term assessment of EEG self-tracked data in cloud. Lastly, the security and privacy of the EEG data has to be taken care at all times.

Acknowledgments

This work is partially supported by the National Science Foundation under grants CNS-0751205 and CNS-0821736.

References

Android. Developers available: http://developer.android.com/index.html.

Buxton, R. B.; Uluda, K.; Dubowitz, D. J.; and Liu, T. T. 2004. Modeling the hemodynamic response to brain activation. *NeuroImage* 23, Supplement 1(0):S220 – S233. Mathematics in Brain Imaging.

Chen, H., and Lee, J. 2008. The implementation of a wireless electroencephalogram information system using wlan. *IJCSNS International Journal of Computer Science and Network Security* 8(2):166–172.

Ericson, K.; Pallickara, S.; and Anderson, C. 2010. Analyzing electroencephalograms using cloud computing techniques. In *Cloud Computing Technology and Science (CloudCom), 2010 IEEE Second International Conference on*, 185 –192.

Faro, A.; Giordano, D.; and Spampinato, C. 2006. A multifacets analysis of the driver status by eeg and fuzzy hardware processing. In *Engineering in Medicine and Biology Society, 2006. EMBS '06. 28th Annual International Conference of the IEEE*, 6095 –6100.

Freeman, B. N. Pasley, R. D. 2008. Neurovascular coupling. *Scholarpedia* 3(3):5340.

Gad, S. H. 2011. Cloud computing and mapreduce for reliability and scalability of ubiquitous learning systems. In *Proceedings of the compilation of the co-located workshops on DSM'11, TMC'11, AGERE!'11, AOOPES'11, NEAT'11, & VMIL'11*, SPLASH '11 Workshops, 273–278. New York, NY, USA: ACM.

Haas, L. F. 2003. Hans berger (1873 to 1941), richard caton (1842 to 1926), and electroencephalography. *Journal of Neurology, Neurosurgery, and Psychiatry* 74(1):9.

Lin, C.-T.; Lin, H.-Z.; Chiu, T.-W.; Chao, C.-F.; Chen, Y.-C.; Liang, S.-F.; and Ko, L.-W. 2008. Distraction-related eeg dynamics in virtual reality driving simulation. In *Circuits and Systems, 2008. ISCAS 2008. IEEE International Symposium on*, 1088 –1091.

Lysesoft. Andftp available: http://www.lysesoft.com/products/andftp/index.html.

Neurosky. Available: http://www.neurosky.com/.

SPM. Statistical parametric mapping available: http://www.fil.ion.ucl.ac.uk/spm/.