International Conference on Mathematics and computational science and Engineering (ICMCSE 2017) **Recommendations**

(manuscript.doc or PDF outline and ancillary.zip contents)

---------------- Recommended Manuscript Outline for the DOC file or PDF Files ---------------------

Abstract: Summarize your project goals and accomplishments (include no references). Your Abstract and Keywords are what attracts readers to your paper.

Keywords: Application areas addressed, model numbers of the microprocessors used, types and model numbers of the commercial sensors employed, software tools used, other special features.

I. Introduction: Background on the application area; why it is important (include references). State clearly the problem that is being addressed. Review previous published attempts to solve the problem and evaluate their success and failure (include references).

II. Concept Development: Describe how your proposed system will improve over past attempts, and what features your system offers. Describe any surveys you have conducted to select the features you are including in your solution. Story boards for use examples.

III. System Design: Provide clear descriptions of the design steps what your followed for both hardware and software.
Hardware Design (block diagrams, sensor interfaces, circuit schematics, communication links, CAD tools, etc.)
Software Design (flow charts for all processors, databases, GUIs, smart-device apps, etc.)

IV. System Prototyping: Give complete details of the phase of your prototype implementation process.
Hardware (sensors, microprocessors, protoboards, solder boards, PCBs, 3D printing, communication links, etc.)
Software (coding procedure, coding tools, adopted and adapted software routines and tools, etc.)

V. System Testing: Describe the testing procedures that you followed to demonstrate the functionality of your system. Include a summary of the various instruments and devices that were employed (include references).

VI. Results and Evaluation: Give examples of real data collected and processed by your system demonstrating its functionality. Describe the metrics used in evaluating the success of the system.

VII. Conclusions and Future Work: Did your project meet its goals? Does it help fulfill the need you identified in the Introduction? What plans do you have for continuing the project in the future? What new features do you recommend?

Acknowledgements: Identify individuals and organizations that have aided you in this project. The contributions should be important, not not at the level of those listed as authors.

References: Please acknowledge all sources of the materials you relied upon to generate the manuscript. ICMCSE 2017 screens all conference publications using CrossCheck to verify the originality of every paper it publishes .

Letter of Support: If your project was mentored by an instructor or sensor professional, you may include a letter of support from that person. He/she should include a brief paragraph about this professional background.

---------------- Required Contents of the ZIP file ------------------------

Ancillary_Files.zip
- Readme.txt (with a list of all included files)
- Presentation Slides (in PPT or PDF format)
  - Hardware Folder (with schematics, PCB layouts, GUI sketches, case renderings, mechanical drawings, etc.)
  - Software Folder (with all computer code, signal processing routines, CAD design files, etc.)
  - Bill of Materials (part numbers, sources, quantities, to allow others to reproduce your system)

Assessing Neurosky Mindset´s capability to measure the attention mind states during car driving

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Abstract— This paper presents the results of Neurosky Mindset evaluation attention levels mind states while driving and operating other side distractive tasks. This BCI (Brain Computer Interface) is composed by a wireless headset equipped with a single dry contact electrode for measuring the user's EEG signals on the user's forehead EEG is the recording of electrical brain activity through electrode sensors placed on the scalp. It uses an Attention Meter algorithm, which indicates the intensity of mental "focus" or "attention". The aim of this study is to investigate how well the headset performs quality and quantity of data it gathers by measuring the attention levels in drivers operating under side distractive tasks. This is one of the studies, which can help to determine whether this headset could be more widely used as a cost effective means of recording EEG output related to attention and for future studies in preventing car collision. The results of Neurosky Mindset evaluation suggests a positive correlation between measured and self reported attention levels. However, this was only an initial study intended to be extend in near future, in terms of sample size and characteristics, the type and tasks and devices used for it. The idea will be to measure what is happening with the user when doing specific programming activities and determine how specific parts of the brain or other body elements can measure different functions.

INTRODUCTION

Brain Computer Interfaces (BCI) are direct functional interactions between a human brain and an external device (Diettrich et al., 2010). BCI have recently gained a new interest as a practical Human Machine Interface (HMI). It measures the brain activity of a user and then identify the thought pattern or desired action of the user. Brain activity is measured by detecting minute voltage changes in specific areas of the brain. This can be done in three ways: 1) invasive, where electrodes are placed on the brain itself, 2) partially-invasive where electrodes are placed in the skull and 3) non-invasive where electrodes are placed on the scalp (Vourvopoulos et al., 2012).
Electroencephalography (EEG) is the only currently available non-invasive brain activity measuring method and therefore it is the most widely used. It has been shown that using EEG is a viable method of BCI (Rodrigues et al., 2010).

Wireless BCI systems for consumer use: Neurosky Mindset

Although early BCI was proposed in the late '70s widespread use was limited due to equipment cost and complexity (Vourvopoulos et al., 2012). However, recent technological advances have enabled the development of low cost BCI devices that are aimed at the mass market. With portable wireless BCI applications, various real-life applications are under development now. In the early days of BCI researches, cursor control and speller applications were developed mainly targeted for helping the disabled people. Recently, with growing interest, wireless BCI systems have been applied in entertainments as well. For example, Emotiv and Neurosky companies have recently released their wireless BCI headsets for entertainment uses such as brain gaming and mind monitoring. Moreover, international research groups have applied wireless BCI systems for interesting new applications such as home automation system based on monitoring human physiological states, cellular phone dialing, and drowsiness detection for drivers. (Lin et al.,2010).
The device Neurosky Mindset has along with the capability of raw EEG recording and eye blinking measurement, the Mindset has the patented algorithm, named as eSense. This algorithm interprets the user's mental states such as attention and meditation. In this study we will only concentrate on the attention mental state, which indicates the intensity of a user's level of mental 'focus' or 'attention' to determine levels of concentration. The value ranges from 0 to 100. The attention level increases when a

user focuses on a single thought or an external object, and decreases when distracted, has wandering thoughts, lack of focus, or anxiety (Neurosky, 2017). This information is presented in Table 1.

Value	eSense Attention levels	Description
0	Unable to calculate	Excessive noise
1-20	“Strongly lowered” levels	Distractions, agitation
20-40	“Reduced” levels	Wandering thoughts, lack of focus
40-60	“Neutral” levels	Normal
60-80	“Slightly elevated” levels	Focus, concentration
80-100	Heightened levels	Elevated attention

Table 1 – Description of Attention eSense meter values

Related studies EEG and attention

There has been a great deal of research works focusing on detecting the attention state of mind from the characteristics of EEG (Aftanas & Golocheikine, 2001; J; Hamadicharef et al., 2009; Rebolledo-Mendez et al., 2009; Jiang et al., 2011; Li et al., 2011; Liu, Chiang & Chu, 2013;Patsis et al., 2013). The detection of the attention is important in many fields, including clinical studies of stress reduction, sleep deprivation, fatigue, driving behaviour, educational studies of learner attention and game studies of player concentration and engagement.

Attention, has been defined as the ability to focus our cognitive resources on one relevant aspect of the environment while ignoring other irrelevant aspects (Riccio et al., 2013). Many BCI-based neurofeedback games (Wang, Sourina & Nguyen,2010; Jiang et al., 2011; Pires et al., 2011) employ attention-related EEG feature as the control parameter, as attention is a key factor of human cognition. However, automatic determination of subjects' attention state is challenging because attention involves complex human cognitive functions. Previous research (Liang et al., 2005; Hamadicharef et al., 2009; Li et al., 2011) has demonstrated evidence that EEG signals (esp. the beta band) contain considerable information about attention, indicating the possibility of recognizing a subjects' attention level by studying the EEG data.

II. Experimental setup

The goal of the current study is to analyse the quality performance of this Brain Computer Interface by measuring the attention levels while driving under tasks which decreases the attention level, against the participant's self reported attention levels. The specific objective is to measure the attention levels in drivers operating:

1. under real and moderate traffic conditions, like a motorway at approximately 100km/h, during the daytime with given parallel tasks which decreases the attention level, such listening music, mobile talking, eating. Each task takes approx. 3 min.
2. driving in higher traffic conditions at approximately 50Km/h, namely in a city center with highly traffic, without any other parallel task. This task takes aprox. 3 min.

The output of these tasks were exported to an Excel file and to Matlab and the results sought to determine whether the Headset is able to provide useful and/or reliable data. Before the test, the participants were asked to answer a short questionnaire, which includes identification questions and driving habits and regularity. On completion of each task the participant was asked to respond a self-completion experience assessment. The results from these were correlated to the headset data.

1. Questionnaire

The following questions were posed to each participant before the experiment:

● Name
● Age
● License drive issued date
● Driving regularity (how many times per week and how long each time in which kind of route)
● Habit of driving with other parallel tasks (listening music, mobile talking and eating) 1

The following questions were posed to each participant after the experiment:

● Did you feel work loaded or distracted with any parallel task?

The results are evaluated under a scale a Likert from 0 to 5 (1- highly distracted, 2- low distracted, 3 - normal, 4 - focus , 5 - highly focus).2

2. Participants

A total of 4 participants (3 female and 1 male) aged between 29 and 42 (M = 35,5) took part in the study. Participants were given standard instructions before each test like informing the group of side tasks to be executed and also that the purpose of the trial is not to evaluate their own performance.

3. Hypothesis

The purpose of the experiment is to test different cases while driving and to understand if really the attention level decreases in one of which of those cases. Therefore it is assumed there are 5 Hypotheses to test and to check its results:

H1 - Driving and listening music implies reduced eSense Attention level (under 40) for all participants.
H2 - Driving and eating implies low eSense reduced eSense Attention level (under 40) for all participants.
H3 - Driving and talking on the mobile implies reduced eSense Attention level (under 40) for all participants.
H4 - Driving in city center implies low eSense reduced eSense Attention level (under 40) for all participants.
H5 - There is a correlation between the eSense attention levels and the self reported driving experience.

III. Results

Each of the hypotheses was tested and the results are presented below on Figure 1. There were some issues in obtaining data, meaning the Headset required some time to obtain eSense meter values above 0. This special value indicated the ThinkGear is unable to calculate an eSense level with a reasonable amount of reliability. The waiting time for getting a value above 0 was around three minutes. It was also observed occasionally wide ranges for each interpretation which means that some parts of the eSense algorithm are dynamically learning, and at times employ some “slow-adaptive” algorithms to adjust to natural fluctuations and trends of each user, accounting for and compensating for the fact that EEG in the human brain is subject to normal ranges of variance and fluctuation.
The 0 and extremes variations values were removed from the result data, justified by the facts above mentioned. The data for around 100 timestamps (ca. three minutes), without 0 and extreme values variation, was measured by each participant for each of one of the four tasks, and then analysed by its median. Sample data variation is higher than 20%, showing its heterogeneity, which reflects still a considerable fluctuation data recording. 51% of the average values are on the eSense attention range of [20-40] and remaining on the range [40-60].
To obtain these results, it was first compared the Attention meter output of the headset for all participants for each of one of the tasks.

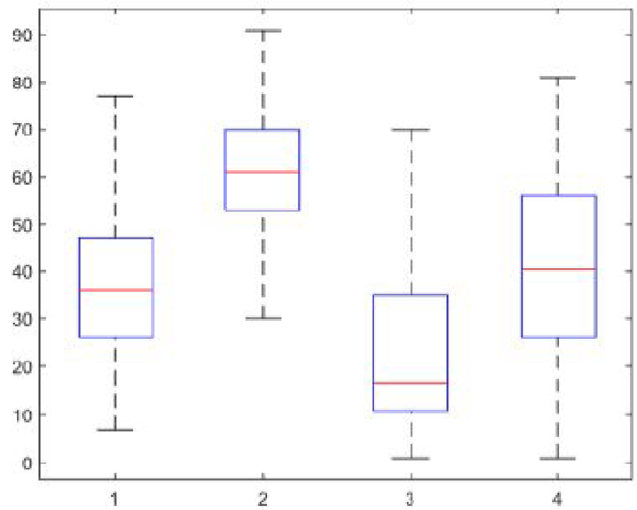

Fig. 1 – Results eSense Attention for all the four participants for task driving and listening Music

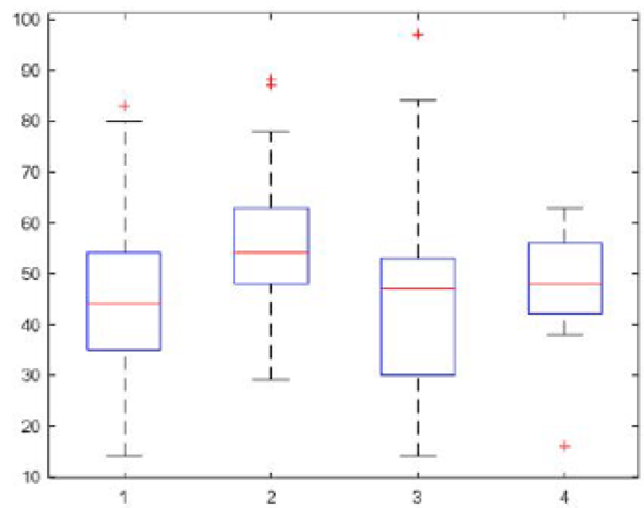

Fig. 2 – Results eSense Attention for all the four participants for task driving and talking into mobile

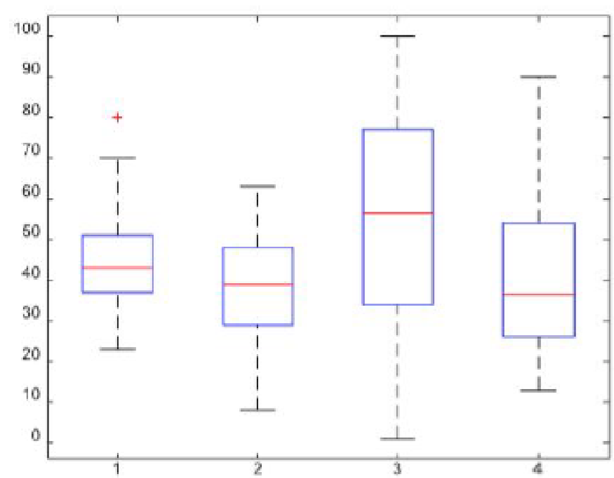

Fig. 3 – Results eSense Attention for all the four participants for task driving and eating

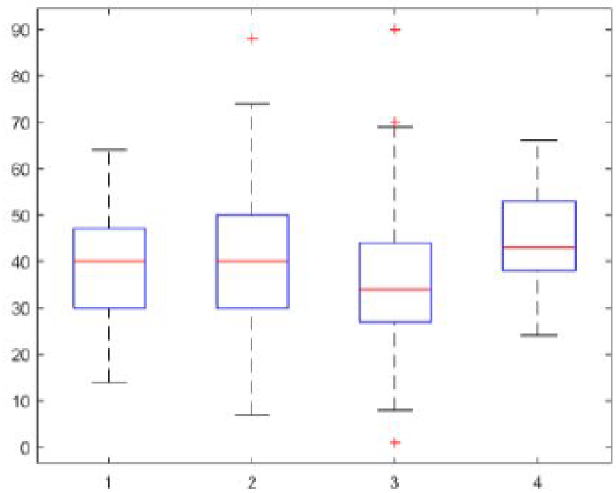

Fig. 4 – Results eSense Attention for all the four participants for task driving on city center with high traffic

Secondly, the Attention values were compared for all tasks: driving and listening music, talking into mobile, eating and driving in the center with high traffic.

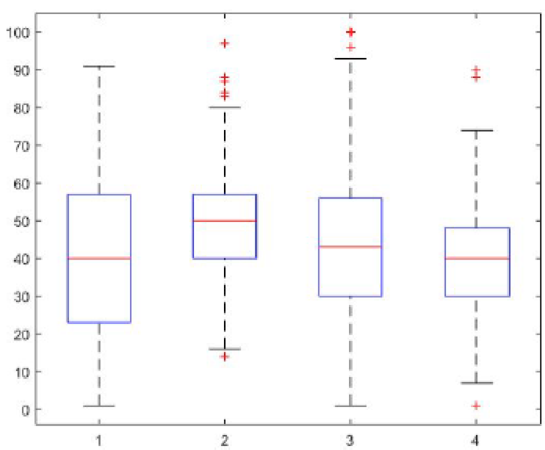

Fig. 5 – Results eSense Attention for all participants for all the four tasks

A one-sample t-test (df=100) was run to test if the difference of the meter values between each of the participants for each single task was significantly different from 0. We observed a significant variability among participants, mainly by driving and listening music and then by driving and eating. For the remaining tasks, the comparison of the average of meter values between the participants is 50% equal.

		Paticipants Variability	
		h	**p**
Driving and Listening Music	P1-P2	1	1,43E-25
	P1-P3	1	1,45E-03
	P1-P4	0	0,1033
	P2-P3	1	8,96E-24
	P2-P4	1	6,90E-08
	P3-P4	1	8,56E-06
Driving and Talking Mobile	P1-P2	1	1,69E-02
	P1-P3	0	0,7202
	P1-P4	0	0,0621
	P2-P3	1	1,8304E-02
	P2-P4	1	8,7570E-01
	P3-P4	0	0,0549
Driving and Eating	P1-P2	1	6,78E-01
	P1-P3	1	5,07E-01
	P1-P4	0	0,0576
	P2-P3	1	7,94E-07
	P2-P4	0	0,1580
	P3-P4	1	1,20E-01
Driving in city center	P1-P2	0	0,2249
	P1-P3	0	0,0948
	P1-P4	1	2,54E-01
	P2-P3	1	0,0106
	P2-P4	0	0,0839
	P3-P4	1	2,66E-02

Table 2 – Results t-Test comaprison between individuals

It was also executed a one sample t-test for tasks comparison. Just between driving and listening music and driving in city center with high traffic was not observed a difference of their average values. All other tasks comparisons show significant variability.

	Task Variability	
Driving and	h	p
Listening Music and Talking Mobile	1	3,72E-06
Listening Music and Eating	1	0,0025
Listening Music and City Center	0	0,5025
Talking and Eating	1	0,012
Talking and City Center	1	2,74E-12
Eating and City Center	1	1,09E-01

Table 3 – Results t-Test comaprison tasks

On Figure 6, the results of questionnaire done to each of the participants after the driving experience are presented. Values range are between 1 and 5, 1 - highly distracted, 2 – low distracted, 3 - normal, 4 - focus , 5 – highly focus. Questionnaire results show us that P1 and P3 reported a little less attention while talking into mobile and listening music. Remaining subjects shown to have a normal attention level by driving and executing side tasks.

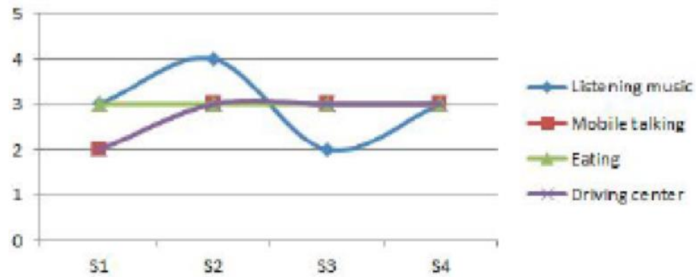

Fig. 6 – Results questionnaire of attention values by driving executing parallel tasks

IV. Discussion

In conclusion, there is a positive correlation between the real time headset data and the self-reported driving experience. Nevertheless, the Headset produced a high data variability which implies less data accuracy. The hypotheses tested produced slightly mixed results by different participants: Not all side tasks implies a reduced attention level, namely under 40 on eSense meter scale, but still the data average is on the interval of wandering thoughts, lack of focus and normal attention levels. Considering that all subjects have driving experience and periodically execute all these side tasks, it is understandable that attention levels are sometimes kept normal. This study proved that Neurosky Mindset capabilities regarding attention levels shown to be positive and that tasks which normally distracts an individual of his main task, do not make him more focused or concentrated.

V. Future Research

We consider this research very promising as there is much to do and it could have applications in several fields. In the near future, we are particularly interested in applying this study to analyse problems students face when learning to program. One of our goals is to measure what is happening with the user and determine how specific parts of the brain or other body elements can measure different functions while doing programming activities. The development of programming problem solving skills is the more complex aspect for novices. Therefore, it is necessary to define adequate exercises at each programming learning stage. The sequence of exercises shouldn't be predefined and might not be the same for all students. Therefore, it should be adapted for each student needs and current level of knowledge. Activities that are too easy in a particular moment might not give a good contribution to the student's cognitive development, but if they are too difficult for the student they may cause frustration, demotivation and dropouts. In our view, it is important to propose activities that create some difficulty to each student, but that they may be able to solve, at least partially. This may contribute to increase the student motivation and self-confidence, making him/her believe that it is possible to be successful, and that solving problems is an effective way to learn. However, analysing these cognitive and non-cognitive aspects while students program with BCI is a complex work that has to be divided by phases. Firstly, we intend to make an analysis of several suitable tasks described in pre-defined scripts using various BCIs and comparing the results. Secondly, the extension of the sample in order to enable comparisons between gender, subjects with different background (compare experts vs beginners), among others will be done, allowing the building of cognitive and non-cognitive behavioural modes. This study will involve the testing and studying of intended functions in order to find patterns that measure the ability of individuals to formulate abstract principles, emotional states or other elements of interest based on the feedback received after each test. Another problem identified in previous programming studies is the lack of motivation that students show when having to learn to program. Therefore, another phase includes the creation of a set of experimental protocols that will allow us to verify the motivation of the users for programming learning. Extracting very important parameters such as excitement or frustration levels, attention, sleepiness or stressful conditions will be our intention. At the end of this phase we intend to have the EEG signal characterization and classification of several programming-learning profiles.

Another objective of this research is to develop an adaptive system based on BCI and HCI. BCI is used to provide information on the cognitive and non-cognitive capabilities of the user. After we identify the different patterns that occur in the electrical brain activity on different programming learning performances we will use these patterns to build a learning system that will adapt to the abilities and interests of the user. For instance, if the user shows more difficulty in solving a specific problem the system will identify the patterns (for instance frustration levels) to provide clues or tips for the user in order to improve their learning abilities. To build this system we will use a typical BCI system that identifies the specific patterns discovered in the previous tasks. As outputs of the BCI we will provide ways to improve the learning abilities of the user, providing for instance tips on how to solve the problem.

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