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Smart Testing Environment for the Evaluation of Students' Attention

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Abstract. Attention is a key factor that influences learning processes and it is generally regarded as a success generating factor. Distributed attention has been shown to be very important in processing information and its integration in comprehensive knowledge areas. This research aims to directly test the distributed attention capacity of university students through a smart testing environment designed to integrate classical testing methods such as the Prague test for measuring distributed attention with means of neuro-sensorial devices. The Smart Testing Environment is endowed with several sensors that measure physical characteristics such as: attention, blood pressure, eye tracking. Captured data is processed by a rule-based expert system that achieves time series analytics and computes correlations between experiments. This pilot study will be continued with experiments that measure students' attention during various courses and labs.

Keywords: distributed attention, smart testing environment, EEG device, Prague test

1 Introduction

Attention is a human characteristic that is involved in each activity and it is an important factor in the educational process with direct implications on its effectiveness and efficiency. The quality of the educational system can be affected by issues connected to human factors such as: attention, self-motivation, study habits, persistence and frustration tolerance, expectations and student's own personal values. Higher Education Institutions (HEI) should consider such factors when adapting their educational system and curricula to the needs of the students.

Attention refers to an internal state of the brain that can be rapidly modified by instructions. Teachers are able to sense and detect affect states of their students, which relate to their attention and restlessness states, their "*boriness*" or their motivation towards the class. In this sense, the identification of students' attention level is required for the improvement of the teaching process.

This paper presents a pilot study aiming at increasing teachers' awareness towards the importance of student's attention in class and consequently at increasing their responsibility for adapting and developing class activities in accordance with student's needs and to capture their attention. The assessment of attention levels and resistance to prolonged concentration efforts also offers a better identification of students at risk. Thus, problematic individuals can be early spotted and intervention can be readily prepared in order to improve the success rate. In general, it is expected that such approach lead to a successful upgrade in the classroom towards students' commitment.

The reminder of this paper is organized as follows: section two presents a general outline of related research on distributed attention in connection with visual short term memory, section three presents the general architecture of the smart testing environment, section four presents two experiments performed on an experimental lot of 5 participants, section five discloses findings and discussions and section six presents conclusions and further work.

2 Related Research on Distributed Attention

Extensive cognitive research has shown that selective and distributed attention filter out irrelevant perceptual input and has a close relationship to the formation of the visual short-term memory (VSTM) in brain. VSTM retains objects and scenes for a few seconds in brain after their disappearance [1]. The attention also determines which subset of visual input is encoded in VSTM [2]. Nevertheless, few studies have investigated attentional selection of information already maintained in VSTM. Attention is needed both for memory encoding and for memory maintenance [3].

Progress of detecting attention in educational settings has been reported by the framework proposed to recognise learner's emotions and attention using electroencephalography (EEG), skin conductance and blood volume pressure [4]. Attention evaluation of students attending e-learning courses is conducted using physiological measurements [4].

To measure brain activity, the electrooculogram (EOG) or the electroencephalograph (EEG) are usually used. EOG provides a measure of the difference in electrical activity between cornea and retina, and it is primarily used when measuring eye movements such as: eye blink rate and eye closure. Limited research has been conducted into the benefits of using EOG for workload measurement [5]. The most common type of electrophysiological indicator used for workload studies is the EEG. EEG records electrical brain activity through electrode sensors placed on the scalp, and EEG signals are classified into wave bands to indicate various states or activity levels. The different wave bands are outlined as follows:

- *Gamma Waves* (>30 Hz): relate to some senses and memory;

- *Beta Waves* (13-30 Hz): focus, active attention, thinking, problem-solving. Beta Waves dominate when the brain is aroused and mentally engaged in activities;
- *Alpha Waves* (8-13 Hz): relaxation, meditation, non-arousal, relaxed awareness without any concentration. Alpha waves can be induced by closing the eyes and relaxing, and abolished by opening the eyes or engaging the brain in activities such as thinking or calculating. Low alpha frequencies relate to attention and that high alpha frequencies relate to some cognitive processes such as memory [6];
- *Theta Waves* (4-8 Hz): drowsiness, deep relaxation, daydreaming;
- *Delta Waves* (0.5-4 Hz): deep sleep, unconsciousness.

EEG wave classification has been used to help diagnose sleep disorders. It is also used in the construction of brain computer interfaces (BCI's) to assist disabled people with daily living tasks [7]. A brain computer interface (BCI) is a communication pathway which interprets the user's command from their brainwaves to enable simple tasks to be carried out. BCI systems have primarily focused on assisting disabled people through neural prostheses to restore damaged hearing, sight and movement to facilitate them to interact with their environment.

Recent advances in EEG technology have led to the development of cheaper and easier to set up products which use dry electrode-based EEG hardware, such as the NeuroSky MindSet. The NeuroSky MindSet consists of a headband with three sensors. The reference and ground electrodes are clipped onto the earlobe, whilst the EEG recording electrode is positioned on the forehead. The sensors require no gel or saline for recording, and no expertise is required for set up. In terms of the accuracy of the mental state measurement, in [8] is stated that "*Even with the limitations of recording from only a single sensor and working with untrained users, the MindSet distinguished two fairly similar mental states (neutral and attentive) with 86% accuracy*."

The NeuroSky MindSet reads electric signals generated by neural activity in the brain and decodes them by applying algorithms to provide readings on a scale of 0 to 100. It provides information on user's brainwaves (Delta, Theta, Alpha, Beta and Gamma) in order to determine levels of attention and relaxation. The reported advantages of the NeuroSky MindSet include features such as: wireless, portable, relatively cheap, lightweight and non-invasive. As stated in [9], NeuroSky MindSet provides "*…the potential to conduct accurate user studies in more practical and naturalistic settings without inducing the stress or distractions of more elaborate scanning processes*". However, they also criticise the MindSet for providing a much coarser reading of brain activity compared to other multi-electrode EEG and BCI technologies [9]. Guðmundsdóttir argues that the MindSet's single point electrode is able to monitor a substantial part of the entire brain's activity and that there is a stronger, steadier signal because there is no hair between the electrode and the scalp [6].

3 Smart Testing Environment Architecture

In an ambient intelligence approach for HEI, personalised and adapted learning is a matter of tailoring curriculum, teaching, and assessment to 'fit' the individual in order to improve individual learning performances. The entire educational system has to be viewed as an intelligent, context-aware system having the ability to adapt autonomously to the current context, in order to provide a better response and experience for the user [10]. The general architecture of the smart testing system is formalised as in Fig. 1. Being a three tier architecture, the Smart Testing Systems achieves recognition, computation, and action in parallel. The environment that is represented by learning ambience and subjects (students and teachers) is tested by sensors for characteristics such as: brain activity, blood pressure, skin humidity, body temperature, luminosity of the room, temperature of the room, sound accuracy, air quality, noise level, etc. Data is captured and transmitted to the server. The main constructs are: intelligent multimodal interfaces, sensor networks and user tracking, personal assistance, anticipation of user behaviour, context modelling, device interoperability, and middleware for information processing and exchange.

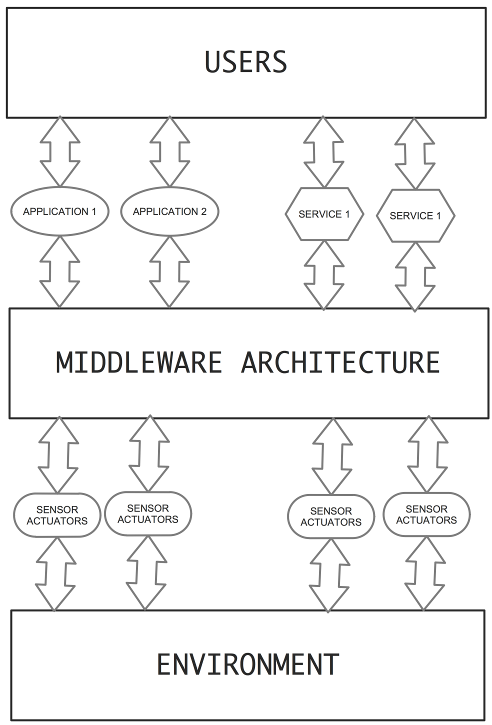

Fig. 1. General Architecture of the Smart Testing Environment (STE)

The work flow of the STE is presented in Fig. 2. Physical data comes from the assessed subject and/or ambience, as the STE contains various sensors that capture data. Captured data are stored in a warehouse. The combination and fusion of multiple sensor output can be used. A rule-based expert system transform this data into relevant contextual data. The problem of sensor fusion is particularly important in the extraction of contextual data: a sensor might not produce sufficient information due to uncertainty and unreliability of the sensor itself. Two types of sensor fusion may be applied: the competitive and the complementary. The competitive sensor fusion is based on sensors which detect equivalent physical data, trying to diminish the errors in the measurements of every sensor. The complementary sensor fusion uses different typologies of sensors to extract high level data.
Various sensors and actuators connect the environment to the middleware level. Data and knowledge are transferred to applications and services that are accessed by end users on mobile devices or client-server-type information systems.

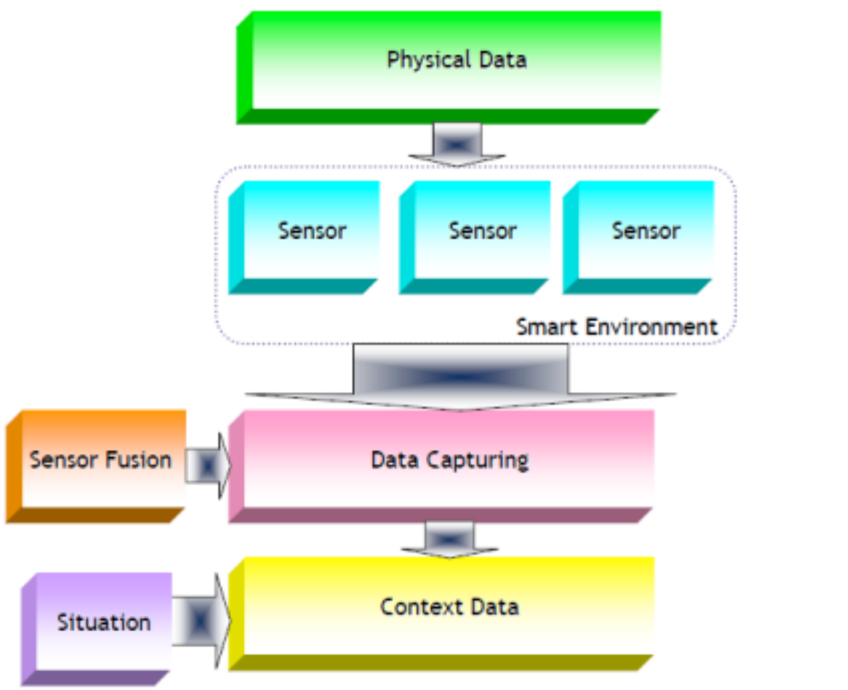

Fig. 2. Work flow in the Smart Testing Environment

Testing activities include:

- *Building* an artefact to perform a specific task
- *Evaluating* the artefact to determine if any progress has been achieved
- *Determining* why and how an artefact whose performance has been evaluated worked or did not work within its environment, finally results are *theorizing* and *justifying* theories about various IT artefacts.

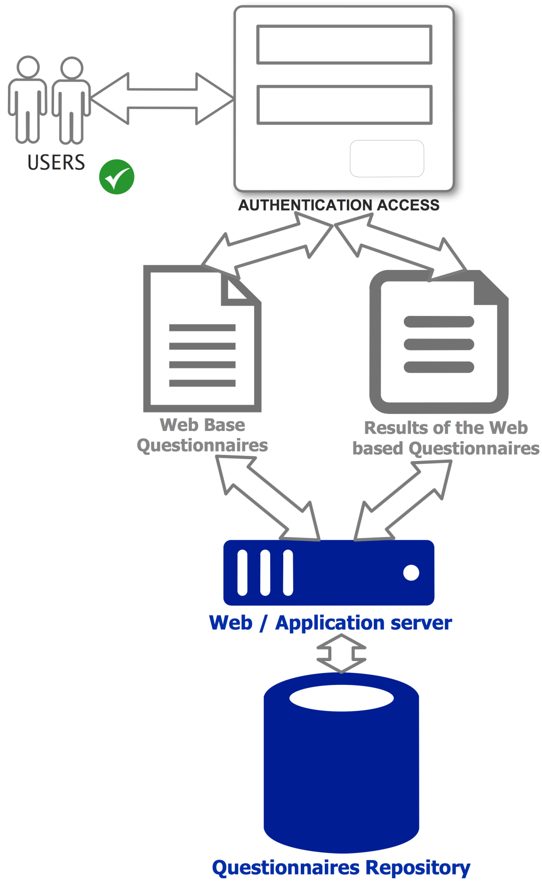

Fig. 3. Client side of the Smart Testing Environment

A three-tier model has been adopted for developing the prototype of the Smart Testing Environment (STE), in which the queries are sent to an intermediate level (also called application server), which returns the SQL request to the database server. The database server processes the request and sends the result to the middle tier, which forwards it to the user. Java technology – Java Server Pages (JSP) – was developed using Apache Tomcat with Java Server Faces technology. Implementation is free and provides a set of graphical reusable components and a good separation between the presentation tier and the logic tier, being an event oriented system. Database management uses MySQL, one of the simplest and most popular database servers, which has proved its stability and reliability. MySQL allows the connection of multiple clients, simultaneously, and clients can use multiple databases simultaneously. One can get access on MySQL interactively using several interfaces that allow users to enter queries and view the results in command-line clients, web browsers, or Window system clients. MySQL can be fully used in networks and databases are accessible from anywhere on the Internet; the user can share data with anyone, anywhere, protected by access control options. Some of the battery tests have been presented in [12]. The three tier architecture is presented in Fig. 3. The Client side of the STE has system identification number and password for authentication parameters. After authentication STE opens a menu offering the student the possibility of choosing the questionnaire, in this case, the Prague test.

In order to complete the questionnaires and to receive test results, each student must create an account. Student registration requires the following information: identification number, study programme, study year, sex, age, and password. The developed system allows the access of each student to his specific resources, depending on the identity and access rights. Authentication is achieved by using an identification number and a password to access system resources.

4 Experiments

Experiment1. This experiment applied the Prague test for measuring the distributed attention of students. This test can be collectively as well as individually applied. The Prague Test for distributive attention was elaborated by the Psycho-technical Institute in Prague by adapting some individual characteristics. The distributed attention is evaluated through the capacity of numbers detection on a special board.

The Prague test was applied collectively, in four rounds, each round of four minutes, with a pause between rounds of one minute. The test is consisted of numbers written in cells with bold character and another number beneath it, in smaller characters. The participant has to write the number identified beneath the bolded number from each cell in a table nearby. The test is given in the Fig. 4. The experiments have been conducted with the participation of 5 students hearing Environmental Engineering. The age of students was between 20 and 23 years old.

73 96	**18** 39	**7** 13	**4** 66	**97** 68	**33** 62	**31** 22	**69** 48	**49** 52	**35** 92
23 38	**8** 55	**79** 43	**96** 30	**92** 73	**40** 19	**78** 28	**22** 4	**65** 88	**1** 84
19 87	**24** 18	**72** 12	**51** 75	**62** 25	**81** 35	**9** 97	**91** 31	**17** 89	**61** 50
30 17	**41** 8	**98** 46	**80** 95	**66** 2	**59** 20	**55** 80	**95** 67	**58** 11	**6** 83
54 32	**21** 40	**45** 9	**84** 81	**99** 49	**75** 69	**56** 63	**10** 41	**67** 29	**38** 76
3 64	**93** 14	**2** 98	**20** 71	**44** 56	**77** 5	**82** 1	**36** 6	**32** 47	**88** 27
42 3	**94** 65	**50** 60	**76** 61	**90** 51	**71** 70	**53** 33	**5** 86	**27** 72	**13** 59
57 79	**63** 45	**48** 54	**68** 91	**39** 85	**29** 74	**16** 99	**52** 82	**60** 26	**89** 36
47 34	**64** 58	**28** 42	**83** 10	**87** 57	**86** 37	**11** 100	**85** 21	**34** 23	**26** 44
37 78	**46** 94	**100** 24	**15** 75	**43** 93	**12** 16	**74** 7	**14** 90	**70** 53	**25** 15

75		34		46		100	
20		78		56		44	
79		3		7		14	
26		18		4		36	
2		81		17		8	
11		62		12		33	
74		71		61		82	
21		45		9		31	
57		13		38		49	
19		63		28		43	
83		1		89		77	
6		73		94		84	
39		76		95		54	
52		5		29		72	
27		99		37		60	
47		15		85		35	
25		90		55		48	
64		67		51		65	
96		10		22		98	
58		66		30		41	
42		70		53		80	
68		69		23		86	
88		92		32		93	
59		87		40		24	
50		91		97		16	

Fig. 4. Prague test

Scoring for Prague test is proposed in Fig. 5:

E - Excellent	81-97
G - Good	61-80
A- Average	41-60
S - Sufficient	21-40
I - Insufficient	1-20

Fig. 5. Scoring for Prague test

Experiment 2. In the second experiment the lot of 5 students was provided with Mindwave headset and connected to the Lucid Scribe software. Also the Prague computerized test was selected from the battery of test in the smart testing environment.

The aim of this experiment was to investigate how well the headset performs with regards to the quality and quantity of data it gathers and how useful is the NeuroSky MindWave in measuring attention levels.

The experimental lot of 5 participants were given standard instructions before each test and were told that they should try hard to achieve the goals of each task.

Prague test has been applied individually by connecting to the STE. In this case the round was also set for four minutes.

Attention measurement was achieved through Neurosky Mindwave headset connected to the forehead of the student. The NeuroSky MindWave monitored electrical signals generated by neural activity in the brain. The device was worn on the head and consists of a headband, an ear-clip, and a sensor arm containing the EEG electrode which rested on the forehead above the eye. Compared to traditional EEG devices, it is inexpensive, simple to operate, and unobtrusive.

The measurement outputs of the MindWave are:

- Raw signal
- EEG power spectrum: provides information on a user's brainwaves (Delta, Theta, Alpha, Beta and Gamma).
- E-Sense meters for attention and meditation: determine how effectively the user is engaging attention (similar to concentration) or meditation (similar to relaxation) by decoding the electrical signals and applying algorithms to provide readings on a scale of 0 to 100.

The e-Sense Attention meter indicates the intensity of a user's level of mental 'focus' or 'attention'. Distractions, wandering thoughts, lack of focus, or anxiety may lower the attention meter level.

For all the different types of e-Senses (i.e. attention), the meter value is reported on a relative e-Sense scale of 1 to 100. On this scale, a value between 40 and 60 at any given moment in time is considered "*neutral*", and it is similar in notion to "*baselines*" that are established in conventional EEG measurement techniques. A value from 60 to 80 is considered "*slightly elevated*", and may be interpreted as levels being possibly higher than normal (levels of attention or meditation that may be higher than normal for a given person). Values from 80 to 100 are considered "*elevated*", meaning they are strongly indicative of heightened levels of that e-Sense.

Similarly, on the other end of the scale, a value between 20 and 40 indicates "*reduced*" levels of the e-Sense, while a value between 1 and 20 indicates "*strongly lowered*" levels of the e-Sense. These levels may indicate states of distraction, agitation, or abnormality, according to the opposite of each e-Sense.
An e-Sense meter value of 0 is a special value indicating that the ThinkGear is unable to calculate an e-Sense level with a reasonable amount of reliability. This may be (and usually is) due to excessive noise. The reason for the somewhat wide ranges for each interpretation is that some parts of the e-Sense 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. This is part of the reason why ThinkGear sensors are able to operate on a wide range of individuals under an extremely wide range of personal and environmental conditions while still giving good accuracy and reliability [13].

5 Findings and Discussions

Findings of experiment 1. This section presents a preliminary report conducted on an experimental lot of 5 students from Environmental Engineering aged 20 to 21 years old, the Prague test was collectively applied. Results achieved by 5 participants in the experimental lot are presented in Table 1. Three of them scored excellent as concerns their distributed attention, one scored good and one scored sufficient. For example, I.T. has a low level of the distributed attention (23%), with fluctuations of the attention, and a more difficult integration into the task as can be seen in Table 2. The participant identified in the first 4 minutes only 4 correct numbers (40%), in the second round of 4 minute, 4 correct numbers (44%), in the third round, 8 correct numbers (57%) and in the fourth round, 7 correct numbers (53%).

Table 1. Results of the Prague test

No.	Participant	Age	Gender	T1	T2	T3	T4	Total
1	M.M.M.	20	F	15	28	25	14	82
2	C.D.I.	20	F	17	16	18	19	70
3	I.T.	20	F	4	4	8	7	23
4	L.S.	21	M	12	26	25	24	87
5	S.I.R.	21	F	18	15	20	29	82

Table 2. Low score of the Prague test

Participant I.T.	T1	T2	T3	T4
Total answers	10	9	14	13
Correct answers	4	4	8	7

The way students are able to concentrate influence the achievement of higher performances in learning. The concentration level and duration are closely related to the specific activities performed by the students.

S.I.R. presented an excellent distributed attention and also the test revealed its resistance to fatigue, as his performance in the fourth round increased significantly as shown in Fig. 5.

M.M.M., even if he achieved high scores concerning its distributed attention, its resistance to fatigue is the lowest, in round four the performance decreased dramatically in comparison with round two and three (Fig. 6). All participants presented fluctuations of the attention during testing.

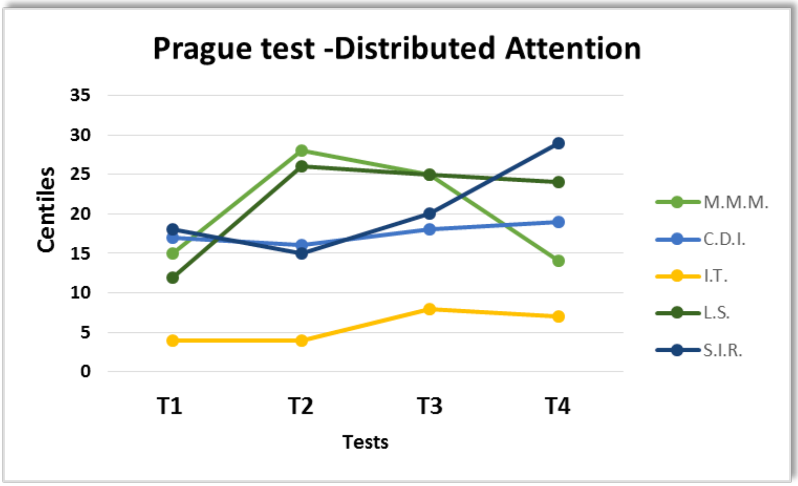

Fig. 6. Distributed attention evaluation of the experimental lot

Findings of Experiment 2. Attention levels and fluctuations have been measured in one round of four minutes for each subject. The results reveal average levels of attention between 7.3 and 67.5. Fluctuations of attention levels have been registered in the database as in Table 3.

Table 3. Attention measurements with Mindwave and Lucid scribe

				T1			
No.	**Participant**	**Age**	**Gender**	1	2	3	4
1	M.M.M.	20	F	44.2	47.5	55.0	49.0
2	C.D.I.	20	F	48.4	7,3	43.1	44.2
3	I.T.	20	F	59.7	65.6	56.4	56.5
4	L.S.	21	M	40.4	54.4	65.4	62.1
5	S.I.R.	21	F	67.5	59.2	48.8	52.7

Subject I.T. who performed sufficiently in the previous experiment, in the second experiment has shown a significant improvement in terms of concentration, thus the number of correct answers increased to 10 of 14 (71.4%) and the level of attention measured was constantly high (e.g. 59.7 in the first minute of measurement, 65.6 in the second minute, 56.4 in the third minute, 56.5 in the fourth minute).

I.T. is the only one subject who gave wrong answers but the performance was gradually improved and the measurements disclosed the improvement. Some of the fluctuations of attention for subject I.T. are given in Fig. 7.

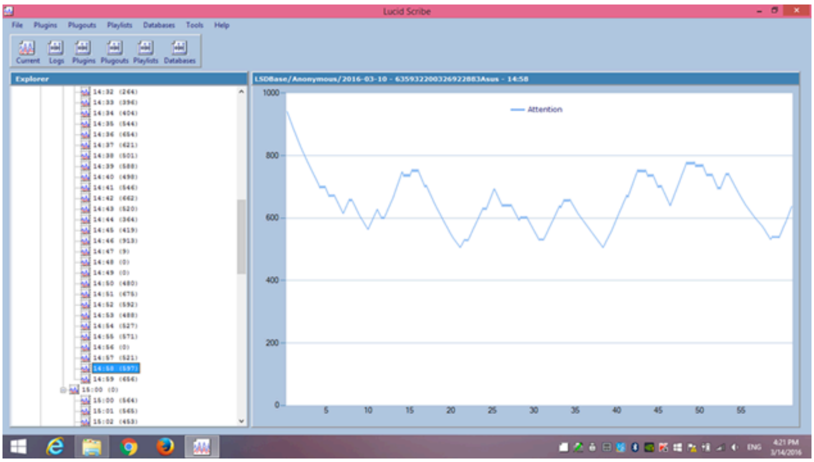

Fig. 7. Attention Measurements detected with Lucid Scribe software

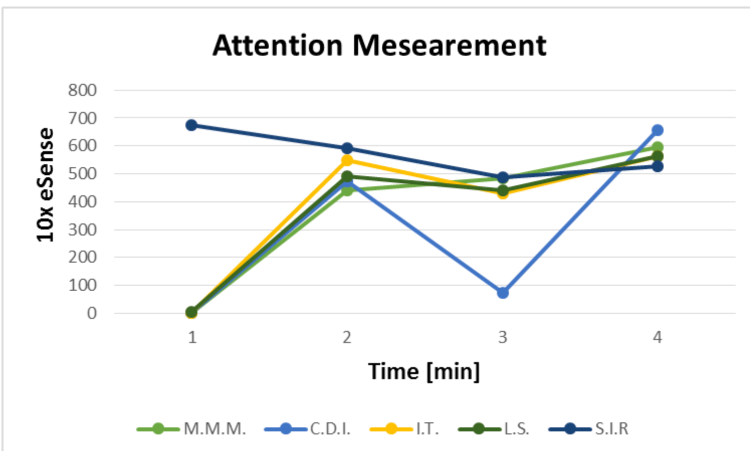

Fig. 8. Attention Measurements with Neurosky MindWave

In minute one, I.T.'s attention was high with some plateaus of seconds. Such fluctuations were monitored and registered in the Lucid Scribe database for each subject per every second and are available for further investigations.

LucidScribe – ThinkGear - EEG was used to monitor the EEG data from NeuroSky ThinkGear compatible devices like the MindSet and MindWave. It was set up to measure and record brain wave patterns using an EEG device connected to the computer. For recording the correspondings, plugin for EEG was installed along with the main software. The intensity of the participants' level of mental "focus" or "attention" was measured during intense concentration and directed (but stable) mental activity. Distractions, wandering thoughts, lack of focus, or anxiety that lower the attention meter levels will be further investigated by additional sensors that provide information on the emotional states of the students.

As an observation subsequent to the data presented in the above tables and figures, progress can be noticed in terms of attention level of participant I.T. and a confirmation of excellent attention level and resistance to fatigue was proved for S.I.R. Participants L.S and M.M.M. have shown an excellent level of attention during experiment 1 and also experiment 2 confirmed the increase of attention during the four minutes round.

6 Conclusions and Future Work

The analysis of attention levels by classical testing methods in conjunction with data generated by real-time physiological signal readings from devices can provide information (e.g. analytics) on students' interest in a subject/courseware and on their motivation to attend a class. The teacher will then be able to adapt the teaching process and later report the successful methods to the academic community. This paper focused on innovative smart techniques for determining distributed attention capacity of university students.

Further investigations will be carried out on the concentration time, in order to study the variation of the attention/concentration during various classes.

Future work will be based on the achieved results and it is foreseen that the conjunction of self-assessment by using computerised testing batteries in the STE with physiological measurements carried out by bio-sensorial devices will generate results that will improve the overall process of evaluating students and learning ambiances. Further on, our research aims at selecting best methods and eventually include new physiological measures that increase the quality and readiness of the evaluation process. Methodologies will be designed and deployed in order to assist students towards success in their studies and in personal fulfilment. Additionally, the work will be also integrated in various projects and contexts.

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