

COGNITIVE LOAD MEASUREMENT FOR VISUALIZATIONS IN LEARNING COMPUTER PROGRAMMING USING EEG (ELECTROENCELOGRAPHY)

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Abstract

Computer programming is a complex skill to acquire for novice learners who are in their initial phase of learning programming. There are many factors that results in difficulties in learning programming. This paper addresses to resolve one core difficulty which is cognitive load [2] [3]. Cognitive load theory [13] is a famous theory of learning. It states that the schema of the long term memory is not well built in the case of novices and also there is a limitation of working memory's capacity. This makes it hard for novices to understand the concepts and equip with the skills necessary to become programmers. Some efforts used to overcome the cognitive load are the visualization tools for learning programming [14]. There is no accountability on how effective these visualization systems helped in reducing the load. The mechanism to measure cognitive load is not used in the visualization systems. There are two methods of cognitive load measurement namely physiological and non physiological measures. Physiological measures include EKG, GSR [12], EEG [11], Temperature [11] etc. and non physiological measures includes rating scale [6] and recent research studies have used EEG as a index for cognitive load measurement [7]. We felt that using the physiological measures could be accurate as they are the reflections of the body impulses. There is no user's control over the measurement. We also found out that among the physiological measures EEG could be more effective as the latest efforts of measuring the cognitive uses EEG. This paper addresses the cognitive load measurement while using visualization tools by the novice programmers using EEG as an index of cognitive load.

Keywords - Cognitive load, Visualization tools, EEG.

1 INTRODUCTION

The first section of the paper discusses the experimental set up used to monitor the cognitive load and the second section discusses on the experimental design for the experiments. The third section of the paper discusses briefly on the signal interpretation of the EEG. The fourth section of the paper analyses the results of the experiment using EEG and final part summarizes to end with the overall discussion on the experiments. The main contribution from the paper will be to report on the suitability of the EEG measure for measuring cognitive load and also to determine whether the visualization tool really helps in reducing the cognitive load.

2 EXPERIMENTAL SETUP

We already mentioned to use EEG as indicator of cognitive load. The device for the purpose of measuring cognitive load was identified. The device that was used in our study is Procomp Infiniti biofeedback device [5]. A brief idea on the device is given below. The hardware component includes

- One encoder unit (ProComp Infiniti)
- One TT-USB interface unit
- A supply of fiber optic cable
- Four alkaline AA Batteries.



Figure 1: Hardware setup of the device

2.1 Sensors

The experimental setup consists of sensors which is useful to measure the feedback. Feedback is measured using any one of the following sensors

- EEG Z Sensor or EEG Flex or Pro sensor

2.1.1 EEG-Z Sensor

The EEG-Z is a pre-amplified electroencephalograph sensor with built in impedance sensing capabilities. This sensor can be toggled to record regular EEG or monitor skin impedance (both the reactive and resistive elements) to help optimize electrode hook-up. It can be used for assessment and EEG biofeedback. Each EEG-Z sensor comes with a monopolar/bipolar electrode kit shown in the figure below (Infiniti 2009)



Figure 2: EEG Sensor of the device

2.1.2 Software for EEG (Electroencelelography)

The software used in recording the feedback.

- Biography infiniti software
- EEG Suite

The following figure 3 [15] shows the introductory screen of the biograph infiniti software.



Figure 3: Screenshot of the Biograph Infiniti

The load is monitored by using the Bio Feedback device Procomp Infiniti by observing the EEG signals.

3 EXPERIMENTAL DESIGN

The aim of the experiment is to measure the cognitive load by using various visualization techniques. It is widely believed that the visualization is expected to reduce the load experienced due to the fact that using visualization expands working memory and thereby reducing the cognitive load during the learning process. In this experiment the students are exposed to different visualizations by using different visualization tools namely Jeliot [7], Ville [9] and Teaching Machine.

The experiment was conducted at University of Malaya, Kuala Lumpur with a group of students doing the introductory programming course. All the students were expected to be having the same level of knowledge in terms of programming and most of them are novice programmers. The number of students who took part in the experiment was twelve. Each of these students was made to learn different concepts of programming using different visualization tools. When the learning takes place EEG recordings will be carried out using the Procomp Infiniti device and Biograph infiniti software. In addition to using the visualization systems some experiments were conducted by handing over the programs in a piece of paper manually and try to understand the code and during that process also the EEG readings will be recorded. This is done to analyze the difference between the use of visualization and normal mode of learning programming.

Table 1 explains the test bed of experiments used. The sampling is done in such a way every student is exposed to different visualization tool and at the same time taking into consideration that the learners come across different concepts.

Concept of Programming	Position	Visualization Tools		
		Ville	Jeliot	Teaching Machine
Variable declaration	C	1,4,7,10	2,5,8	3,6,9
Conditional statements	F	1,4,7,10	2,5,8	3,6,9
Looping statements	P	1,4,7,10	2,5,8	3,6,9
Functions	C	2,5,8	3,6,9	1,4,7,10
Functions call by values	F	2,5,8	3,6,9	1,4,7,10
Simple Array program	P	2,5,8	3,6,9	1,4,7,10
Difficult Array program	C	3,6,9	1,4,7,10	2,5,8
Factorial program using recursion	F	3,6,9	1,4,7,10	2,5,8
Difficult program of recursion using Towers of Hanoi	P	3,6,9	1,4,7,10	2,5,8
Sorting program	C	1,4,7,10	2,5,8	3,6,9

Table 1: Test bed sample for physiological study

In the above table, the number in each visualization column indicates the subjects and position indicates the placement of the EEG-Z sensor in different parts of the cerebral hemisphere. The following Figure 4 gives an overview of the placement of the sensors during the process of the experiment.

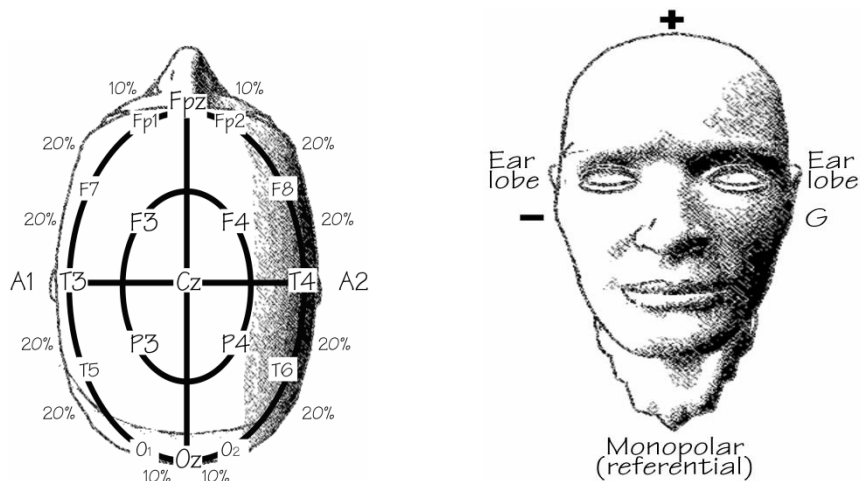


Figure 4: Placement of Electrodes for EEG measurement

In our experiments the sensors were placed in the points C4, F4 and P4. The points were taken as standard to ensure the consistency of the results.

4 INTERPRETATION OF THE EEG SIGNALS

EEG waves are very of different types. They are differentiated based on their frequency. Each wave reflects various states of the human brain. So in this study it becomes vital to interpret the EEG signals. Table 2 explains about the various types of EEG waves and their interpretation [4].

Types of Waves	Frequency	State of Mind – Inference
Alpha	8-12 Hz	<ul style="list-style-type: none"> • State of Relaxation and represent brain shifting into a idling gear • Shows a state of bit relaxed and disengaged. • Closing eyes for half a minute can cause more generation of alpha waves.
Beta	Above 13 Hz	<ul style="list-style-type: none"> • State of Intellectual activity and outwardly focused concentration. • It shows state of alertness – Bright eyed and bushy tailed
Theta	4-8 Hz	<ul style="list-style-type: none"> • State of day dream like • Associated with mental in efficiency
Delta	0.5 to 3.5 Hz	<ul style="list-style-type: none"> • Slowest and highest amplitude wave – representing a sleep like scenario • When brain goes offline • Drowsy and having learning disabilities • When excessive waves are present it becomes difficult to control attention, behavior of humans.
Gamma		<ul style="list-style-type: none"> • Gamma waves is associated with problem solving, higher mental activity. It is indicative of attentiveness of sensory stimulation

Table 2: Interpretation of EEG signals

In our experiment the results are interpreted using the pattern of alpha, beta, gamma waves. More intellectual or problem solving activity will suppress the emergence of alpha wave and emergence of beta and gamma waves. So we assume that the increase of alpha means results in cognitive load as the mind goes to idling state. On the contrary the increase of beta and gamma mean that the student is focused and involved in mental activity [16]. A total of 121 experiments were conducted. Each experiment was given to different subjects using different visualizations and with a fixed time quantum of 15 minutes.

The next section, we analyze the results using the two different approaches namely

- Concept wise analysis.
- Student wise analysis.
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5 ANALYSIS OF EXPERIMENT RESULTS –CONCEPT WISE

The following graphs illustrate the alpha, beta and gamma frequency for different concepts using different visualization tools.

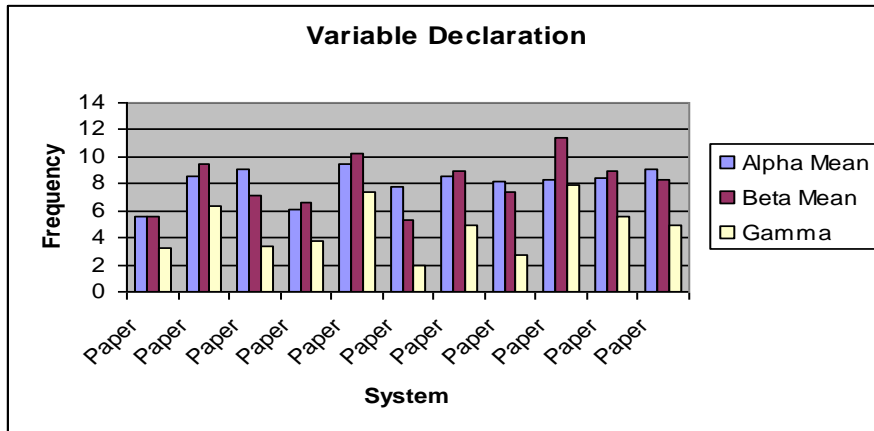


Chart 1: Results for the concept variable declaration

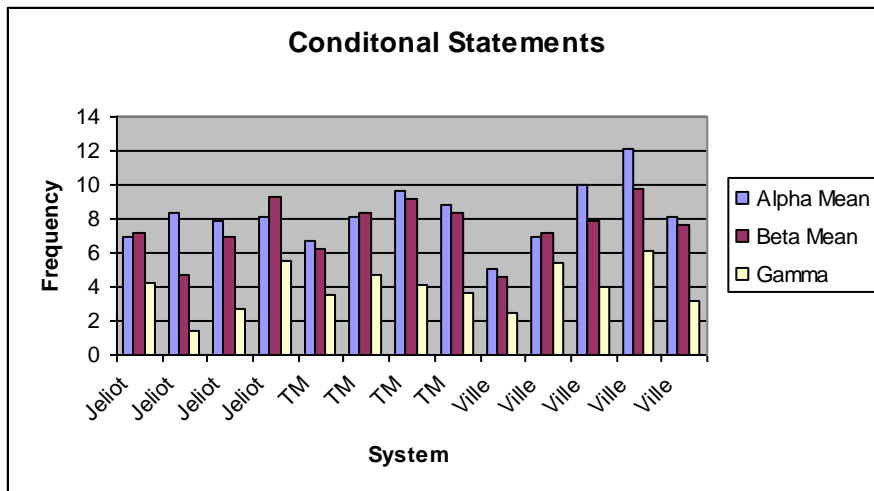


Chart 2: Results for the concept conditional statement

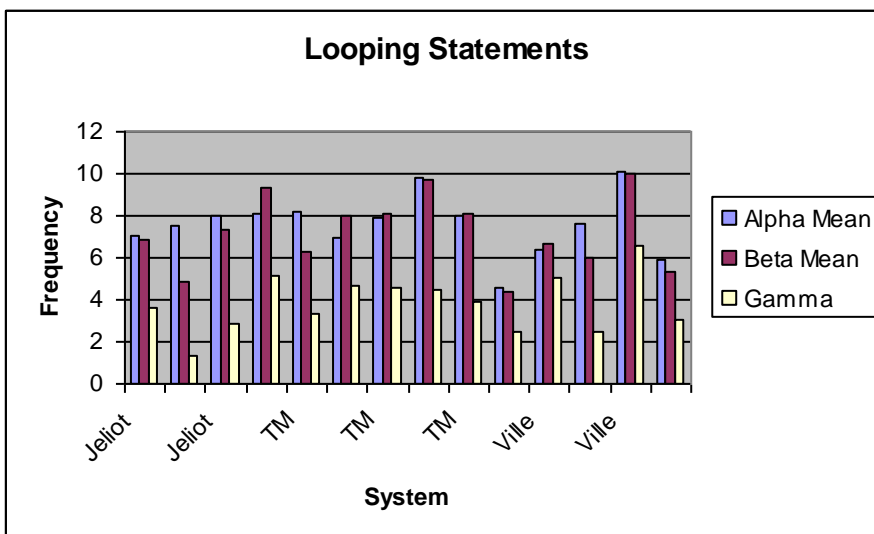


Chart 3: Results for the concept looping statements

The first concept of variable declaration which was considered by many students as the easy concept based on the survey done. The results are indicated in chart 1. All the students were given paper and try to understand the program. But it is found irrespective of the same system difference alpha, beta and gamma values are recorded for various students. The highest value for gamma and beta was recorded for the subject 8 .The alpha value was lowest for the first subject. This shows that the uniformity does not exist in the level of difficulty irrespective of the same system and same concept been attempted. Chart 2 indicates the alpha, beta and gamma for the concept of looping. The first four subjects used Jeliot, followed by four subjects using TM and five other subjects used Ville. The consistency was not observed in the patterns of the means of the alpha, beta and gamma even while using the same system .The chart 3 indicates the alpha, beta, gamma means for the concept of the conditional statements. A strong co relation exists between beta and gamma waves. Beta and gamma waves tend to increase or decrease proportionally in most cases.

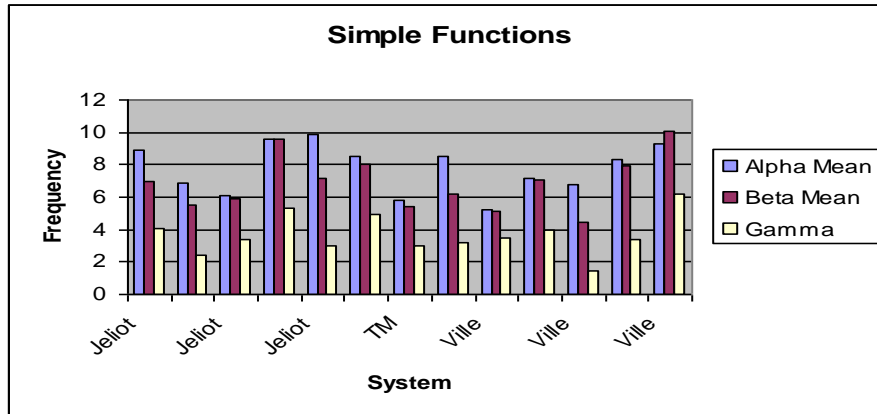


Chart 4: Results for the concept simple functions

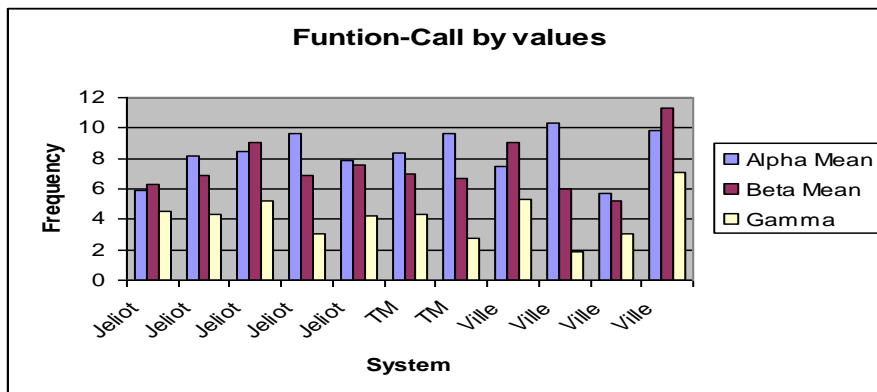


Chart 5: Results for the concept function-call by values

Chart 4 indicates the EEG recording for the concept of simple functions and Chart 5 indicates the alpha, beta and gamma means for the concept of function-call by value. Even though the concept is similar to one another, there is a variation in the mean of alpha, beta and gamma while using across different systems. Even when using the same system we observe variations between each learner.

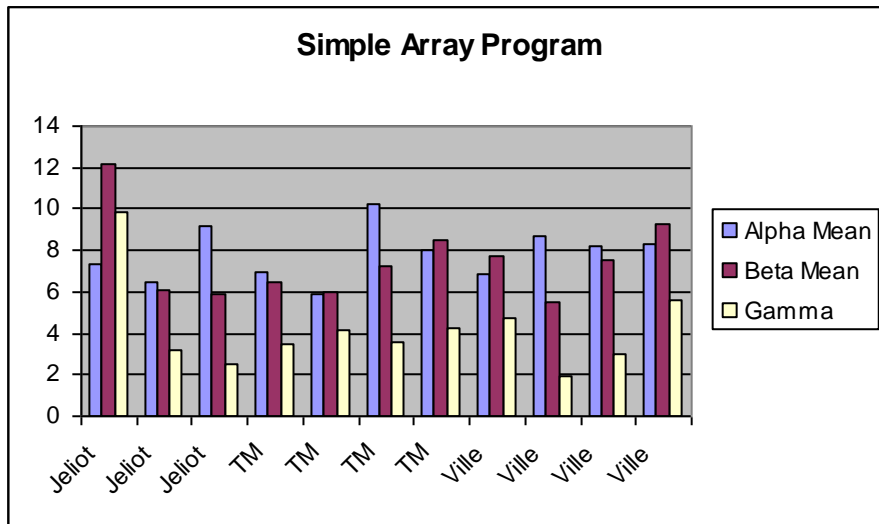


Chart 6: Results for the concept simple array program

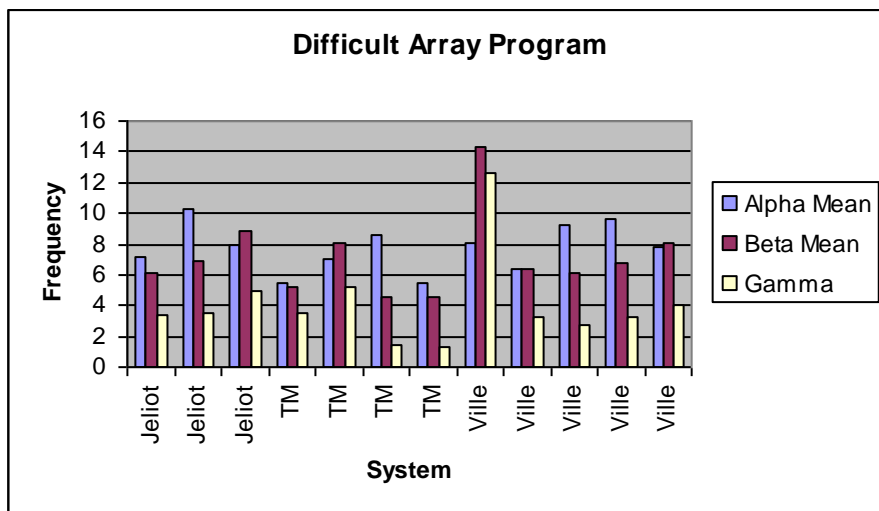


Chart 7: Results for the concept difficult array program

The chart 6 and 7 indicates the values of alpha, beta, gamma for the concept of arrays. One program was simple and the other was little tedious form of using the array. In the case of simple array program highest beta and gamma mean was recorded when using the Jeliot system while Ville system recorded the highest beta and gamma means in the case of difficult array program.

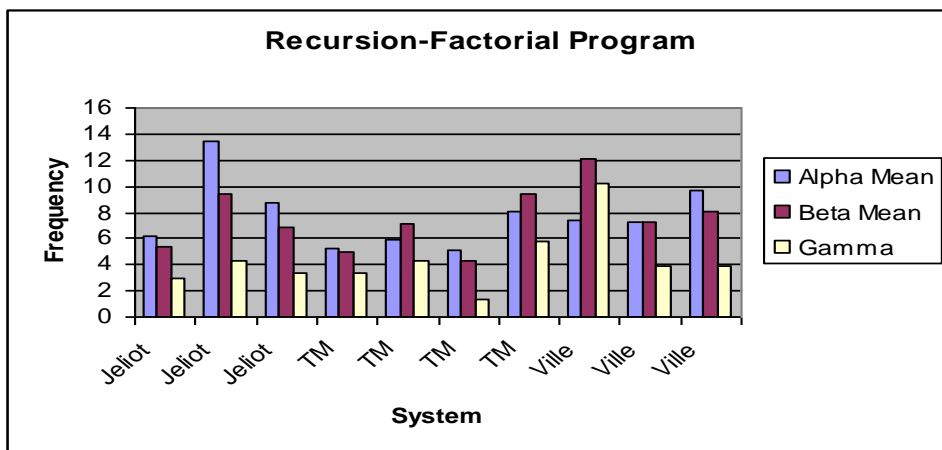


Chart 8: Results for the concept recursion

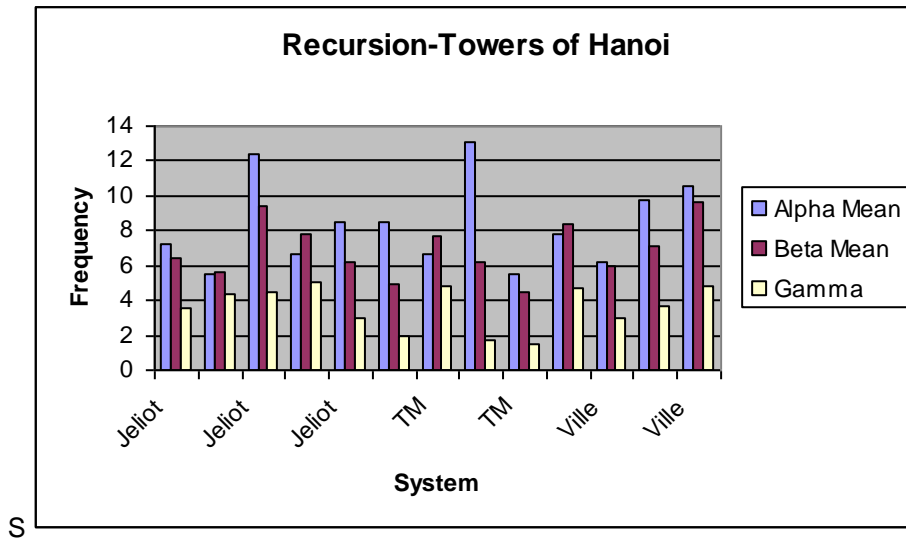


Chart 9: Results for the concept recursion- Towers of Hanoi

Chart 8 and 9 indicate the results of learning the concept of recursion. It was observed that the Ville showed higher beta and gamma values showing problem solving activity. Highest alpha value was recorded in Jeliot for recursion (factorial) program and in the case of recursion concept for towers of Hanoi program TM had the highest alpha value.

Chart 10 indicates the results of the concept of sorting. In this concept most of the subjects experienced using the Ville system. It was found that the some subjects recorded the highest value for alpha while using Ville and highest beta value is recorded while using Ville and peak gamma was seen when using Eliot system.

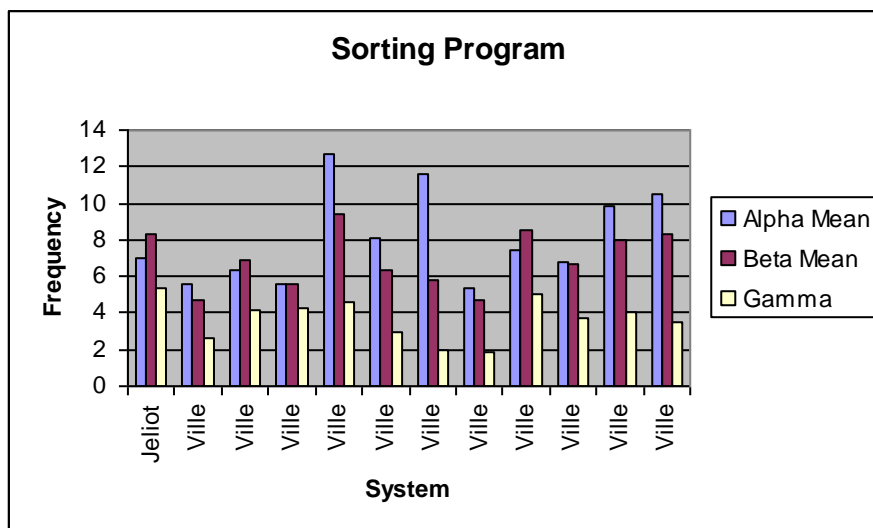


Chart 10: Results for the concept sorting program

The results of the experiment is summarized as table as shown in Table 3.

Concept of Programming	Alpha Mean		Beta Mean		Gamma Mean	
	High	Low	High	Low	High	Low
Variable declaration	9.748	5.621	11.44	5.375	7.868	1.976
	Paper	Paper	Paper	Paper	Paper	Paper
Conditional statements	12.141	5.025	9.815	4.582	6.098	1.354
	Ville	Ville	Ville	Ville	Ville	Jeliot
Looping statements	10.092	4.579	9.978	4.354	6.553	1.356
	Ville	Ville	Ville	Ville	Ville	Jeliot
Functions	9.878	5.272	10.053	4.464	6.239	1.472
	Jeliot	Ville	Ville	Ville	Ville	Ville
Functions call by values	10.298	5.695	11.321	5.201	7.071	1.885
	Ville	Ville	Ville	Ville	Ville	Ville
Simple Array program	10.206	5.843	12.149	5.476	9.865	1.924
	TM	TM	Ville	Jeliot	Jeliot	Ville
Difficult Array program	10.337	5.407	14.318	4.548	12.592	1.303
	Jeliot	TM	Ville	TM	Ville	TM
Factorial program using recursion	13.457	5.093	12.095	4.333	10.241	1.394
	Jeliot	TM	Ville	TM	Ville	TM
Difficult program of recursion using Towers of Hanoi	13.103	5.468	9.623	4.438	5.026	1.476
	TM	TM	Ville	TM	Jeliot	TM
Sorting program	12.674	5.386	9.458	4.739	5.345	1.867
	Ville	Ville	Ville	Ville	Jeliot	Ville

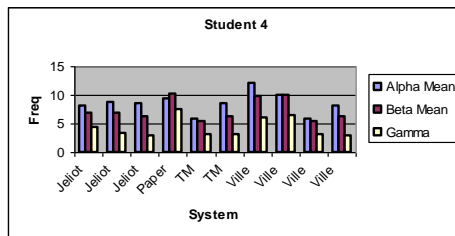
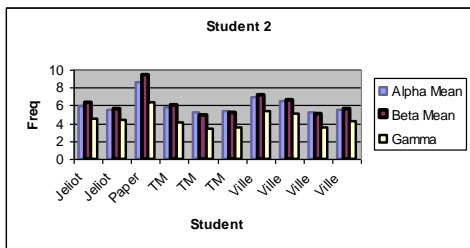
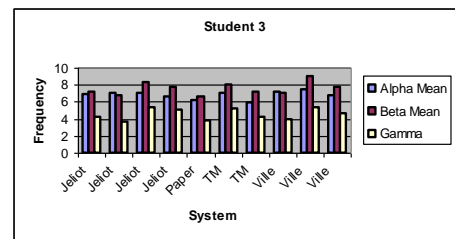
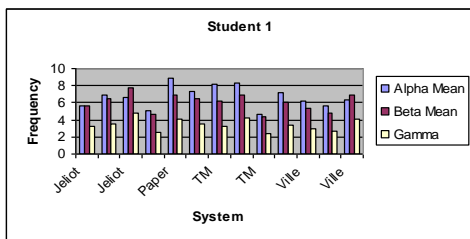
Table 3: Results of EEG experiment – concept wise

6 ANALYSIS OF RESULTS-STUDENTWISE

The following table tabulates the experiment results on the basis of the students.

	Alpha Mean		Beta Mean		Gamma Mean	
	High	Low	High	Low	High	Low
Student 1	8.911	4.579	7.707	4.354	4.827	2.448
Student 2	8.617	5.199	9.479	4.928	6.33	3.414
Student 3	7.466	5.932	9.084	6.674	5.345	3.622
Student 4	12.141	5.851	10.275	5.369	7.409	2.94
Student 5	13.103	6.728	6.213	4.464	2.007	1.354
Student 6	8.517	5.695	14.318	5.201	12.592	3.057
Student 7	9.851	7.468	11.44	8.388	7.868	4.27
Student 8	9.592	6.235	9.558	5.978	5.568	2.956
Student 9	9.878	9.188	9.702	5.924	4.522	2.466
Student 10	10.561	7.771	9.623	7.536	5.616	3.457
Student 11	13.457	6.844	9.476	5.537	4.556	2.414

Table 4: EEG experiment results –Student wise



When we analyze the results from the table and the simple graphs for certain students above we can infer that the same student experience different measure of alpha, beta, and gamma means even in case the same visualization is used. This makes us to conclude that the same visualization does not reduce the cognitive load in a similar way for all the concepts. Some visualization helps in reducing the load in some concepts while it does not in other concepts. These variations in the patterns are due the levels of the concepts according to the difficulty level. Bloom's taxonomy refers to the levels of concepts according to the levels of difficulty.

As mentioned earlier, most of the visualization system are monotonous and does not provide room for user interaction at time when the learners faces difficulty. The choice of the visualization tool to the learning is done randomly. Cognitive Load Theory (CLT) also considers the long term memory schema of the learners. The Long Term Memory (LTM) may be different for each learners as they have different levels of expertise in domains related to programming such as mathematics, analogy etc. In our experiment we also employed the rating scale of 10 to rate the difficulty of learning by the learners. It is found that there is no proportionality between the rating difficulties expressed by non physiological measures to that of the physiological measures. This lack of co relation might be due to the frustration experienced by the subjects due to the fixing of electrodes. It is also observed that the students tend to increase their alpha mean when the same system is given consequently. This is due to the reason that they become more relaxed as they are getting familiar with the same system and also they get bored due to the same type of visualizations. It is also our conclusion that visualizations do help in reducing the difficulty of learning .But what we see from the results is that all visualizations are not equally effective in reducing the load. Some visualization are not clearly understood by the novices and it increases the load.

7 CONCLUSION

Physiological measures are expected to be better indicator of cognitive load since the measures are monitored without the knowledge of the learner. This is quite contrary to the non physiological measures that are used traditionally to monitor cognitive load. In non physiological measures the cognitive load is measured based on the user's feedback. It is found that not all visualizations are not equally helpful in helping to reduce cognitive. Some students found the reduction of load using certain visualizations for certain concepts. Some visualization did not help in reducing the load for some concepts. A mechanism to monitor the load and customize the instruction by using different visualizations could help further in reducing the cognitive load. This optimization could be implemented using techniques like Artificial Neural Network. This optimization becomes necessary as the cognitive load reduction is not uniform for all students and same concepts. On the other hand when the results are analyzed on the basis of the concepts using the different visualization tools we also infer that it is difficult to conclude that a certain visualization tool is effective in reducing the cognitive load. This is due to the reason the cognitive load could increase for certain students when they are newly introduced to visualization tools. It is also to be taken into consideration that all novices are not same as they have varied levels of background and associated skills of learning programming.

The results of the experiment also helped us to conclude that physiological measures like EEG could not be a good indicator for cognitive load in a normal class room setting. It may be suitable to use the physiological measures in a controlled experimental setting. The participants faced some difficulties to fix the wire and many learners were not happy that the experiment involves fixing of electrodes in their head. It was quite a difficult task to motivate the students in taking part in the experiments. This type of experimental setup for observing or analyzing the cognitive load created a stress and some learners experienced frustration.

Another important factor that needs to be addressed in the effort of measuring cognitive load is the background of mathematical skills possessed by the learners. This is due to the fact that mathematics and computer programming have a strong correlation and the background of mathematical skills, analogy, problem solving and the ability to perform in mathematics should also be considered in order to find how effective the visualizations could reduce the cognitive load. The consideration of this factor can attribute to the Cognitive load theory which also considers the long term memory and that is attributed by the prior knowledge related to the learning and it is represented in the form of schemas. So the study has helped to report the suitability of using EEG for measuring cognitive load. The study also helped to find out how effective the visualization tool in reduces the cognitive load.

8 REFERENCES

- [1] A.Badley, G. H. (2008). "Baddley's model of working memory." Retrieved July 2008, from http://en.wikipedia.org/wiki/Baddeley%27s_model_of_working_memory.
- [2] Garner, S. (2002). Reducing the Cognitive Load on Novice Programmers. ED-MEDIA World Conference on Educational Multimedia & Telecommunications, Denver, Colorado, Association for the advancement of computing in Education.
- [3] Gomes, A. and A. J. Mendes (2007). Learning to program-difficulties and solutions. International conference on Engineering Education - ICEE 2007. Coimbra, Portugal.
- [4] Hammond, D. C. (2004). "A introduction to Neurofeedback." Journal of Neuro Therapy.
- [5] Infiniti, P. (2009). "Procomp Infiniti Hardware Manual." Retrieved July, 2008, from <http://www.thoughttechnology.com/pdf/manuals/SA7510%20Rev%206.pdf>
- [6] Paas, F., J. E.Tuovinen, et al. (2003). "Cognitive Load Measurement as a means to Advance Cognitive Load Theory." Educational Psychologist **38**(1): 63-71.
- [7] Pavlo Antonenko et.al. (2010). Using Electroencephalography to Measure Cognitive Load. Educ Psychol Rev **22**:425–438
- [8] R.Ben-Bassat Levy, M. B.-A., P.A.Uronen (2003). "The Jeliot 2000 program animation system." Education **40**(1): 1-15.
- [9] Rajala, T., et.al, (2007). VILLE- MultiLanguage Tool for Teaching Novice Programming. TUCS Technical Report TUCS.
- [10] Rajala, T., Laakso, M-J., Kaila, E and Salakoski, T. (2008). "Effectiveness of Program Visualization: A Case Study with the VILLE Tool." Journal of Information Technology Education: Innovations in Practice **7**: 15-32.
- [11] S.Ikehara, C. and M. E.Crosby (2005). Assessing Cognitive Load with Physiological sensors. 38th Hawaii International Conference on System Sciences 2005, Hawaii, USA.
- [12] Shi, Y. (2007). Galvanic Skin Response (GSR) as an index of Cognitive Load. CHI 2007, San Jose, CA, USA.
- [13] Sweller, J. (1988). "Cognitive load during problem solving: Effects on learning." Cognitive Science **12**: 257-285.
- [14] Sweller, J. (2008). "Visualisation and Instructional Design." Retrieved January, from <http://www.cmu.edu/teaching/trynew/sweller-visualinstructionaldesign.pdf>.
- [15] Technology, T. (2008). "Getting Started with Biograph Infiniti." Retrieved January, from <http://www.thoughttechnology.com/pdf/manuals/SA7951%20ver%205.1%20EEG%20Suite.pdf>.
- [16] Wikipedia. (2009). "Electroencephalography." Retrieved August, 2009, from <http://en.wikipedia.org/wiki/Electroencephalography>.