Understanding Effects of Cognitive Load from Pupillary Responses Using Hilbert Analytic Phase

Gahangir Hossain
Electrical and Computer Engineering
The University of Memphis
Memphis, TN USA
gahangir@gmail.com

Mohammed Yeasin
Electrical and Computer Engineering
The University of Memphis
Memphis, TN USA
myeasin@memphis.edu

***Abstract*—Task-evoked pupillary responses reveal the relationship between working memory capacity and its effect on cognitive states. Understanding the effects of cognitive load requires robust analysis of pupillary responses. In this paper, we introduced a Hilbert transform analytic phase based method to compute temporal patterns from pupillary responses. Analysis reveals that sharp change in incorrect task response may be attributed to the cognitive overload. It was also observed that a sharp change and continuation of the ramp in Hilbert unwrapped phase relates to the cognitive dissonance.**

Keywords- pupillary response; cognitive load; cognitive dissonance ; cognitive overload; Hilbert Transform.

I. INTRODUCTION

Studies on cognitive load established the relationship between mental workload related to the executive control of working memory (WM). The cognitive Load Dynamics (CLD) explains the transition of mental states. Also, there is evidence related to mental efforts and cognitive intervention. For example, cognitive overload may occur if the resource needed to process information exceeds the maximum capacity [12]. Accurate measurement of cognitive load and its effect on cognitive states is important in personalized communication [19], adaptive user interface design [4], modeling social interaction between human and artificial agent [30].

The definition and interpretation of cognitive load differs across the research areas in cognitive psychology, instructional design, and neurobiology. The most commonly used definition is the amount of working memory resources required in cognitive task execution [10, 11]. The effect of cognitive load can be manifested as a "cognitive overload" or "cognitive dissonance" depending on the complexity of task and also the context. The interdependency of contributing factors was explained in the 3D (execution time, complexity and number of alternatives in case of multi-tasking) cognitive task load model [4]. The classification of cognitive loads, such as under load, vigilance, lock-up and overload were performed based on this model. The classification was performed based on heuristics and fixed set of rules as illustrated in the Table I. The rule-based classification schemes are known for their poor generalization and are not suitable for nonstationary data.

Studies suggest that pupil dilation is related to cognitive load. It was reported that, Pupil size variation has a direct relation to the mental activities [7, 9]. In [3], it was noted that pupillary responses are non-stationary in nature. Short-time Fourier transform (STFT) was applied on spontaneous pupil size fluctuation to find the task-evoked pupillary responses [2, 14]. However, such time-frequency analysis are limited by the temporal resolution of the FFT as it is bounded by the Nyquist criteria [16]. It also requires the duration of segments for decomposition must exceed at least one cycle of the lowest part frequency.

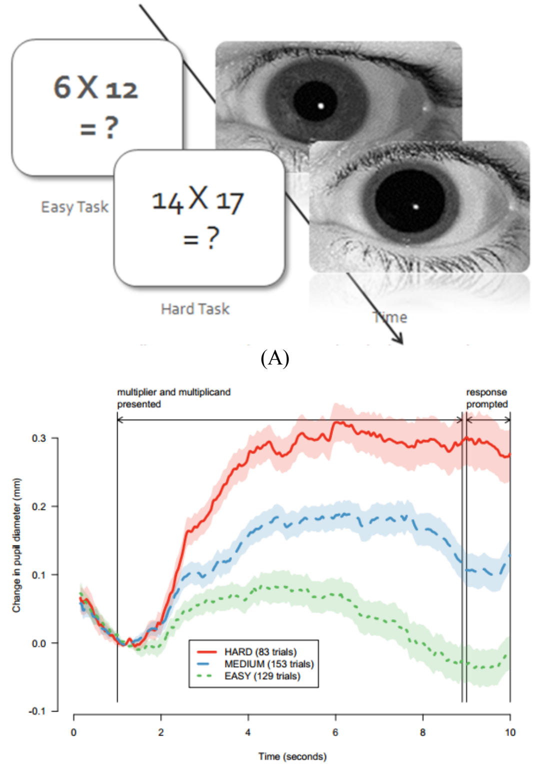
Given the cognitive task evoked pupillary responses [8]; effects of cognitive load can be estimated from the time-frequency analysis of pupillary time series [2]. However, the temporal changes of pupillary response are boisterous, nonstationary, nonlinear, and rife with temporal discontinuities. To achieve the desired robustness, we introduce an approach using Hilbert transform analytical phase based approach to compute temporal patterns from the pupillary responses. This was subsequently used to classify the effects cognitive load. Here, we focus on uncovering cognitive lock-up and overload from the analytic phases of Hilbert transform.

TABLE I. 3D COGNITIVE TASK LOAD APPROACH OF CLASSIFYING COGNITIVE LOAD EFFECTS

Dimensions	**Task Performance Periods**		
	Short (<5min)	Medium (5-20min)	Long (>20min)
Time occupied = Low Info Processing = Low Task switches = low	No problem	Under-load	
Time occupied = High Info Processing = Low Task switches = low	No problem		Vigilance
Time occupied = High Info Processing = All Task switches = High	Cognitive lock-up		
Time occupied = High Info Processing = High Task switches = High	Overload		

II. RESEARCH CONTEXT

Pupil size change in a given cognitive task interaction indicates whether the subject is in cognitive control, attentive, or overloaded situation. The temporal variation of pupil size differences can be computed from the time series data obtained from the participants performing a series of



(A)

(B)

Figure 1. Illustration of pupillary responses in cognitive task execution, (A) Mental multiplication task and pupil size change, (B) Difficulty effect on pupil dilation evoked by mental multiplication of two numbers displayed together for eight seconds (adopted from Klingner's Dissertation (Figure 5.5) [1]).

cognitive tasks. Figure 1(A) illustrates cognitive tasks (easy, hard) with respect to pupil dilations. The change of pupil diameter was shown in [1, 32] with three curves representing easy (black), medium (blue) and hard (red) with time (Figure 1B).

Cognitive load dynamics is considered as the change of cognitive load over time. It may manifest in one of the two forms: cognitive dissonance and cognitive overload. The cognitive psychology defines cognitive dissonance as inconsistency or psychologically uncomfortable situation [12, 13]. More specifically, cognitive dissonance states the uncomfortable feeling by holding two contradictory ideas simultaneously in working memory. For example, the differences between "how we should act" and "how we act" in a particular situation may cause dissonance. Cognitive dissonance [or lock-up] acts as a key factor mediating conceptual change in response to human-machine interactions [4]. Psychologists explain two hypothesis of cognitive dissonance: (1) The existence of dissonance [or conflict / inconsistency], being psychologically uncomfortable, will motivate the person to try to reduce the dissonance and achieve consonance [or consistency]. (2) When dissonance is present, in addition to trying to reduce it, the person will actively avoid situations and information which would likely increase the dissonance [13]. Cognitive overload may arise in the context of a goal oriented, time bound and complex task interaction.

TABLE II. CATEGORIZATION OF COGNITIVE LOAD MEASUREMENT [29, 21]

Objectivity	Causal Relationship	
	Indirect	Direct
Subjective	Self-reported invested mental effort [21, 23]	Self-reported stress level Self-reported difficulty of materials [24]
Objective	Physiological measure [25] Behavioral measure [24] Learned outcome measure [22]	Brain activity measure (e.g., EEG, fMRI) [25] Dual-task performance [27, 22]

Cognitive overload may arise in the context of a goal oriented, time bound and complex task interaction. Complex (hard) mental multiplication task, used in [1] is an example. In the context of human-computer (device/machine/system) interaction, load can be measures with the number of ways categorized as subjective/objective or direct/indirect which is shown in Table II.

III. RESEARCH METHOD

Highly precise pupillimetry data collection depends on a good setup in which the pupil spans many pixels in the camera image. To avoid data integrity issues we analyzed a sample from a benchmark dataset [1] for secondary evaluation. Pupil size variation logs are averaged and matched with task performance to identify cognitive load, dissonance and overload. Figure 2 shows two stages of processing: cognitive load assessment and cognitive load effect assessment. This study emphasizes on the later part of the study, considering the result of the first part as a baseline. Initially, the data was passed through some pre-processing steps (e.g., averaging both left and right pupil size, management of missing values, and interpolation) to have a form of time series data. As the main goal of this work is to study dynamics in terms of overload and dissonance, we applied Hilbert transform to see cognitive load effects.

A. The Hilbert Transform

Hilbert transform returns a complex sequence sometimes called the analytic signal, from a real data sequence. It is useful in calculating instantaneous attributes of time series, especially the amplitude and frequency.

The instantaneous amplitude is the amplitude of the complex Hilbert transform; the instantaneous frequency is the time rate of change of the instantaneous phase angle[15]. Let us consider $x(t)$ is a real-valued time domain signal. The Hilbert Transform of $x(t)$ is another real-valued time domain signal, can be denoted by $\tilde{x}(t)$, such that $z(t) = x(t) + j\tilde{x}(t)$ is an analytic signal [12].

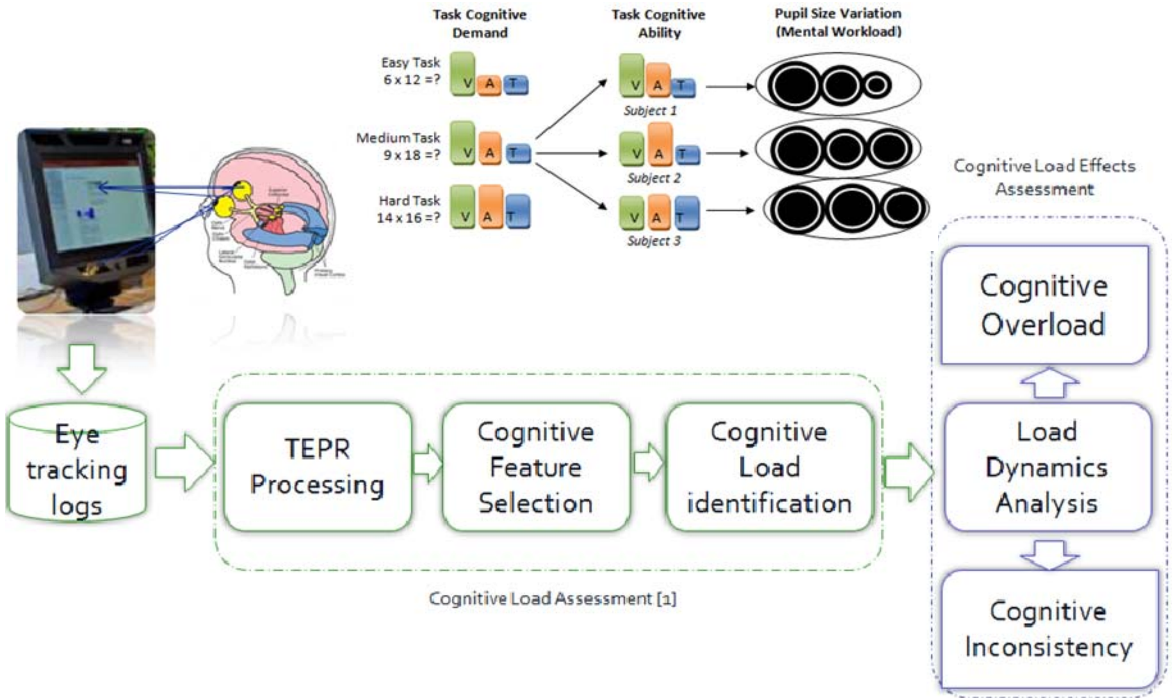


Figure 2. Pupillary data processing in cognitive load effects assessment

From $z(t)$, we can define a magnitude function $A(t)$ to describe the envelope of the original function $x(t)$ versus time. We can also define a phase function $\theta(t)$ to describe instantaneous phase of $x(t)$. Thus, the Hilbert transform of a real-valued function $x(t)$ of infinite time is a real-valued function $\tilde{x}(t)$ defined by:

$$\tilde{x}(t) = H[x(t)] = \int_{-\infty}^{\infty} \frac{x(u)}{\pi(t-u)} du \qquad (1)$$

The analytic signal $z(t)$ associated with $x(t)$ can also be rewritten as:

$$z(t) = A(t)e^{j\theta(t)}$$
(2)

and $$\theta(t) = \tan^{-1}\left[\frac{\tilde{x}(t)}{x(t)}\right] = 2\pi f_0 t \qquad (3)$$

The instantaneous frequency is given by:

$$f_0 = \left(\frac{1}{2\pi}\right)\tan^{-1}\left[\frac{\tilde{x}(t)}{x(t)}\right] = 2\pi f_0 t$$
(4)

More specifically, the Hilbert transform returns the analytic form of the signal. We can plot the original signal, and the real and imaginary parts of the analytic signal. It is easy to note that the imaginary part of the analytic signal is the real part of the analytic signal shifted by 90 degree (i.e., by $\pi/2$). Finally, we can compute the phase of the analytic signal, the amplitude envelope, and the unwrapped phase. The unwrapped phase corrects the radian phase angels in a vector by adding multiples of $\pm 2\pi$ when absolute jumps between consecutive elements of phase are greater than or equal to the default jump tolerance of π radians [16]. An example plot of a sinusoidal signal, sin(2.0*π*1000*2.0) is shown in Figure 3. It is notable in Figure 3 that the angle increases linearly from -π to π, and at πreturns to -π. Also notice that, in this case, the amplitude of the signal is one for all time. The unwrapped phase corrects the radian phase angels.

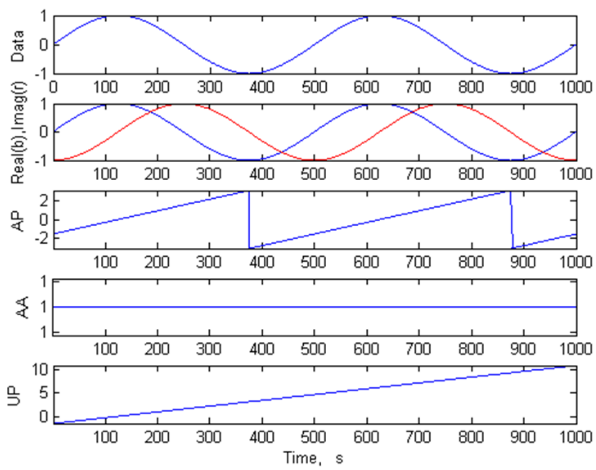


Figure 3. An example of Hilbert analytic phase, amplitude and unwrapped phase.

B. Data Set

Participants were 24 undergraduate students from a large public university in North America. All the participants had normal or corrected-to-normal vision. All participants were compensated by Amazon.com gift certificates with a value ranging from \$15 to \$35 based on their task performance. According to [32], each trial with two seconds pre-stimulus accommodation period was given for student participants to rest and prepare themselves. The multiplicand and multipliers are then presented with two seconds interval on the computer screen in front to them (Figure 2). After 5, seconds, the multiplier was presented. Pupil dilation was averaged across the five seconds window between multiplier presentation and participants' response for the significance testing.

A Tobii 1750 remote eye tracker (Tobii Technologies, 2007) 50Hz is used in data collection. This remote-camera setup enables pupil measurements without encumbrance or distraction. A pleasant room lighting condition also considered for better tracking performance. Eye tracker was placed on a desk with the top of the screen approximately 140 cm from the screen in a relatively bright room.

C. Time-series Extraction

Eye behavior data is logged through Tobii eye tracking software. Missing values are interpolated, and an average of left and right pupils' diameter are used to compute pupillary time series.

Response time is considered as the time interval between, the instant at which a user at a terminal enters a request for a response from the system (computer) and the instant at which the last character of the response is received at the terminal. In mental multiplication task, the time from maxima (hill peak – which we consider the cognition time) to responding (typing the response of the task) is considered as response time. Finally, with mental multiplication dataset, the response time is computed with Hick's law –

$$RT = a + b \log_2(n) \tag{5}$$

Where RT = response time, a = the total time that is not involved with decision making, b = an empirically derived constant based on the cognitive processing time for each option (in this case 0.155 seconds for humans), n = number of equally probable alternatives. The relationship of response time and analytic signals attributes are explained in the next section.

IV. RESULTS

The main purpose of the experiment was to compute temporal patterns in pupillary responses related to cognitive states. To achieve the goal we created an analysis set from [1]. In particular, we considered 10 students performing thirty (30) cognitive tasks (with ten tasks from each category of easy, medium and hard task). The interaction logs are analyzed as the preliminary study. The estimated time series is variable length due to their different task completion times and difficulty level. We considered seven minutes (420s) time of each task as most of tasks competition time is equal or less than seven minutes (Table 3 and Figure 4).

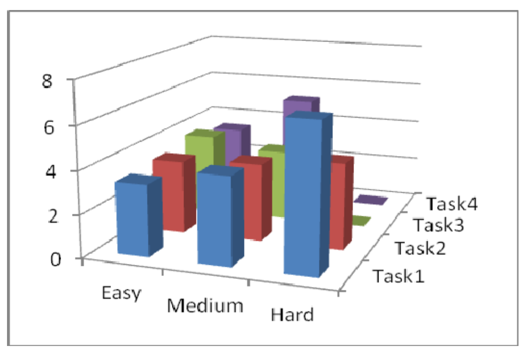


Figure 4. Histogram of task completion time and performance.

TABLE III. TASK COMPLETION TIME (MS) AND PERFORMANCE

Task completion time (ms) Easy	Task Performance	Task completion time (ms) Medium	Task Performance	Task completion time (ms) Hard	Task Performance
12031	T	14719	T	24446	F
12437	T	13168	T	14547	T
13812	F	12045	T		
12218	T	18690	F		

Table 3 and Figure 4 illustrate that the failure tasks took relatively more processing time than the correct tasks. Figure 5 explains the results of Hilbert transform with unwrap phase differences of all ten tasks performed by the subject. Unsuccessful tasks are marked and have higher fluctuations in ramp. To see whether the failure occurs due to cognitive inconsistency or cognitive overload further

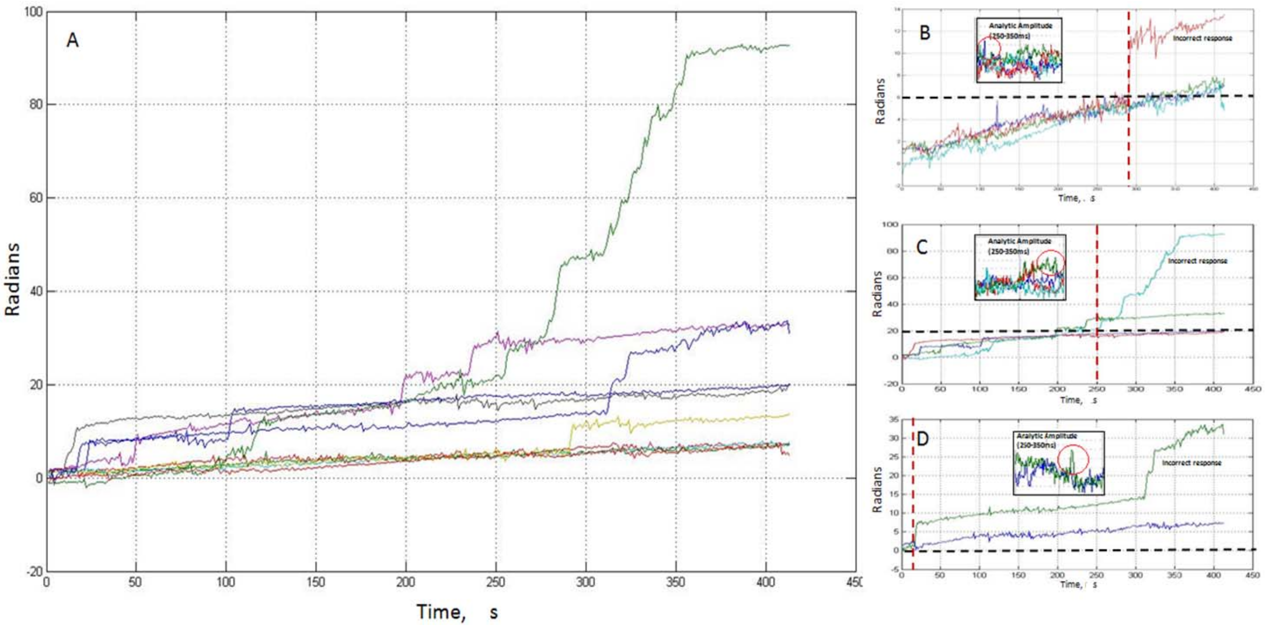


Figure 5. Hilbert Transform of pupillary data. A. Hilbert unwrap phases of all ten tasks. B. Hilbert unwrap plots of easy tasks with analytic amplitude plot (250-350s) in the box; C. Plots of medium tasks with analytic amplitude plot (250-350s) in the box; D. Plots of hard tasks with analytic amplitude plot (250-350s) in the box.

study is made with different task categories (task demands) the easy task, medium task and hard tasks. The diverging intercepts are either due to residual low cognitive effort, having a different spatial distribution from that of the center frequencies. This is as because, some cycles of $\theta(t)$ the peak of cognitive failure to reach the zero from above or below, which prevents an expected branch point, or they are due to residual high frequency oscillations that throw in extra zero crossings and branch points [16].

Comparisons of unwrapped analytic phase across easy, medium and hard tasks are illustrated in Figures 5B, 5C and 5D, respectively. The change in the beginning and its continuation reveal the conflict (dissonance) behavior while the sharp change (fluctuation) may be attributed to the cognitive overload. In medium task failure comparatively, a large change is observed. One reason may be; the subject is confused and astonished for the uncatchable large mistake. Relatively smaller change in easy and hard task failures can be related to the unintentional mistake and inability.

Boxes in Figure 5 are corresponding analytic amplitude in (250-350) to explain the connection of fluctuating unwrap phase ramp. Useful indication of load difference through analytic amplitude are marked with red circles.

V. Conclusion

This paper focuses on understanding the effects of cognitive load on cognitive states (such dissonance and overload) from pupillary responses. The main contribution is to develop robust methods to analyze non-stationary pupillary responses and uncovering temporal patterns.

Analysis reveals that sharp change in incorrect task response is related to the cognitive overload. It was also observed that a sharp change and continuation of the ramp in Hilbert unwrapped phase are related to the cognitive dissonance.

The Hilbert transform method for the study of cognitive overload and cognitive dissonance reveals new insight into the association between task variation and pupillary dynamics. However a detailed analysis with larger sample might demonstrate more insightful results. In keeping with current methods of cognitive load dynamics assessment, we show that pupillary time series data are attenuated but not extinguished following cognitive markers like an electroencephalogram (EEG) processing with Hilbert transform. Future works may clarify the pupillary signals construction and processing techniques (e.g., Hilbert and Huang Transform with empirical mode decomposition). Furthermore, this novel experimental structure and signal processing methodology should also be explored grounding with EEG or other physiological data [6] from same experimental structure.

Acknowledgment

We acknowledge Klingner et al. [1] for eye tracking data. We also acknowledge all research subjects participated in that study. This work is partially supported by NSF grant number (NSF-IIS-0746790).

REFERENCES

[1] J. Klingner, B. Tversky and P. Hanrahan, "Effects of visual and verbal presentation on cognitive load in vigilance, memory, and arithmetic tasks," Psychophysiology, Vol. 48(3), pp. 323-332, 2011

[2] W. Nowak, A. Hachol and H. Kasprzak, "Time-frequency analysis of spontaneous fluctuation of the pupil size of the human eye,"Optica Applicata, Vol. 38(2), pp. 469-480, 2008.

[3] A. Murata, and H. Iwase, "Evaluation of mental workload by fluctuation analysis of pupil area," In Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 6, pp. 3094-3097. 1998.

[4] M. A. Neerincx, "Cognitive task load design: model, methods and examples," In: E. Hollnagel (ed.), Handbook of Cognitive Task Design. Chapter 13 pp. 283-305, 1999.

[5] J. Rasmussen, "Information processing and human-machine interaction: an approach to cognitive engineering," Amsterdam, Elsevier, 1986.

[6] A. F. Kramer, "Physiological metrics of mental workload: A review of recent progress," In: Damos, D. L. (ed.) Multiple-task Performance. London: Taylor & Francis Ltd., 1991.

[7] B. P. Bailey and S. T. Iqbal, "Understanding changes in mental workload during execution of goal-directed tasks and its application for interruption management," ACM Trans. on Computer-Human Interaction, Vol. 14(4), pp. 1–28, 2008.

[8] J. Beatty, "Task Evoked Pupillary Responses, Processing Load and Structure of Processing Resources," Psychological Bulletin, Vol. 91(2), pp. 276-292, 2008.

[9] E. H. Hess, J. M. Polt, "Pupil size in relation to mental activity during simple Problem-Solving," Science, Vol.143 (3611), pp. 1190-1192, 1964.

[10] F. Paas, J. E. Tuovinen, "Cognitive Load Measurement as a Means to Advance Cognitive Load Theory," Educational Psychologist, Vol. 38, pp. 63 – 71, 2003.

[11] E. Ophir, C. I. Nass and A. D. Wagner, "Cognitive control in media multitaskers," Proc Natl Acad Sci USA 106:15583–15587, 2009.

[12] S. A. McLeod, "Cognitive Dissonance Theory", 2008. Retrieved from http://www.simplypsychology.org/cognitive-dissonance.html

[13] L. Festinger, A theory of cognitive dissonance, Evanston, IL: Row & Peterson, 1957.

[14] W. Nowak, A. Hachol, and H. Kasprzak. Time-frequency analysis of spontaneous fluctuation of the pupil size of the human eye. Optica Applicata, Vol. 38(2), pp. 469–480, 2008.

[15] J. S. Bendat "The Hilbert Transform and Applications to Correlation Measurements," Bruel & Kjiaer, Denmark, 1985.

[16] J.W. Freeman "Hilbert transform for brain waves," Scholarpedia, Vol. 2(1), pp. 1338, 2007. doi:10.4249/scholarpedia.1338, revision #91355

[17] L. Festinger, "Cognitive dissonance" Scientific American, Vol. 207(4), pp. 93-107, 1962.

[18] F. Paas, A. Renkel and J. Sweller,"Cognitive Load Theory: Instructional Implications of the Interaction between Information Structures and Cognitive Architecture" Instructional Science, Vol. 32: pp. 1–8, 2004,

[19] S. Oviatt, "Human-centered design meets cognitive load theory: designing interfaces that help people think," In Proceedings of the 14th annual ACM international conference on Multimedia, pp. 871-880, ACM, 2006.

[20] G. Hossain, A. S. Shaik and M. Yeasin, "Cognitive load and usability analysis of R-MAP for the people who are blind or visual impaired," InProceedings of the 29th ACM international conference on Design of communication , pp. 137-144, ACM, 2010.

[21] G. Hossain and M. Yeasin, "Cognitive Load Based Adaptive Assistive Technology Design for Reconfigured Mobile Android Phone," In Mobile Computing, Applications, and Services (pp. 374-380). Springer Berlin Heidelberg, 2012.

[22] G. Hossain and A. H. M. A. Habib, "Designing Twin 7-Segment Display for Bangla Numeric Characters," Asian Journal of Information Technology, Vol. 3(1), pp. 49-55, 2003.

[23] F. G. Paas, J. J. Van Merriënboer and J. J. Adam,"Measurement of cognitive load in instructional research. Perceptual and motor skills," Vol. 79(1), pp. 419-430, 1994.

[24] S. Kalyuga, P. Chandler and J. Sweller, "Managing split-attention and redundancy in multimedia instruction," Applied cognitive psychology, Vol. 13(4), pp. 351-371, 1999.

[25] R. E. Mayer and R. Moreno, "A split-attention effect in multimedia learning: Evidence for dual processing systems in working memory," Journal of educational psychology, Vol. 90(2), pp. 312, 1998.

[26] E. Haapalainen, S. Kim, J. F. Forlizzi, and A. K. Dey, "Psycho-physiological measures for assessing cognitive load," In Proceedings of the 12th ACM international conference on Ubiquitous computing, pp. 301-310, ACM, 2010.

[27] J. Gwizdka, "Using stroop task to assess cognitive load," In Proceedings of the 28th Annual European Conference on Cognitive Ergonomics, pp. 219-222. ACM, 2010.

[28] R. E. Mayer, R. Moreno, "Nine ways to reduce cognitive load in multimedia learning," Educational psychologist, Vol. 38(1), pp. 43-52, 2003.

[29] R. Brunken, J. L. Plass, D. Leutner, "Direct measurement of cognitive load in multimedia learning," Educational Psychologist, Vol. 38(1), pp. 53-61, 2003.

[30] H. M. Cuevas, S. M. Fiore, B. S. Caldwell, B. S., and L. Strater, "Augmenting team cognition in human-automation teams performing in complex operational environments, "Aviation, space, and environmental medicine, Vol. 78(Supplement 1), pp. B63-B70, 2007.

[31] R. Q. Quiroga, A. Kraskov, T. Kreuz , P. Grassberger. "Performance of different synchronization measures in real data: A case study on electroencephalographic signals," Physical Rev E, Vol. 6504:U645-U6 58 - art. No. 041903, 2007.

[32] J. Klingner, Measuring Cognitive Load During Visual Tasks by Combining Pupillometry and Eye Tracking, Ph.D. dissertation, Stanford University Computer Science Department. 2010.