Cognitive Load Based Adaptive Assistive Technology Design for Reconfigured Mobile Android Phone

Gahangir Hossain and Mohammed Yeasin

Electrical and Computer Engineering, The University of Memphis,
Memphis TN, USA
{ghossain,myeasin}@memphis.edu

Abstract. In assistive technology design, it is indispensible to consider the sensory, physical and cognitive level of target users. Cognitive load is an important indicator of cognitive feedback during interaction and became the critical research issue in designing assistive user interfaces, incorporated with smartphone based assistive technology like in the android platform. In this paper, we proposed a cognitive load based user interface integrated with reconfigured mobile android phone (R-MAP) based on user's cognitive load level. We performed some cognitive tasks within a small group of sighted but blindfolded people and blind people or visually impaired using R-MAP. Based on task performance and cognitive load levels we manually annotated some data of 24 participants and finally applied some machine learning algorithms to automate the mobile interface. Based on our novel design and experimental finding, we recommended that "cognitive load enabled feedbacks based assistive user interface" would be a useful assistive tool for the people who use mobile phone for their daily operations.

Keywords: Assistive technology, android phone, cognitive load, virtual sound, user interface.

1 Introduction

Smart phone as an assistive technology tool became popular to the users who are mostly dependent on them. Blind people or visual impaired feel more comfortable using feedback enabled user interfaces for day-to-day operations. In this study we used Reconfigured Mobile Android Phone (R-MAP), a fully integrated standalone system that has an easy-to-use interface to reconfigure an Android mobile phone with assistive virtual sound (VS) feedback [1]. The ultimate goal of this study is to design an automated feedback enabled mobile phone user interface based on cognitive load of the people who use it as an assistive technology tool. Along this direction, the very first objective we considered is to measure cognitive load. The second objective was to map different task based on task-complexity. The third challenge considered was to use machine learning algorithms to automate the user interface. Hence, the objective set was to find relatively better algorithm based on cognitive load classification performance.

J.Y. Zhang et al. (Eds.): MobiCASE 2011, LNICST 95, pp. 374–380, 2012.
© Institute for Computer Sciences, Social Informatics and Telecommunications Engineering 2012

Cognitive load [3][4] refers to the amount of working memory load imposed on the human cognitive capacity when performing a particular task. Measuring cognitive load of people who are blind or visually impaired can be considered different, because of their different memory model, their more active phonological loop and special sketchpad rather than visuospatial sketchpad [5][6].

People having problem with any one organs are categorized in assistive group. The memory model of assistive technology user is therefore different and their cognitive capabilities demand special consideration in designing technology tools using mobile phone.

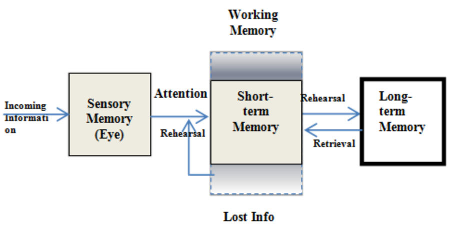
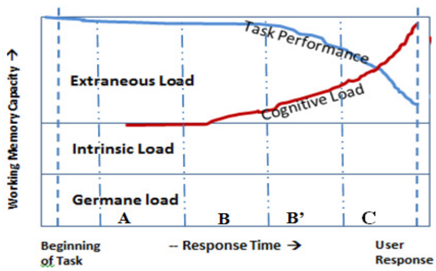


Fig. 1. Human memory system



A-Normal load, B, B'-Average Cognitive load, C-Cognitive overload section

Fig. 2. Working memory capacity and cognitive load

In particular working memory is considered very sensitive to extraneous load. When working memory capacity exceeds the available resources for a task, we feel cognitively overloaded. The scenario can be explained by a simple graph in Fig. 2. It is the job of user interface designer to make the layout and presentation material as simple as possible for the user to better understand with few working memory resources and to reduce extraneous cognitive load.

In this study two types of cognitive load measurement are considered. The objective method we adopted into R-MAP is the secondary task based performance rating with VS feedback. Another method is the subjective rating of formative questionnaires representing three types of cognitive load index (intrinsic load, extraneous load and germane load) that is administered during post experiment interview [8].

The rest of the paper is organized as following: Section 2 describes a brief literature review on cognitive load, assistive technology tools and relationship of human memory model. In Section 3 the design of R-MAP interface is explained. In Section 4 the experimental protocol is explained. Finally in section 5 experimental results are explained with discussion and possible future improvements.

2 State of the Art

Measuring cognitive load in ordinal cognitive load scale is important in designing an optimal interaction approach between humans and assistive technology systems in order to produce the highest task performance. These loads deal with mental processes of learning, memory and problem solving. Sweller [14] defined the Cognitive Load theory. There are three types of cognitive loads [15][16], namely intrinsic, extraneous and germane. The cognitive load theory suggests increasing the germane load while decreasing intrinsic and extraneous load. In task description, decision task involves different form of Boolean or fuzzy based decisions. Memory retrieval task involves query and information retrieval from main memory or secondary memory. Presentation format is the representation of task materials which is organized (with data structure) or unorganized form.

Recently, Pradipta and Rabinson [13] proposed a novel approach, user interface simulator, to designing and evaluating inclusive systems by modeling users' performance with a wide range of abilities. Another method with i-phone touch screen based cognitive interfaces is researched by Young et al.[12], expecting the future generation of computer based system will need cognitive user interfaces to achieve sufficient, robust and intelligent human interaction.

3 Design of Interface

In our study we applied a similar approach using assistive technology tool R-MAP [1], and our own designed user interface to discover the similarities and differences of cognitive performances shown by blindfolded and blind subjects. A mini-shallow structure user interface like Fig. 3 in R-MAP is experimented.

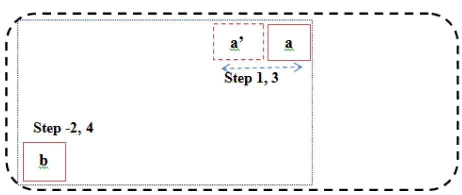


Fig. 3. R-MAP mini-shallow structure interface Layout

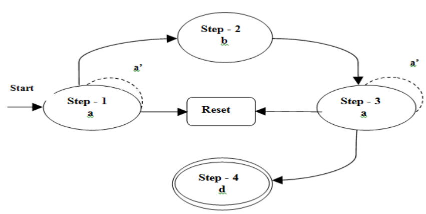


Fig. 4. Automata of R-MAP operation (interface interaction)

Considering space of the interface operation, only two /three special locations are selected for operational execution. In depth of interface operation only two layer of information, same locations are used twice for two steps. For example, step 2 and step 4 works in same location. In addition to these two locations for the secondary task purpose a third location 'a'' that is basically instructional shifted location of 'a' (dashed marked box in the figure) is included in this design. Therefore, it is a mixed mini-shallow structure layout of interface. An automaton of this interface is shown in Fig. 4.

4 Experiment and Data

4.1 The Experiment

Twenty four subjects (20 sighted but blind-folded and 4 blind people) participated in this study. Among them 12 subjects (including 2 blind people) are selected as expert based on their prior smart phone use experience. All subjects had first a quick tutorial to learn how to use the system. In each session, the R-MAP and a text book is provided to the subject.

In primary task, subjects are asked to use the assistive tool (R-MAP) for their daily purpose; reading labels of text in object and location, reading from text book etc. The secondary task consisted is an interruption task (dual-task) to keep track of the shift of the operational location with continuous visual monitoring task. More specifically, in this experiment the primary task was set to read a text from a book provided to them. They were asked to open the book and to reach any text location. The operation of R-MAP with four steps and sound feedback is shown in Fig. 5.

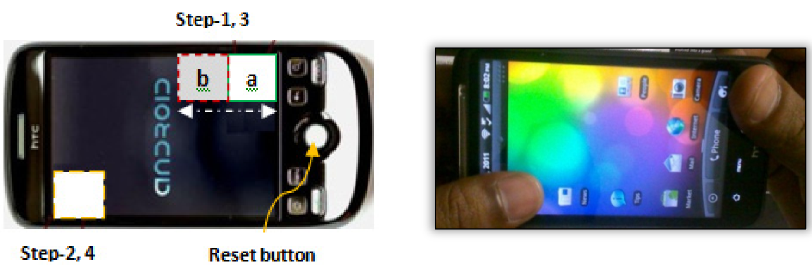


Fig. 5. RMAP with virtual sound feedback for secondary task

Step-1: Open application, *// Virtual sound alert (VS1 or VS2),* ***Step-2:*** Enter into capture mode. **Step-3:** Capture image, *// Virtual sound alert (Vs1 or VS2),* Pause for 5-20 sec. **Step-4:** Speech (Voice o/p).

In secondary task, R-MAP operation was changed a little with guidance of two virtual sounds (VS_1 and VS_2) following speech based cognitive load measurement technique [9][10]. A special shift of first push location (*'a' to 'b' or 'b' to 'a'*) in R-MAP (Fig. 5) was made with VS_1. The second virtual sound VS_2, instructed subject to push the reset button to cancel secondary task mode. The task performance was scored by the examiner in 0-5 range. The more mistakes means subjects were cognitively overloaded. The highest score 5 which indicates the subject were fully loaded with secondary task. The cognitive load scores were then computed separately. Z-score normalization was used before computing the cognitive load index. Dependent variables considered for the secondary task were reaction times (RTs) and accuracy. We computed cognitive load index to find tentative cognitive load of a person performed all three tasks or partially one or two tasks. CLI was calculated by cumulative averaging of task performance and normalizing with respect to total task scores. We also followed an annotation guideline of overload (High load –HL), average load (AL) and Low Load (LL) from some earlier literature [4]. For simplicity and useful operation, we ignored LL and consider only AL and HL as a feature for our classification. The four blind people spontaneously participated in all tasks and showed good performance with significant load. Based on their task performance and cognitive load level we manually labeled all data of 24 participants and finally applied three machine learning algorithm (J48, Random forest and Naïve Bays) from Weka toolbox [7].

4.2 Data

A sample of data we collected is shown in Table 1 below. The task value -1 indicates that participant did not participate in that task. Error value is the cumulative sum of number of errors a participant did in three different tasks.

Table 1. Sample data

UsersID	*Age*	*Ethnicity*	*Subjects*	*Gender*	*Smart Phone User*	*# of Tasks*	*Task types*	*Task-1*	*Task-2*	*Task-3*	*Error*	*CLI*	*Load Type*
User-1	29	Asian	BF	M	N	1	E	3	-1	-1	3	3	HL
User-4	31	American	BF	F	Y	3	E,M,C	0	1	3	4	1.333333	AL
User-7	30	African	BF	F	Y	2	E,M	0	4	-1	4	2	HL
User-10	30	American	BF	M	N	2	E,M	0	3	-1	3	1.5	AL
User-25	42	American	BP	M	Y	3	E,M,C	0	1	2	3	1	AL

***n- novice user, y- expert user, M- Male, F- Female, BF- Blind-folded, BP- Blind People,**
E- Easy, M-Moderate, C-Complex, CLI – cognitive load index, HL – high load (Overload), AL – Average load.

5 Results

We applied Welch's *t-test* with 95% confidence interval and standard error calculation on the preprocessed data before application of machine learning algorithms for classification. The result is shown in Table 2a and Table 2b.

Table 2a. Cognitive load score comparison between Non-expert group and Expert group

	Cognitive Load (Subjective)		Cognitive Load (Secondary Task)	
	M	SD	M	SD
Non-Expert (N=12)	6	2	3.73	0.79
Expert (N=12)	3.33	0.65	2.73	0.90
t-value	4.391		0.361	
p-value	0.0007		0.0123	

Table 2b. Cognitive Load Score comparison between blindfolded and visual impaired

	Cognitive Load (Subjective)		Cognitive Load (Secondary Task)	
	M	SD	M	SD
Blind Folded (N =20)	5.2	0.95	3.65	0.93
VP (N =4)	6.312	0.77	4.25	0.96
t-value	2.5193		1.1489	
p-value	0.0532		0.3146	

Table 2a. shows the *t* values during error calculation and two-tailed p-value for significance judgment. As non-expert subjects do not have prior smart phone use experience, the result shows that in all case of cognitive load measure, difference between non-expert and expert are statistically significant. For same test on blindfolded versus visually impaired people (Table 2b) shows significant differences. In case of subjective cognitive load, the difference is considered not quite statistically significant and same for the secondary task performance. Box and whisker diagram (Fig. 6) are also plotted to see the impression of sample data.

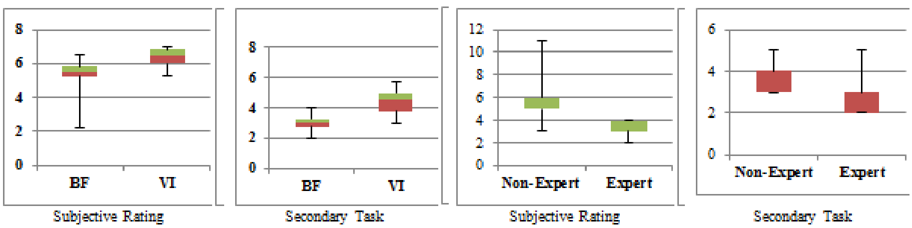


Fig. 6. Cognitive Load assessments between sighted but Blindfolded (BF) and Visual Impaired (VI)

J48, Random Forest and Naïve Bayes classifiers were used with 10 fold cross validation. Random Forest shows relatively better performance. The performance classification is shown in table 3.

Table 3. Performance Classification

Classifier	*Accuracy (%)*	*Kappa*
J48	72	3.91
Random Forest	78	4.32
Naïve Bayes	67	3.56

6 Conclusion

This study signifies the difference of blindfolded subjects to act as a blind people during cognitive experiment through android phone based assistive interface. It also supports the evidence of different cognitive map, sometimes superior performance shown by people who are blind or visually impaired based on smart phone use experience. As a novel step to automate an assistive interface, the random forest algorithm found better to classify cognitive load indices based on the sample data. In future we are working with more blind subjects and different methods for load measurement and adaptation to improve the existing ststem.

Acknowledgment. This project is partially funded by National Science Foundation (NSF-IIS-0746790), USA.

References

1. Shaik, A., Hossain, G., Yeasin, M.: Design, development and performance evaluation of reconfigured mobile Android phone for people who are blind or visually impaired. In: ACM SIGDOC 2010, pp. 159–166. ACM, New York (2010)
2. Klatzky, R.L., Marston, J.R., Giudice, N.A., Golledge, R.G., Loomis, J.M.: Cognitive load of navigating without vision when guided by virtual sound versus spatial language. Journal of Experimental Psychology: Applied 12, 223–232 (2006)
3. Paas, F., Tuovinen, J.E., Tabbers, H.K., Van Gerven, P.W.M.: Cognitive load measurement as a means to advance cognitive load theory. Educational Psychologist 38(1), 63–71 (2003)
4. Paas, F., Merriënboer, J.J.G.: Instructioqnal control of cognitive load in the training of complex cognitive tasks. Educational Psychology Review 6, 51–71 (1994)
5. Pylyshyn, Z.: Return of the mental image: are there really pictures in the brain? Opinion. TRENDS in Cognitive Sciences 7(3) (March 2003)
6. Chen, M., Huang, C., Wang, C.: Difference on Spatial Working Memory between the Blind and Sighted People. In: APIEMS 2008 Proceedings of The 9th Asia Pasific Industrial Engineering & Management Systems Conference (2008)
7. Weka Machine Learning tool, `http://www.cs.waikato.ac.nz/ml/weka/`
8. Yin, B., Chen, F., Ruiz, N., Ambikairajah, E.: Speech-based cognitive load monitoring system. In: Proc. IEEE ICASSP, pp. 2041–2044 (2008)
9. Cierniak, G., Scheiter, K., Gerjets, P.: Explaining the split-attention effect: Is the reduction of extraneous cognitive load accompanied by an increase in germane cognitive load? Computers in Human Behavior 25, 315–324 (2009)
10. Brunken, R., Steinbacher, S., Plass, J.L., Leutner, D.: Assessment of cognitive load in multimedia learning using dual-task methodology. Experimental Psychology 49(2), 109–119 (2002)
11. Welch, B.L.: The significance of the difference between two means when the population variances are unequal. Biometrika 29, 350–362 (1938)
12. Young, S.: Cognitive User Interfaces. Signal Processing Magazine 27(3), 128–140 (2010)
13. Biswas, P., Robinson, P.: Automatic evaluation of assistive interfaces. In: International Conference on Intelligent User Interfaces, Hong Kong (February 2010)
14. Sweller, J., Chandler, P.: Why some material is difficult to learn. Cognition and Instruction 12(3), 185–233 (1994)
15. Su, J., Rosenzweig, A., Goel, A., de Lara, E., Truong, K.N.: Enabling the Visually-Impaired to Use Maps on Touch-Enabled Devices. In: Proceedings of MOBILECHI (2010)
16. Miller, G.A.: The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information. The Psychological Review 63, 81–97 (1956)
17. Thomas, C.: Real-Time Sound/Image Manipulation and Mapping in a Performance Setting.pdf. Music/Special Studies, Brown University, `http://www.ciufo.org/media/sound_image.pdf`
18. Keogan, A.: Flowing Rhythms – The Creation of a Rhythm-based Imager and Lumia, masters thesis, Interaction Design Centre, Dept. of CSIS, University of Limerick, Limerick, Ireland