USING EYE TRACKING TECHNOLOGY TO IDENTIFY VISUAL AND VERBAL LEARNERS

Tracey J. Mehigan, Mary Barry, Aidan Kehoe, Ian Pitt

Dept Computer Science, University College Cork, Ireland
Dept Computing, Maths & Physics, Waterford Institute of Technology, Ireland
t.mehigan@cs.ucc.ie, MBARRY@wit.ie, ak2@cs.ucc.ie, i.pitt@cs.ucc.ie

ABSTRACT

Learner style data is increasingly being incorporated into adaptive eLearning (electronic learning) systems for the development of personalized user models. This practice currently relies heavily on the prior completion of questionnaires by system users. Whilst potentially improving learning outcomes, the completion of questionnaires can be time consuming for users. Recent research indicates that it is possible to detect a user's preference on the Global / Sequential dimension of the FSLSM (Felder-Silverman Learner Style Model) through a user's mouse movement pattern, and other biometric technology including eye tracking and accelerometer technology. In this paper we discuss the potential of eye tracking technology for inference of Visual / Verbal learners. The paper will discuss the results of a study conducted to detect individual user style data based on the Visual / Verbal dimension of the FSLSM.

Index Terms— Measurement, Human Factors, Interaction, Eye Tracking, Learner Styles, Adaptive systems

1. INTRODUCTION

In recent years there has been an increased focus on the development of adaptive systems within the field of eLearning. The aim of this type of system is the provision of learning content suited to the individual learner. The delivery of improved learning outcomes for individual learners based on their 'fit' within defined scales of a chosen learner style and / or personality model is the main aim of this type of system.

1.1. Learner Styles

Many learner style and personality models exist with potential for use in the development of adaptive learning systems. Popular models used to date in the development of such systems include The Big-Five model [1], the Myer-Briggs Type Indicator Model [12][13], and the Cognitive Style Analysis Model [14]. The FSLSM (Felder-Silverman Learner Style Model), originally developed in 1988 [2] was initially intended for use with engineering students, but has gained popularity in recent years across many disciplines, becoming a popular means of student analysis in the development of eLearning systems, [6].

The FSLSM distinguishes between student learning styles based on four differing dimensions. The dimensions are Active / Reflective, Sensitive / Intuitive, Global / Sequential, and Visual / Verbal.

Active learners learn best by doing something with information while Reflective learners prefer to think about information quietly first. Sensing learners tend to like learning facts while Intuitive learners prefer to discover possibilities and relationships. Sequential learners require information to be presented in small incremental steps of complexity. Global learners usually achieve a learning outcome through large leaps and bounds. Visual learners remember best what they see and therefore are most suited to learning through diagrams. Verbal learners however gain more from text and spoken explanations. Our focus will be particularly on the Visual / Verbal dimension [2].

1.2. Background

Learner style data has become one of the most analyzed cognitive features for the development of adaptive eLearning systems. In most cases, this data is gathered through the use of questionnaires, to facilitate the analysis of an individual's learner style or personality. There has been a move over the last number of years to explore the potential of systems to automatically detect a user's learner style and / or personality through interaction patterns and behavior whilst using a learning system.

A number of successful studies have incorporated the Global / Sequential dimension of the FSLSM. Spada et al, 2008 [16] examined mouse movement patterns as a means of gathering such data. Other studies have also considered user behavior patterns in LMS (Learning Management System) interaction as a means of extracting user data [5]. Scrolling and time spent on pages were

978-1-61284-350-6/11/$26.00 ©2011 IEEE

included in the study. Bayesian Networks [4] and Feed Forward Neural Networks [18] have also been applied in this respect, showing a positive outcome. However, the incorporation of biometric technology such as eye tracking, for data gathering could potentially provide a seamless and non intrusive system for automatic user analysis.

There are very few examples of work using eye tracking technology in the field. In recent years, computational studies based on human computer interaction [8] and visual cognition [19] have been conducted. Eye tracking studies are now used in web accessibility research and since the eLearning environment is, in most cases, an extension of the web interface, it is a worthwhile exercise to incorporate eye tracking into eLearning research, because of the insight it can provide into '*moment-to-moment processing activities*' [10].

The AdeLE system [7] has explored the use of eye tracking technology for the development of adaptive eLearning systems. In that system, eye tracking data such as saccade velocity, blink rate and the degree of eyelid openness are employed to determine a user's tiredness level to complement other information gained by the system through behavior patterns. User interaction based on eye movement and visualization offers us a potential means of data gathering and learner style assessment in eLearning and now potentially in mLearning (mobile learning) systems.

By continuously tracking the user's eye movement, the eye tracking data should provide more insights into the user's decisions and sequence of actions as the learning material is viewed. A gaze path and associated fixation data indicate where the user's attention is focused and how the user reacts to a stimulus or a task to be completed [9]. This form of data gathering gleaned from the user's reaction to a given interface, could be a better indicator of cognitive activity and learning style than more traditional means of data gathering based on mouse or keyboard events.

Recent work using eye tracking technology for the Global / Sequential dimension [11], indicates that students with a lower maximum vertical speed of eye movement between fixation points tend to be more sequential than global. This is highlighted by a strong inverse correlation coefficient of r=-0.95615 between the participants' Global / Sequential dimension score and their maximum vertical speed between Areas of Interest (AOIs) as the user viewed the screen. Heat maps and gaze patterns also strongly indicated the distinction between Global and Sequential learners.

Gutl indicates [7] that a learner's gaze behavior could allow the optimization of material to meet a learner's needs, therefore, it is necessary to observe users' learning activities in real time to gain information on their personal characteristics, for example cognitive or learning styles. Gutl suggests that by exploiting data gathered through eye tracking technology *"a finer grained learner profile can be tracked by the system and applied e.g. for personalization of learning content and navigation"*. Gutl states that *"if someone prefers text and ignores pictures the amount of pictures presented could be reduced and visa versa"*.

Based on results to date and Gutl's observation, there is an opportunity to explore the visual / verbal dimension of the FSLSM through eye tracking technology for the development of adaptive eLearning systems.

Eye tracking should allow the sufficient measurement of a user's gaze path and fixation points to ensure that they are looking at either images or text. On this basis we are investigating two hypotheses as follows;

- Visual learners, as defined by the FSLSM, exhibit longer total time (fixation) duration on visual learning content (images / graphics) than their Verbal counterparts.
- Verbal learners (as defined by the FSLSM) will exhibit longer total time (fixation) duration on textual learning content than their Visual counterparts.

1.3. Eye tracking

Eye tracking technology is widely used in many disciplines from special needs education right through to commerce where it is employed as a tool for market research.

Gaze motion research, conducted by Javel in 1879, highlighted that reading text involves fixations and saccades, rather than a smooth sweeping of the eye in relation to the text. "*Eye tracking works by reflecting invisible infra red light onto an eye, recording the reflection of the pattern with a sensor system*" [17]. A pause over an information area of interest indicates a fixation whilst a rapid movement between points of fixation represents a saccade [15]. The emergence of eye tracking relates directly to Javel's research.

1.3.1. Tobii eye tracking system

The Tobii system uses a PC-like screen that is non-intrusive or restrictive to the user, providing an analysis system for experimental design (including gaze paths and heat maps), calibration, eye tracking, data gathering, analysis and statistical results presentation. Using near Infra-red LEDs to reflect the pupil movement of the user, the system stores and calibrates for each user's vision and stores each user's data. The system adjusts to suit users with glasses, contact lenses from different age groups.

2. USING EYE TRACKING TECHNOLOGY TO DETECT VISUAL AND VERBAL LEARNERS

2.1. The interface

For the purpose of the study the interface was designed to constitute static screen images for display to the user via the Tobii eye tracker monitor. The interface included two learning screens for use with the system.

No scrollbars were included. The purpose of this is to ensure that the only interaction with the screen is of a visual nature. The only exception to this was that the user was required to click a mouse button to move to the next screen. Other than this, no mouse or keyboard interaction was permitted for the purpose of interacting with the system. It was necessary to ensure that the user is looking at the screen content rather than cursor movement facilitated by the use of a mouse device.

Screens were clearly divided in two distinct sections. One half of the screen offered visual based information whilst the second half of the screen offered textual information. Therefore each screen provided a balance of text-based and visual-based information that required the user to focus on or read from specific areas of the screen. The screens are sized at approx 800*600 pixels. These were presented to the user for interaction purposes. A similar screen was included to provide the user with a multiple choice task; again the screen was balanced in its textual / visual content in that one question included a graphic, while the other question was text based.

2.2. Study outline

A study was conducted to assess the potential of eye tracking technology for gathering user data to allow the detection of Visual / Verbal learners in eLearning environments. It was believed that user eye movement data would potentially provide sufficient data to efficiently measure a learner's style based on the Visual / Verbal dimension of the FSLSM. To gather this data, the measurement of users' eye movements on screen was based on the duration of fixation on hot points and gaze patterns as recorded by the eye tracking system.

Each user undertook the test independently, unprompted by the tester. This ensured that each user operated the application on an equal level. The test was controlled through the inclusion of the user task screen. Each user's interaction with the learning screens, as detected by the Tobii monitor, was recorded by the system. The test focused particularly on the fixation duration on textual and visual AOIs (areas of interest). The user's gaze pattern between fixation points was also measured.

2.3. Participant selection

A balanced sample was used for the study. Ten subjects were selected to take part in the initial study, comprising five Visual learners and five Verbal learners, which acted as the independent variables for the test. These variables were measured against each other once the tests were completed to establish the distinctions between them. The selected subjects included students, researchers, and others, selected from the department of computer science. The participants' ages ranged between 16 and 65 years. Potential subjects were first invited to complete the Felder-Solomon Index of Learning Styles (FSILS) questionnaire to identify Visual and Verbal learners [3]. The FSILS questionnaire contains unambiguous closed questions that require users to select from two possible answers per question. The information gathered was then processed online.

The screening of subjects continued until five (50%) Visual learners and five (50%) Verbal learners were identified and confirmed their willingness to take part in the test. Both male and female subjects were represented in the test

To complete the study, both groups were asked to complete the same task. The system tested users who looked through the screens provided. The mouse was used to move between screens. Measurements were made using the participants' eye movements as they viewed the screen based on the users' gaze duration and focus / fixation points (hot spots) on both textual AOI and visual AOIs. These acted as dependant variables in the study.

2.4. Method

Participants were asked to undertake a PC based eLearning task. The participants interacted with the system using the Tobii Eye Tracker.

Subjects were first instructed in how to use the system, but received no further help or prompting from the test coordinator once the initial instruction was completed. Before beginning the test, each user logged in to the system and the system carried out the calibration process for each individual. No user failed to complete the test.

During the task, subjects were presented with one page of learning information on a topic in the form of text and images, followed by a multiple-choice question relating to that topic, the purpose being to ensure that a learning experience had occurred.

3. STUDY EVALUATION

Gaze patterns, heat maps and fixation count were employed to evaluate the results of the study. Correlation coefficients were established between participant focus duration on individual AOIs and the participants score on the Visual / Verbal dimension of the FSILS questionnaire.

3.1. AOIs and fixation count

As permitted by the Tobii system, AOIs were selected for each screen presented to the user during the test. This permitted a more detailed analysis in the establishment of specific screen areas fixated on by the user when viewing the screen. This established the duration of fixation on each AOI. Each AOI represents a specific learning object. For example, one AOI represents a textual learning object whilst another AOI represent a graphic.

The results from the Visual Learners also show a strong result when looking at the fixation chart produced by the Tobii system. It is clear from the chart that Visual participants had a higher fixation count on the visual content represented by AOI_1. A smaller fixation count is obvious on AOI_2 representing the textual content. Again this is supported by the mean fixation count per screen AOI, with visual learners having a mean fixation count above forty on AOI_1 and less than twenty on AOI_2 (see figure 2).

The fixation counts for the verbal learners are illustrated in figure 1. It is clear from the chart that the verbal participants had a larger focus count when viewing AOI_2 which contained the textual content.

The fixation count for verbal learners on AOI_1, which represents the visual content, is significantly smaller. This is further indicated by the mean fixation count for each AOI. The mean fixation count represented for AOI_2 is 40, while it stands at less than 10 for AOI_1.

Interestingly, it is also evident from the chart that one verbal participant had quite a small and almost equal fixation count of approximately 5 on both AOI-1 and AOI_2.

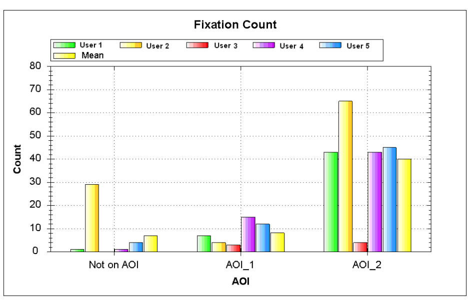

Fig. 1. Verbal Learners AOI Fixation Plot

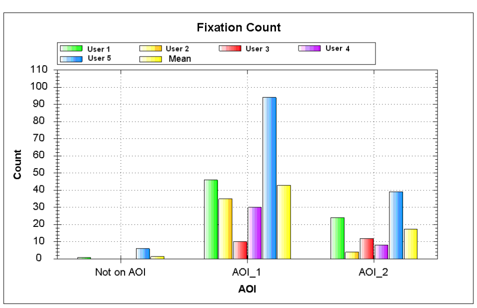

Fig. 2. Visual Learners AOI Fixation Plot

The results from the Visual Learners also show a strong result when looking at the fixation chart produced by the Tobii system. It is clear from the chart that Visual participants had a higher fixation count on the visual content represented by AOI_1. A smaller fixation count is obvious on AOI_2 representing the textual content. Again this is supported by the mean fixation count per screen AOI, with visual learners having a mean fixation count above forty on AOI_1 and less than twenty on AOI_2 (see figure 2).

3.2. Gaze plots and heat maps

The heat maps and gaze paths in relation to the participants' visualization of both textual and visual areas of interest were examined. The gaze pattern or visual route taken by a user indicates where the learner had viewed the screen and the extent to which he / she had looked at text and / or graphics. Heat maps show where a user has concentrated the most, within the learning screen. Both gaze patterns and heat maps for each of category of participants were recorded by the Tobii system during the test (see Figures 3, 4, 5 & 6).

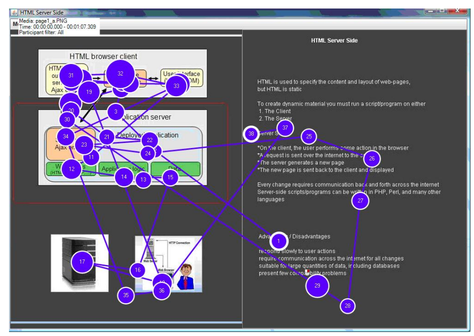

Fig. 3. Sample Visual Learner Gaze Path

Gaze patterns represent the visual route taken by the user's eye as they move across the screen. A numbered fixation disk of varying size is used by the Tobii system to represent the duration of time spent on each gaze area by the user, with each fixation disk is numbered based on its occurrence. The user's visual (gaze) route is indicated by connecting lines.

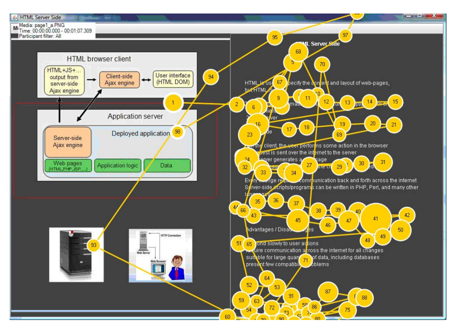

Fig. 4. Sample Verbal Learner Gaze Path

While the heat map for each user also shows the position where the participant viewed on screen in relation to fixation points, the duration of focus on the screen is represented by warm colors. The smallest duration is represented by the color green whilst red represents fixation.

The gaze patterns and heat maps indicate that there is a significant difference between visual and verbal learners. The manner in which the participants viewed and read from the page AOIs as part of the learning experience differs greatly from one category to the other. When looked at in relation to this Visual / Verbal dimension of the ILS model, it is clear to the viewer that one participant is a visual learner and the other participant is a verbal learner.

The gaze patterns illustrated in figure 3 for a selected visual learner clearly indicate that the spent a larger duration of time focused on the visual learning objects in AOI_1. Few fixation disks are present on AOI_2, which contains the textual learning object content.

The fixation disks present are scattered across the text indicating that the participant only glanced at the particular sections of text. In most cases these fixation disks are smaller in size than those present on the graphical content.

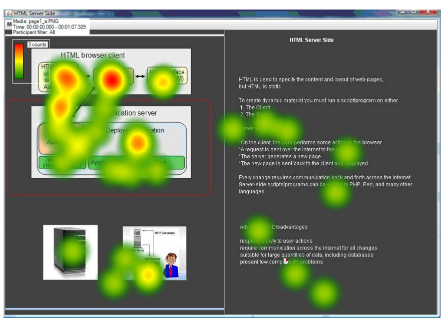

Fig. 5. Sample Visual Learner Heat Map

As illustrated in Figure 4, the opposite is evident in the gaze plot of the sample verbal learner. This learner has higher focus duration on AOI_2 (the textual content). Only 4 fixation disks are present on the graphical content of AOI_1, which are widely scattered across the images, again indicating that the user simply glanced at the content of AOI_1. Indeed, it is clear when taking figures 3 & 4 together that the visual learners viewed the graphical side of the screen while the verbal learners viewed the textual side of the screen.

Again, this is reflected when viewing the participants' heat maps (figures 5 & 6) for each learner category (visual & verbal). Similar to the gaze plots a significant difference between the visual and verbal learners is evident from the heat maps. Taking two sample heat maps, one from each category, it is clear that the visual learner's visualization of the learning screen (figure 5) shows that a higher fixation occurred on the graphical side of the screen (AOI_1). While the verbal learner (figure 6) exhibited the opposite, that is, the verbal learner had a higher fixation level on the textual side of the screen (AOI_2).

Little visualization has occurred outside the learning objects, where this did occur it was more evident on the textual side of the screen (AOI_2) for the visual learner and on the graphical side of the screen (AOI_1) for the verbal learner

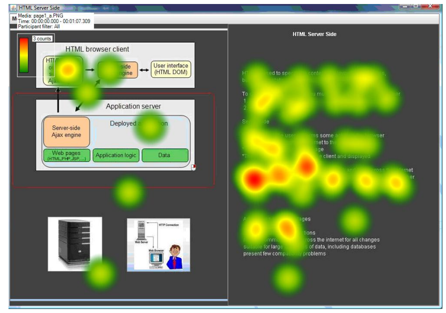

Fig. 6. Sample Verbal Learner Heat Map

3.3. Correlation

It was also necessary to establish a correlation coefficient in the case of each prediction to allow the assessment of eye tracking in relation to visual / verbal learning style inference. It was expected that visual learners would spend a longer overall fixation duration on visual learning objects and verbal learners would spend longer overall time duration on the text. Therefore, a correlation co-efficient was established based on the users' score on the Visual / Verbal learning style dimension and each of the following:

a. total fixation time on areas of image/graphic interest as accessed through data gathered using the eye gaze tracking

b. total fixation time on areas of textual interest as accessed through data gathered using the eye gaze tracking

The study findings clearly indicate a strong correlation coefficient of $r = 0.723$ between total fixation duration per msec on AOI_1 (visual content) and each participant score on the visual / verbal dimension of the FSILS questionnaire. This is illustrated as a scatter graph in Figure 7.

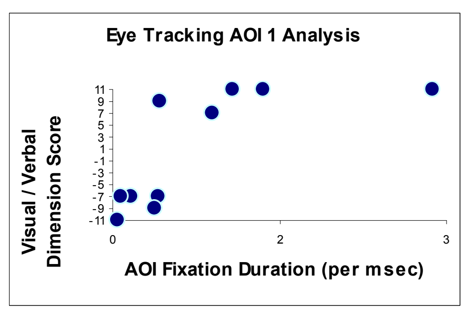

Fig. 7. Total Fixation Duration per msec AOI_1 vs. Visual / Verbal Dimension Score

A strong inverse correlation of r = -0.77504 was established where student overall duration on AOI 2 (textual content), was measured against their score on the Visual / Verbal dimension of the FSILS questionnaire. Again, this is illustrated in figure 8 as a scatter-graph.

The correlations clearly indicate that students with longer overall focus duration on visual content, tend to be more visual in their learning style. Whereas learners with longer overall focus duration on textual content, tend to be more verbal in their learning style, when measured against the FSILS.

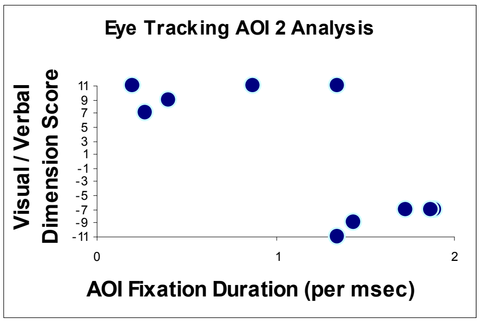

Fig. 8. Total Fixation Duration per msec AOI_2 vs. Visual / Verbal Dimension Score

4. FUTURE WORK

There is an opportunity to explore the potential of eye tracking in determining a user's placement on the remaining dimensions of the FSLSM including the active / reflective and the sensitive / intuitive dimension.

As eye tracking devices are now available to suit work with mobile devices, we propose extending this work to include handheld devices. We also propose extending this work to include other biometric interaction tools such as accelerometers, now becoming a standard inclusion in many high end mobile devices.

As learner styles reflect how a person perceives and processes data presented to them, there is also potential to extend this work for use with other adaptive interfaces and systems, within both eLearning and other fields.

5. REFERENCES

[1] Busato, V., V., Prins, F., J., Elshout, J., J., Hamakera, C. (1999). The Relation Between Learning Syles: The Big Five Personality Traits and Achievement Motivation in Higher Education, Personality and Individual Differences 26, 129 - 140

[2] Felder, R., M., Silverman, L., K. (1988). Learning and Teaching Styles in Engineering Education. Engineering Education 78 (7) 674–681. Proceeded by a preface in 2002

[3] Felder, R.M., Solomon, B.A., http://www.engr.ncsu.edu/learningstyles/ilsweb.html

[4] García, P., Amandi, A., Schiaffino, S., Campo, M. (2005) Using Bayesian Networks to Detect Students' Learning Styles in a Web-based education system, 7th Symposium of Artificial Intelligence. Rosario, Argentina, 115 – 126

[5] Graf, S., Kinshuk. (2006). An Approach for Detecting Learning Styles in Learning Management Systems. The Sixth International Conference on Advanced Learning Technologies. Kerkrade, the Netherlands. 161 – 163.

[6] Graf, S., Liu, T., C., Kinshuk., Chen., N.,S., Yang, S.,J.,H., (2009), Learning Styles and Cognitive Traits – Their Relationship and its Benefits in Web-Based Educational Systems, Computers in Human Behaviour 25 (2009) 1280 – 1289.

[7] Gutl, C., Pivec, M., Trummer, C., Garcia-Barrios, V., M., Modritscha, F., Pripfl, J., Umgeher, M.,(2004) AdeLE (Adaptive e-Learning with Eye-Tracking): Theoretical Background, System Architecture and Application Scenarios, In proceedings I-Know'04, Graz, Austria.

[8] Ivory, M. Y., Hearst, M. A. (2001). The State of the Art in Automating Usability Evaluation of User Interfaces; ACM Computing Surveys (CSUR), ACM Press, 33, 4, 2001, p. 470-516.

[9] Jacob, R.J.K, and Karn, K.S. (2003) Commentary on Section 4. Eye tracking in Human-Computer interaction and usability research : Ready to deliver the promises. In J. Hyona, R. Radach and H. Deubel (eds), The Mind's Eyes: Cognitive and Applied Aspects of Eye Movements. Oxford: Elsevier Science.

[10] Jay, C., Lunn, D. & Michailidou, E. (2008). End User Evaluations. In S. Harper & Y. Yesilada (eds), Web Accessibility, A Foundation for Research. London: Springer

[11] Mehigan, T., Barry, M., Pitt, I., Individual Learner Styles Inference Using Eye Tracking Technology, I-HCI 09, 3rd conference of the Irish HCI Community, Dublin, Ireland, 17-18 September, 2009, pp 63 - 69.

[12] Myer Briggs Foundation http://www.myersbriggs.org/my-mbti-personality-type/mbti-basics/

[13] Pittenger, D., J. (1993). The Utility of the Myers- Briggs Type Indicator, In Review of Educational Research 63(4) 467-488

[14] Riding, R. Cognitive style analysis CSA administration. 1991 / 1998, Birmingham: Learning & Training and Technology.

[15] Salvucci, D., D., Goldburg, J.,H., 2000, Identifying Fixations and Saccades in Eye Tracking Protocols, Eye Tracking Research Symposium, Florida, USA, 2000, pp 71-78

[16] Spada, S., Sánchez-Montañés, M., Paredes, P., Carro, R., M., 2008, Towards Inferring Sequential-Global Dimension of Learning Styles from Mouse Movement Patterns. Lecture Notes in Computer Science 5149, 337 – 340.

[17] Tobii , www.tobii.com

[18] Villaverde, J., E., Godoy, D., Amandi, A. (2006). Learning Styles' Recognition in e-learning Environments with Feed-Forward Neural Networks. Journal of Computer Assisted Learning 22, 197–206.

[19] Zhai, S. (2003). What's in the Eyes for Attentive Input; Communications of the ACM (Association for Computing Machinery), 46, 3, 2003, p. 34-39.