A GESTURE INFERENCE METHODOLOGY FOR USER EVALUATION BASED ON MOUSE ACTIVITY TRACKING

Luis A. Leiva Torres, Roberto Vivo Hernando
Department of Information Systems and Computation, Technical University Of Valencia
Camino de Vera, s/n 46022 Valencia (Spain)
luileito@doctor.upv.es, rvivo@dsic.upv.es

ABSTRACT

This paper describes a user modelling methodology focused on mouse activity. A straightforward web-based mouse tracking tool is used to record in real time users' activity remotely. Later both data post processing and analysis are carried out to evaluate and classify users' conducts, thus creating a collaborative web page profile. User and web page models are used to assist the design team and make suitable corrections. A case study is introduced as a successful demonstration example.

KEYWORDS

Mouse tracking, web interaction, usability evaluation, user activity, user modelling.

1. INTRODUCTION

Good usability is critical to the success of websites. There is a need to evaluate their user interface especially in earlier development stages, because websites must attain the goal that they were designed for. Moreover, this need has noticeably aroused the interest both in user activity tracking and user behaviour inference, inspired in earlier works such as [1,28]. It is necessary to know whether an interface does not just work for a generic user, but how it can work for different kind of users [12]. In practice, the design of web sites is often based on either the structure of the content or the structure of the organization the site belongs to, rather than on how users access the site [16]. Involving users in the design and evaluation of web-based systems has the potential to considerably improve the systems' effectiveness, efficiency and usability [13]. Besides, users of web sites often know exactly neither what information they are looking for nor what the site has to offer [15].

Usability testing has a number of possible goals and purposes and tends to be rather labor-intensive [23]. One procedure to evaluate the usability of a web interface is the use of eye tracking [14,24]. These studies need to be performed in a laboratory with a small user sample, and they are not accessible to everyone [21]. Unfortunately, thorough in-situ usability testing is not always feasible. Projects take longer than expected, budgets get tightened, and target users can be hard to find. On-line tests provide a wider range of user samples, so a new layout design sometimes can be evaluated in a faster and economical way [3,4,19].

People mainly handle on a website interface with the mouse and, to a lesser extent, the keyboard. The mouse is undoubtedly the most widely used device and it can reflect user behaviours [20,17]. Furthermore, this is something that is not usually registered and traditional web server logs do not provide useful information about navigation habits and user interaction; they only report the click stream on a website. What is more, the vast majority of web sites do not deal with log files. The fact is that if we want a site in order to do better, we need to understand how users behave on that site. And most of the time their behaviours are reflected by an apparently random process: the mouse activity. It is apparently random because most of the time it is conditioned by the web page's layout (it is a major factor of analysis, because of the types of websites). When we take the expected value, or average, of a random process we measure several important characteristics about how the process behaves in general. This proves to be a very important observation [10]. However, if we measure different aspects of an apparently random process such as the user's movements, the relationship between these different parameters will also be an important observation.

By analysing customer click stream data, companies can learn much about customer behaviour [25]. But there is a big problem when analysing only the user clicks: it is very difficult -almost impossible- to know more about user's navigational habits. That is the reason why mouse tracking systems appeared. Some studies such as [3,4,8,17,19,20,27] have demonstrated that most users move the mouse in accordance with those elements they are focusing their attention on. Therefore, many approaches to user activity evaluation have been developed based on mouse tracking by using standard web technologies for years [3,4,17,19,20]. These systems log and display the mouse trail -the path followed by the user until deciding to click a hyperlink or exiting the page-, sometimes as a static overlay image [3,17,20] and other times in real time [4,19]. In particular, [4] is the more advanced system so far. However, it has serious privacy concerns because they manage significant personal user information in great detail, such as user's keyboard inputs. All in all mouse tracking applications can provide helpful information about its users and their ways of navigation [11], going beyond the mere click stream data analysis.

A major lack in all these mouse trackers is that they generate neither a user model nor a web profile. Consequently, we have extended one of these mouse tracking systems, thus developing a statistical module which categorizes user behaviour and creates a web page model based on collaborative users' mouse movements. So, the aim of this paper's research is of a double nature: on the one hand, (1) to provide numerical results about user's activity on websites and, on the other hand, (2) to develop both a general user classification model and a collaborative web page profile based on mouse tracking data. In the first case, a statistical approach is carried out by means of confidence intervals, instead of traditional hypothesis tests. A confidence interval is an interval containing the most believable values for a parameter. The probability that this method produces an interval that contains the parameter is called the confidence level. Confidence intervals are in many ways a more satisfactory basis for statistical inference than hypothesis tests, and they can be derived by methods based on probability theory [29]. In the second case, users are classified according both to mouse's kinematics activity and gesture analysis. This methodology let us infer navigational behaviours in a more transparent, simpler way than conventional approaches with less restrictive assumptions [29].

2. METHODOLOGY APPROACH

2.1 Logging the user activity

There exist some open source web-based mouse tracking tools such as [3,4,19]. We developed a straightforward tracking application [19] that works in all modern browsers and no special requirements are needed (e.g.: external proxy server [4], special database [3], external server data storage [3,17]), so that we could apply it to some shared hosting servers -the most frequent situation in the "real world"-. Also, external clients such as user-adaptive applications can submit and retrieve information about users [18]. As with other web analytics packages, a single line of JavaScript code must be added to those web pages that will be monitored. The JavaScript file collects browsing data and transmits them asynchronously to the server. This mouse tracking system logs anonymously user movements in real time and stores that information both in flat XML and HTML files, so massive post processing tasks can be carried out easily, apart from being possible to check visually the users' implicit interaction by replaying the HTML logs [19].

2.2 Data analysis

A random sample of these XML logs were processed off-line, in order to infer the average user model based on previous users' activity evaluation. Because of the confidence intervals, users are classified into three categories, based on mouse kinematics: passive, normal and active. In [26] a similar approach is discussed, but the proposed categories have different meanings. Once the corresponding statistics are generated, two types of data are provided: concrete and abstract [4,19]. The first ones show detailed information directly obtained from client's data. For example, how many times and where the mouse was clicked, the moment it was clicked, whether something was highlighted, the total visit time, interruptions, etc. The second type includes a small data that informs about the users' skills, how they use the web interface, whether they are impatient persons or skilful with the mouse, etc. These data are provided once the statistical user's classification is made. Also, a rudimentary clustering technique is implemented to cut the mouse trails down to a single point of interest.

2.3 User inference

A collaborative approach is employed in our statistical user modelling methodology, that is, the user's behaviour is predicted from the behaviour of other like-minded people. On the one hand, a single user classification model is reported, informing about the user's expertise level. On the other hand, a web page model is created by analysing all visitors' data and inferring average values. With these data and enough representative samples we can therefore create a customized user profile or one common profile for a web page.

Statistical and probabilistic models are concerned with the use of observed sample results to make statements about unknown, dependent parameters. These parameters represent aspects of a user's behaviour, such as his or her goals, preferences, and forthcoming actions or locations [2], whenever they are reliable (statistically precise) and valid. We have studied the covariance and correlation of a whole set of variables, in order to find the relationships between the chosen user's metrics. In short, the user model is composed by a static (or motion) index and the number of mouse clicks. The web page model is inferred by means of both the mouse activity and browser's information.

3. METHODOLOGY DESCRIPTION: CONCEPTUAL VARIABLES

For each user we have studied a set of variables grouped into three gesture categories: attention, distances and position. The user model is inferred by using the attention and distances categories, and the position category is mainly used to create the web page profile.

3.1 Attention

3.1.1 Session Time

This parameter is the total tracking time, measured in seconds. The time that a user remains on a site is the main currency in the attention economy of Internet [21]. But it is important to distinguish between attention and hesitation. So, the mouse trails fall into different categories according to the analysis of the registration points obtained from the mouse tracking tool.

3.1.2 Registration Points

The users' paths are reported at time regular intervals, measured in frames per second (fps). So, these registration points make it possible to divide the mouse path into two components: a static part and a motion part. The former is associated with passive users; whereas the latter is associated with impatient, active users. Experienced users show sparser registration points, as it was observed using the visualization module from the mouse tracking tool.

3.1.3 Kinematics: Static and Motion Activity

These indexes are computed as a fraction of the session time given the following formula:

$$I_{s,m} = \frac{A_{s,m}}{T \cdot fps} \leq 1 \qquad \text{(Eq. 1)}$$

Where:

- I is the index for static (I_s) and motion (I_m) components.
- A is user's activity: the number of registration points for static (A_s) and motion (A_m) components.
- T is the session time.
- fps are frames per second, which represents the accuracy of the mouse trail.

3.1.4 User Rest Activity Index

This parameter is computed by dividing the user rest vector by the raw user rest vector. The former informs about the coordinates of the page on which the mouse was stopped (that means a null distance), and for how long there has been no movement. It is necessary to distinguish between real mouse pauses and normal mouse activity because of the mouse tracking accuracy: the higher the fps number, the more precise the mouse trail. Thus, the mouse movements were tracked at 24fps and a single pause was considered if time was greater than 0.5 seconds. In this way, we needed to measure the fraction of real pauses by using a raw user rest vector able store the whole mouse pauses and their absolute coordinates. Given the User Rest Activity Index, we compensate the Static and Motion Activity indexes with accurate results.

3.1.5 Number of Clicks

For a long time, and understood as an implicit indicator of user feedback, clickthrough data have been the subject of increasing popularity. We are taking into account the number of clicks and the moment (time) they were done. It is a good indicator about user activity, because impatient users use to click the mouse a lot of times in nearby time intervals.

3.2 Distances

The Euclidean distance between two adjacent mouse coordinates is measured. We computed the average distance both vertically and horizontally, the standard deviation and the full distances vector for each user. As proposed and defined in [9], the spatial-temporal outliers (STO) in the mouse tracking data sets are identified. STOs can lead to the discovery of unexpected, interesting, and implicit knowledge, such as local instability [9]. Besides, a vertical distances vector is measured, in order to discover user's navigational key strokes (up/down, pageUp/pageDown, spacebar) and the usage of the mouse wheel.

Experienced users generate higher mouse distances among registration points: they move faster and use the keyboard as well. This was checked visually in the HTML logs, where sparse registration points were displayed.

3.3 Position

As mentioned previously, this set of variables is used mainly to generate the web page model.

3.3.1 Entry and Exit Points

These are the indicators of where the user came and where she went, measured as mouse coordinates (x,y). The mouse trail is highly determined by the entry point, conditioning users to achieve their goals quickly or slowly. The exit point is an indicative of the destination of the visitor, i.e. what he was looking for or what made him leave the site.

3.3.2 Amplitude (Minimum and Maximum Mouse Coordinates)

It is a weak variability metric from a statistical point of view, because it discards every point inside its rank. However, it makes it possible to reveal the maximum mouse distance both in X and Y axes, which is a good indicator about the navigation window (browser size) and the user's routing (mouse displacement).

3.3.3 Relative Scroll Reach

This is a fraction of the page fold[1], both horizontally and vertically. Users often decide whether to stay or leave based on what they can see without scrolling [22]. In this regard, the relative scroll reach is very often a good indicator of users' interest and page relevance. It is computed as the maximum x and y coordinate divided by the browser effective size (usually less than the screen resolution, depending on the browser's toolbars and other artifacts).

[1] The page fold is a concept in web design referring to location of an item near the top of a web page, which can thus be viewed in a browser without scrolling.

3.3.4 Centroid

The centroid C of a mouse trail M is the intersection of all hyperplanes that divide M into N parts of equal moment about the hyperplane. It is computed as the arithmetic mean of all mouse coordinates c_i in M:

$$C_{x,y} = \frac{1}{N}\sum_{i=1}^{N} c_i \bigg|_{x,y} \qquad \text{(Eq. 2)}$$

We have previously said that it is a rudimentary clustering technique, but the main aim is that it enables us to quickly summarize the mouse path up to a single point of interest. We also compute the standard deviation of the centroid to provide an indicator of the data's dispersion.

3.4 User and Web page Models

Taking into account the above-mentioned parameters, the user classification model (UM) is considered within a features vector as follows:

$$UM = f(I_{s,m}, c) \qquad \text{(Eq. 3)}$$

Where:

- I is the index for static (I_s) and motion (I_m) components, compensated by the User Rest Activity Index (see Eq.1 and 3.1.4).
- c are the number of mouse clicks.

As far as it is concerned, the web page model (WM) is considered as follows:

$$WM = f(P_{e,l}, S_{x,y}, C) \qquad \text{(Eq. 4)}$$

Where:

- P is the mouse position when entering (P_e) and leaving (P_l) the page.
- S is the relative scroll reach both in X (S_x) and Y (S_y) axes.
- C is the centroid of the user's mouse trail.

4. IMPLEMENTATION AND RESULTS: A CASE STUDY

Firstly, the website in which our team was involved is described, because each site is unique and the target audience can vary noticeably. Secondly, the data acquisition process is merely overviewed, as the mouse tracking tool did all the hard work. Next, the process of analysis is explained in detail. And finally, the relevant conclusions are shown, as well as the decisions made before entering the re-design phase.

4.1 Website's description

The main subject of this website is studying actual and future trends in the Habitat sector. Thus, a wide range of different computer users is expected. The website's layout is a centered design with a fixed width of 790px (see figure 3). On the Web, users expect vertical scrolling [22]; but in this case all the content is shown above the fold. It was a designers' choice. On every page of the website the content is loaded inside a scrollable layer (no frames) of 430x400px above the navigation menu. The website's owners wanted to add some commercial advertisement, so two blank areas were saved at the top of the page.

4.2 Data acquisition

The tracking system was added to the production website's home page in earlier development states -the first three months-. Each time a user visited one page, she was selected randomly (true/false) to take part in the study (the mouse tracking was activated/inactive). In this way users' data were gained remotely and the website's usability was evaluated at a higher level of granularity. 5232 logs in XML format were selected randomly for the same web page, so the user sample is quite representative. The logs revealed that people used to enter the site between 9 a.m. and 8 p.m. These XML logs store useful information about mouse interaction (movements, clicks) and browser (such as screen size or operating system), among other kinds of data such as session time, URL and registration accuracy (measured in frames per second). These logs were processed off-line with a numerical matrix mathematics program. It is important to remark that this entire user's information is fully anonymous: tracking the mouse activity is our only concern.

4.3 Data analysis

4.3.1 Identifying STOs

Some users were marked as outliers and were discarded if their metrics' values were extremely unusual. For example, three users seemed to navigate on the site for more than 24 hours, which is illogical.

When computing user clicks two clear outliers also appeared: user #126 clicked the mouse 117 times and user #1788 clicked 64 times. So, they were not taken into account when computing the web page statistics.

4.3.2 User and Website's statistics

The following tables summarize the average (AVG) values and their standard deviation (STD) for all users.

Table 1. User Attention metrics

Parameter	*AVG*	*STD*
Session time (seconds)	7.10	9.04
Static activity	36.01%	28.27%
Motion activity	63.99%	28.27%
No. of Clicks	0.88	1.14

Table 2. Mouse Distances (in pixels)

Parameter	*AVG*	*STD*
Mean distance	4.94	1.62
Distance deviation	23.83	7.86
Mean vertical distance	2.60	0.93
Vertical deviation	13.55	4.69

Table 3. Mouse Position (pixels)

Parameter	*AVG*	*STD*
X position	480.54	234.15
X deviation	93.36	77.35
Y position	214.18	134.31
Y deviation	63.26	56.59
Horizontal amplitude	349.58	267.67
Vertical amplitude	237.30	192.95
X scroll reach	56.69%	25.56%
Y scroll reach	52.40%	30.45%
Entry X coordinate	441.68	246.81
Entry Y coordinate	173.06	130.72
Exit X coordinate	443.06	253.98
Exit Y coordinate	175.95	146.57

To maximize the user information entropy we have computed confidence intervals, by means of assuming normally distributed parameters and a probability of 99% (1-α = 0.99) given the standard formula[2]:

$$(\bar{x} - Z_{\alpha/2}\frac{\sigma}{\sqrt{n}},\ \bar{x} + Z_{\alpha/2}\frac{\sigma}{\sqrt{n}}) \qquad \text{(Eq. 5)}$$

This paper's case study analysis is based on the static activity index (see 3.1.3). To that end, the motion activity index (I_m) is computed as 1-I_s. Users on this website are thus categorized in three groups, as shown in Table 4. In order to assist the design team, most of the website metrics were plotted: the average amplitude and its standard deviation, the maximum scroll reach -average value plus standard deviation-, centroids, and the entry and exit uncertainty regions. These uncertainty regions were computed as ellipses centered in the average entry and exit coordinate, with width and height equal to their center's standard deviation horizontally and vertically, respectively.

Table 4. User classification. The average number of clicks is rounded in order to classify a next real user.

Passive	Normal	Active
$I_s > 36.92\%$	$35.10\% \leq I_s \leq 36.92\%$	$I_s < 35.10\%$
$c = 0$	$c = 1$	$c > 1$

[2] We use the sample mean x, a tabulated z-score $Z_{\alpha/2}$ (a value for the specific sampling error α in normal distributions), the sample standard deviation σ, and the population sample n.

4.4 Results

On this website users are most of the time moving (63.99%) relatively slow -mouse distance of 4.04px (SD = 23.83)- and use to click once -0.88 clicks (SD = 1.14)-. The average user also remains on the site about 7 seconds (SD = 9.04). As a consequence of this it can be stated that people scan the page, instead of reading the full content. We also noticed that the only logged operating systems were Microsoft Windows (89.18%) and Mac OS (10.82%).

Only 133 users needed to scroll vertically under the fold (the effective size of their browser window were less than 600 px vertically). Moreover, 198 users needed to scroll horizontally, these being perhaps mobile or PDA users. Thus, the suggested layout was a suitable starting point.

On this website, the average centroid is located at 480.54 px (SD = 234.15) from the left side of the page and 214.18 px (SD = 134.31) from the top of the page. The standard screen resolutions are XGA (1024x768px) and SXGA (1280x1024px). There were a 1.66% of the users that had either bigger or smaller screen resolution's size. Considering also that most users moved horizontally enough (64.62% of the users moved more than 50% of their browser size), we enlarged the layout up to 890px in horizontal (14% wider, see figures 3 and 4).

The Pearson's coefficient for user activity and tracking time on this website is 0.59, so there is a significant relation between, which is almost intuitive: regarding the user, the longer the time on the same web page, the greater the interest in the site. If users do not leave the page is because they feel that the content is relevant. The more interesting characteristic is that this relation is logarithmic, as computed and observed when plotting the graph (see figure 1). A similar slightly approach can be applied when evaluating the relationship between tracking time and number of clicks (Pearson's coefficient of 0.43).

People do not usually type the website's URLs or permalinks manually (only 445 users did it). Users handle on this website using the navigation menu (61.45% of the users visited other section of the website), and 516 users leaved the website by closing their browser window (see figure 2). In this respect, we suggested the design team that the navigation menu is the website's strongest point. It is the main way to access the site's information. Thus, the navigation menu was rearranged and somewhat tidied up, placing the companies' logos below the website's logo. If marketing manoeuvres were needed it is a good idea to place the commercial information (such as banner ads) inside the above-mentioned horizontal blank space at the upper left corner of the screen. The vertical blank space at the bottom right-part was filled with the background image to get a better visual appearance.

5. CONCLUSION

In this paper a straightforward technique based on mouse activity tracking has been introduced to remotely infer user's behaviour on websites. Both user and web page models were created from a statistical analysis of the mouse tracking data, using the average activity of thousand users. These models were used to assist the design team and make some suitable corrections.

Our collaborative analysis has been carried out off-line, just because of the fact that the mouse tracking tool was designed for this goal, so the next logical step is to implement the gesture inference system on-line, in order to develop a self-adapting user interface. This is one of our lines of research work at present. If developed properly, the self-adaptation of the website's user interface is a powerful approach which can lead to a better user experience. Thus, it is possible to customize and render parts of the website's interface, such as changing the width/height of some critical elements or varying the text's font size, for each user's gestures (individual sessions) or for the entire website (collaborative sessions). However, a database on the server side is mandatory because it is important to handle thousands -maybe millions- of user logs simultaneously. But this is not a big concern, since the vast majority of web hosting providers usually offer a database service for their clients. Thus, the big challenge is to compute the users' stats using all mouse tracking logs on-line. A somewhat rough but fast approach is to update the user model when each log is added to the database, instead of re-computing all metrics every time a new user enters the site. For the web page model, it is possible to apply some robust clustering algorithm for the mouse trails, like *k*-means, or even study a probabilistic model based on Markov Models. In general, more statistical analysis can be carried out by using these users' data, therefore enriching thus the study of users' activity on websites.

An inherent limitation is that we have made predictions about the behaviour of an average user from observing many users. The fact is that user modeling-related data changes constantly [2]. New users may appear, and new items may be introduced. Additionally, it is often the case that the behaviour of users changes over time, so must we do the user interface design and analysis, since both stages are iterative. Hence, another interesting line of research may be the time-series analysis of user activity.

We have confirmed some empirical results achieved in previously published usability tests and research papers -such as the fact that people usually scan web pages-. Yet, in this paper we have assigned quantity values to several user metrics, thus modelling user activity and dealing with statistical parameters. Assuming that poorer data than those provided by both eye trackers and traditional usability tests are collected, it is possible to massively increase the number of participants, without being necessary to either schedule or observe them, therefore reducing time and cost. Furthermore, this tool can work also as a complement to the above-mentioned eye-tracking systems and usability tests, not as a supplement, because users first focus their attention and then execute actions. In short, this statistical analysis methodology has helped us to go one step beyond when evaluating both website's interactivity and user's behaviour. The fact is that both velocity and time are successfully taken into account in order to provide new information regarding usability evaluation on websites.

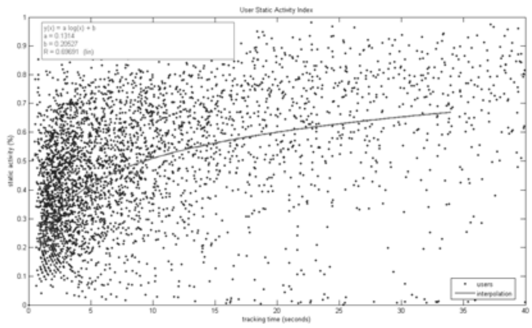

Figure 1. Users' Static Activity Index: Tracking time (X axis), in seconds, and static activity (Y axis), in percentage. Each dot represents a user. The logarithmic interpolation is $y = 0.131 \cdot \log(x) + 0.205$.

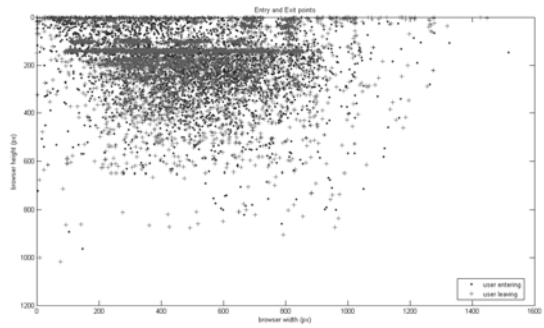

Figure 2. Entry and Exit points: Browser width (X axis) and height (Y axis), in pixels. The navigation menu can be visually identified, as well as the mouse activity in the top part of the browser.

Figure 3. Website as it was designed initially.

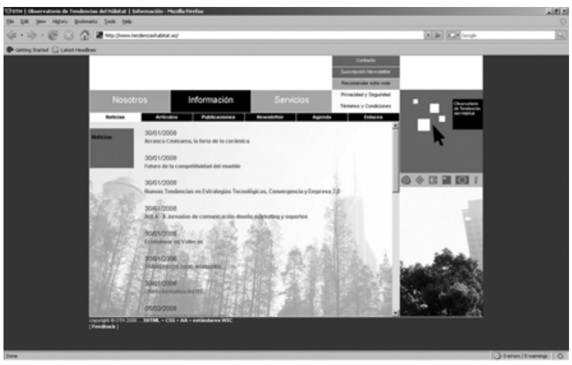

Figure 4. Website's redesigned layout.

REFERENCES

1. Aberg J. and Nahid S., 2001. User Modelling as an Aid for Human Web Assistants. *Proceedings of the 8th International Conference on User Modeling*. Sonthofen, Germany, pp 1-3.

2. Albrecht, D. and Zukerman, I., 2007. Introduction to the Special Issue on Statistical and Probabilistic Methods for User Modeling. User Modeling and User-Adapted Interaction. *Lecture Notes in Computer Science*, Vol. 17, No. 1-2, pp 1-4.
3. Arroyo, E. et al, 2006. Teaching User Interface Design using a Web-based Usability Tool. *Proc. CHI*. Quebec, Montreal, Canada, pp 2-4.
4. Atterer, R. et al, 2006. Knowing the User's Every Move - User Activity Tracking for Website Usability Evaluation and Implicit Interaction. *Proceedings of the 15th International Conference on WWW*. Edinburgh, Scotland, pp 2-9.
5. Brusilovsky, P., 2002. From Adaptive Hypermedia to the Adaptive Web. The Adaptive Web. *Lecture Notes in Computer Science*, Vol. 45, No. 5, pp 30-33.
6. Brusilovsky, P., 1996. Methods and Techniques of Adaptive Hypermedia. User Modeling and User Adapted Interaction. *Lecture Notes in Computer Science*, Vol. 6, No. 2-3, pp 87-129.
7. Carmagnola, F. et al, 2007. User Modeling in the Social Web. Knowledge-Based Intelligent Information and Engineering Systems. *Lecture Notes in Computer Science*, Vol. 4694, pp 745-752.
8. Chen, M. et al, 2001. What Can a Mouse Cursor Tell Us More? Correlation of Eye/mouse Movements on Web Browsing. *Ext. Abstracts CHI*. Seattle, Washington, USA, pp 281-282.
9. Cheng, T. and Zhilin, L., 2004. A Multiscale Approach to Detect Spatial-temporal Outliers. *Proc. ISPRS*. Istanbul, Turkey, pp 1-5.
10. Do M., 2006. *Fundamentals of Signal Processing*. Online book. Available at: http://cnx.org/content/col10360/1.3/pdf
11. Gams, E. and Reich, S., 2006. *An Analysis of the Applicability of User Trails in Web Applications.* Journal of Web Engineering, Rinton Press, Paramus, New Jersey, USA.
12. Gena, C., 2003. Evaluation Methodologies and User Involvement in User Modeling and Adaptive Systems. *Proc. HCItaly*. Torino, Italy, pp 1-5.
13. Gena, C. and Weibelzahl, S., 2007. Usability Engineering for the Adaptive Web. Adaptive Web-Based Systems. *Lecture Notes in Computer Science*, Vol. 4321, pp 720-762.
14. Goldberg, J. H. et al, 2002. Eye Tracking in Web Search Tasks: Design Implications. *Proc. ETRA*. New Orleans, USA, pp 51-58.
15. Hollink, V. et al, 2007. Discovering Stages in Web Navigation for Problem-oriented Navigation Support. User Modeling and User-Adapted Interaction. *Lecture Notes in Computer Science*, Vol. 17, No. 1-2, pp 183-214.
16. Hollink, V., et al, 2007. Navigation Behavior Models for Link Structure Optimization. User Modeling and User-Adapted Interaction. *Lecture Notes in Computer Science*, Vol. 17, No. 4, pp 339-377.
17. Joho, H. et al, 2007. Interaction Pool: Towards a User-centered Test Collection. *Proc. WISI/SIGIR*. Amsterdam, The Netherlands, pp 17-20.
18. Kobsa, A. and Fink, J., 2006. An LDAP-based user modeling server and its evaluation. User Modeling and User-Adapted Interaction. *Lecture Notes in Computer Science*, Vol. 16, No. 2, pp 129-169.
19. Leiva, L. A. and Vivo, R., 2007. (smt) Real Time Mouse Tracking Registration and Visualization Tool for Usability Evaluation on Websites. *Proc. WWW/Internet*. Vilareal, Portugal, pp 187-192.
20. Mueller, F. and Lockerd, A., 2001. Cheese: Tracking Mouse Movement Activity on Websites, a Tool for User Modeling. *Ext. Abstracts CHI*. Seattle, Washington, USA, pp 1-2.
21. Nielsen, J., 2004. *Capturing Thoughts, Capturing Minds? - from Think Aloud to Participatory Analysis*. Working Paper No. 14-2004. Department of Informatics. University of Copenhagen, Denmark, pp 2-5.
22. Nielsen, J., 2005. *Scrolling and scrollbars.* Alertbox, July, 11, 2005. ISSN 1548-5552. Online resource. Available at: http://www.useit.com/alertbox/20050711.html
23. Norman, K. L. and Panizzi, E., 2006. Levels of Automation and User Participation in Usability Testing. *Interacting with Computers*, Vol. 18, No. 2, pp 4-5.
24. Pan, B., Hembrooke et al, 2004. The Determinants of Web Page Viewing Behavior: An Eye Tracking Study. *Proc. ETRA*. San Antonio, Texas, USA, pp 3-6.
25. Parackal, T., 2005. *Web Site Personalization: Data Mining and Web Housing.* StylusInc Pvt. Ltd. Online resource. Available at: http://www.stylusinc.com/website/personalization.htm
26. Razmerita, L. et al, 2003. On the Role of User Models and User Modeling in Knowledge Management Systems. *Proc. HCI*. Bath, England, pp 1-5.
27. Rodden, K. and Fu, X., 2007. Exploring How Mouse Movements Relate to Eye Movements on Web Search Results Pages. *Proc. SIGIR*. Amsterdam, The Netherlands, pp 29-32.
28. Torres, J. M. and Parkers, A. P., 2000. User modeling and adaptivity in visual information retrieval systems. *Workshop on Computational Semiotics for New Media*, University of Surrey, UK, pp 1-5.
29. Wood, M., 2005. Bootstrapped Confidence Intervals as an Approach to Statistical Inference. Organizational Research Methods, *SAGE Journals*,Vol. 8, No. 4, pp 454-470.