Neurocomputing 168 (2015) 179–189

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Combining eye tracking and pupillary dilation analysis to identify Website Key Objects

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ARTICLE INFO

Article history:
Received 30 December 2014
Received in revised form
24 May 2015
Accepted 30 May 2015
Communicated by V. Palade
Available online 12 June 2015

Keywords:
Eye tracking
Pupillary dilation analysis
Web usage mining

ABSTRACT

Identifying the salient zones from Web interfaces, namely the Website Key Objects, is an essential part of the personalization process that current Web systems perform to increase user engagement. While several techniques have been proposed, most of them are focused on the use of Web usage logs. Only recently has the use of data from users' biological responses emerged as an alternative to enrich the analysis. In this work, a model is proposed to identify Website Key Objects that not only takes into account visual gaze activity, such as fixation time, but also the impact of pupil dilation. Our main hypothesis is that there is a strong relationship in terms of the pupil dynamics and the Web user preferences on a Web page. An empirical study was conducted on a real Website, from which the navigational activity of 23 subjects was captured using an eye tracking device. Results showed that the inclusion of pupillary activity, although not conclusively, allows us to extract a more robust Web Object classification, achieving a 14% increment in the overall accuracy.

1. Introduction

With the Web as the biggest information platform ever known, the process of optimizing its access and understanding has gained enormous relevance. One of the main tasks of this challenge deals with the delivery and presentation of the information, specifically, how to display Web content in an effective way that contributes to user engagement [1].

This has several implications. From a purely content-centric point of view, both accessibility and visibility play an important role in the dissemination of the information [2]. Similarly, from a commercial point of view, having an estimation of the user's preferences could contribute to personalize the purchasing experience and maximize profit [3].

Identifying *salient* zones, which means capturing which parts of a Web page receive more attention during each visit, is a key aspect for understanding users' preferences [4]. Several applications can be built on top of that information, such as ad-hoc Website re-design or compact information representations, especially for mobile environments [5].

Historically, detecting and quantifying users' attention has been carried out by mining Web user sessions, both reactively (using Web logs) or proactively (tracking the user in real time through client-side monitoring artifacts) [6]. Unfortunately, these approaches have limited effectiveness and they basically provide an estimation of user interest solely on a navigational path basis, but they are not capable of specifically showing user interests within the set of elements that compose a Web page [7,8]. This level of specificity is necessary to find the underlying factors that drive users to certain behaviors, for instance, the decision-making process of hyperlink clicking or signing up for a service or product.

Additionally, the advance in Web engineering disciplines has added more complexity to the tools used for both developing and foraging the Web. Web browser functionalities have contributed to enriching the visitor's experience, giving the users several options and tools, such as multiple page visualization, back button and collaborative navigation. These have represented a challenge in terms of identifying a pure session for analysis [9]. Another aspect to consider is the evolution of the Websites themselves, which have passed from hierarchies of plain pages to uniform *Web apps*, where transitions are not usually used or not even necessary [10]. The most visited Websites these days rely on client-based

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http://dx.doi.org/10.1016/j.neucom.2015.05.108
0925-2312/

Javascript to provide a more interactive information display [11]. Under this new scenario, it seems more and more difficult to extract user behavior by just using a standard log analysis.

From a performance point of view, since the main goal of Web browsers is to provide better navigation through faster page loading, several content caching and pre-loading techniques have been implemented, resulting in noisy logs which are difficult to process. Finally, the combination between client and server side technologies led to the widespread use of AJAX (Asynchronous JavaScript + XML), which allows asynchronous calls to be performed. Although it has improved the overall usability, it has also further blurred the concept of *user session*, as it is now harder to distinguish transitions. For example, the system could request asynchronously certain content or data to show proactively to the user, which does not represent an explicit request by the user.

Given the issues outlined above, there is a real need to overcome the current difficulties by evolving Web mining research to be consistent with the current state of the Web. One feasible direction is related to the analysis of the human response to graphical interfaces, in the sense of monitoring how the content and structure impact user behavior [12].

The literature presents the use of neuro data-based approaches [13–15] for tracking the user's interest, specifically by means of visual gaze analysis tools [16], such as eye-tracking devices, to identify salient elements. Buscher et al. have conducted several experiments to find salient objects using the concept of *fixation impact* [13]. In an attempt to combine both Web log-centric mining techniques and visual gaze analysis, Velásquez et al. [4] developed the concept of Website Key Objects (WSKO), which are the set of Web objects that attracts user attention and characterize the content of a Web page. This approach takes into account time and frequency of fixations to infer the subset of elements that represent interest. Although it has shown promising results, it presents the following issues:

- *Web object mapping*: The methodology for identifying WSKO consists of grouping Document Object Model[1] (DOM) elements into *Web Objects* that are both semantically and spatially close. For example, a picture and its associated text paragraph are handled as just one entity, since their combined semantic value enriches the user's understanding. Defining the rules for grouping is a challenging task, as different configurations lead to different sets, and several criteria could be used.
- *Time spent on objects*: The identification of Web Objects should be understood in its *Web session* context. In that sense, a user follows a sequence of Web pages which may contain overlapping sets of Web Objects. Then, a Web Object that represents a menu or header (or any structural item) will appear several times. On the contrary, a Web Object associated to specific content may appear just once during the entire Web session. Therefore, some elements might be over represented just because they appear more frequently, which does not necessarily imply that they are perceived as more interesting to the users.

In this work, a major re-design of the WSKO methodology is proposed to overcome the current issues and improve the analysis by incorporating new sources of data. The key contributions are the following:

Pupillary dilation impact: Although visual gaze represents the most direct source for analyzing a user's response, so far the impact of pupillary dilation has remained unexplored in Web Mining research. The main reason could be the complexity involved in both the extraction and analysis of pupil dynamics over time. In this work, we explore the feasibility of using the dynamics of the pupil to improve the identification of WSKO. The main assumption is the apparent pattern that appears in the pupil just before the fixation on a specific zone of interest for the user. We can visualize this phenomenon in Fig. 1, where there is a contraction followed by a dilation around the fixation time. We studied if this additional source of data can contribute to increase the accuracy of the WSKO methodology.

Normalized frequency filtering: The frequency of the appearance of Web Objects within the Website is uneven, basically because some of them, such as menus and headers, belong to the Website structure. On the other hand, content-related objects such as specific paragraphs or pictures may appear just once during the entire session. Therefore, in order to generate a fair ranking, it may be necessary to normalize their frequency before computing any attention-based score. We took inspiration from the Tf-Idf techniques used in Text Mining to generate a metric that provides a normalized frequency score for each Web Object. With this improvement, Web Objects can be compared and ranked in a more effective way, giving more relevance to the content.

In order to test the proposal, an empirical study was conducted using a real Website from which the activity of 23 subjects was recorded. We focused on finding answers to the following research questions:

- Does the addition of the pupillary activity improve the approach by Velásquez et al. [4] in terms of WSKO detection?
- Does a frequency-based weighting filter improve the classification accuracy?

The results reported in this paper allowed us to conclude that including pupillary activity dynamics as a set of new features increases the accuracy of the identification of salient zones (WSKO) by 14% on average. Additionally, better results are obtained when the fixation frequency among Web objects is weighted to decrease the over representation of structural elements. In this case, the gaining is on average 19%.

2. Related work

The literature provides several examples of how neuro data has been applied to enrich Web user analysis [14,15,17–19]. The following is a summary of the most important cases, based on the level of generalization and the novelty provided.

2.1. Salient Web Object identification

One of the most remarkable lines of research has been developed by Buscher et al. [13]. The main motivation comes from the need for understanding how people allocate visual attention on Web pages, taking into account the relevance of this for both Web developers and advertisers.

A study from 2009 performed an eye tracking-based analysis in which 20 users were shown 361 pages while performing information foraging and inspection tasks [13]. The main assumption was that gaze data could represent a proxy of attention. From that, an analysis framework was developed by first generating a tool that allows DOM elements to be characterized and a mapping performed between gaze data and the DOM elements. The second part involved the use of machine learning techniques to predict salient elements on a Web page. In this study, the concept of *fixation impact* is introduced. It allows the identification of which elements are under the gaze of the user at a certain time. It follows empirical studies that show that human vision is characterized by

[1] http://www.w3.org/DOM/.

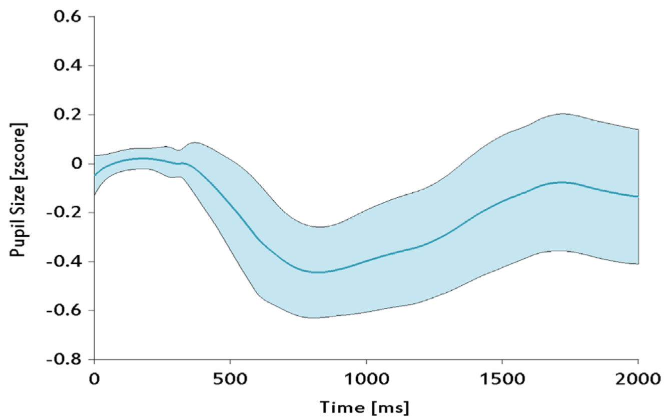

Fig. 1. Signal example with associated confidence interval.

a narrow window of high acuity along with the standard gaze area. Thus, when visualizing an element, it means that other elements in the surroundings are also being considered. Therefore, given a fixation point, a DOM area is selected in order to identify every element within it [20]. A distance score is given to each element based on its coverage, assuming a Gaussian distribution. The fixation impact is computed using this distance and also incorporating a time dimension, which means the fixation duration. The information obtained in the previous step is used to predict salient elements. After performing a selection of the 10 features that provide the highest information gain, Linear Regression was used in order to identify the measures that most influence the fixation impact scores. The results showed that positional features obtained the highest weights.

Another line of research has been developed by Velásquez et al., where the main goal is to identify the most relevant elements on a Website by using the concept of Website Key Objects (WSKO) [21]. A Website Object is considered as any group of multimedia elements that are present on a Web page and that are close both semantically and spatially. Then, from that definition, a WSKO is a Web Object that attracts users' attention and that characterizes the content of a page or Website. The identification of the WSKO involved primarily the analysis of Web logs and a measure of time spent. In order to validate the findings, surveys were conducted, which do not provide a strong level of confidence for the results. The authors addressed this issue, and in [4] they incorporated eye-tracking methodologies to replace the use of surveys. They were thus able to validate the approach by having an objective measure of user attention.

2.2. Implicit feedback retrieval

In [22], Buscher et al. explore the application of eye-tracking techniques for the analysis of user behavior on search engine result pages. In this study, the idea of generating *implicit* feedback through eye tracking is analyzed. Eye gaze data is studied in order to capture which parts of the document were read and which ones were relevant to the user. Additionally, the concept of *attentive documents* is introduced, which means documents that keep track of how they are being consumed by the users, and based on the results generate personalization tasks. This concept is based on previous studies, such as Ohno [23] and Xu [24] where the idea of *intensity* is related to the fixation duration. The use of implicit feedback is interesting as it does not burden the user and does not interfere with his activities. This type of feedback is captured by analyzing user interactions with the system under study and then analyzed to perform certain assistive actions.

2.3. Pupil activity as a proxy for attention

The relationship between user behavior and pupillary dilation has been an important study subject since Eckhard Hess suggested the correlation between mental activity, such as perception and information processing, and pupillary response [25], leading to an increase in research on this particular subject. Some of the most important conclusions and results obtained through the years are presented as follows.

2.3.1. Pupil size and mental activity

The correlation between mental activity and pupil response was first shown by Hess and Polt [26] through a mental multiplication test. They asked the participants to mentally calculate the result of a multiplication of two factors, increasing the difficulty from two factors with just one digit to two factors with two digits each, with the results showing the relation between difficulty level and pupil size. The range of size increase was between 4% and 30% during the period between pre-question to pre-answer, decreasing immediately after the answer was given. Thus, this result shows that pupil activity reflects the information processing load produced by cognitive tasks. Later, Polt in [27] used electric shocks as a threat for incorrect answers on the same test. This resulted in increased amounts of effort to solve the problems, and as a consequence, in greater pupillary dilation. Later, in [28], Beatty concluded that the amplitude of the task-evoked pupillary response (TEPR) is an index of a common factor related to the cognitive demands of memory, language processing, reasoning and perception. In fact, pupillary responses have proven to be very important indicators of mental efforts involved in task resolution.

2.3.2. Perception

Perception has been related to pupil size through various approaches. In [29], Kahneman and Beatty tried to relate the difficulty encountered by subjects in a pitch discrimination test with pupillary dilation. The participants had to judge whether the tone presented was higher or lower than the standard tone. In the cases where the difficulty in distinguishing between the two became greater, participants showed greater dilation. In another experiment, Hakerem and Sutton in [30] measured pupillary response to a barely perceptible threshold visual stimulus. When the light flashes were not detected or when the subject was not asked to detect, pupillary dilation did not occur. When they were required to detect whether a flash was present or absent, or when they correctly discriminated a flash, pupillary dilation occurred. Similar results were obtained by Beatty in [31] when participants were asked to detect a weak tone only present in half of the trials. In this case pupil dilation occurred only when the subjects detected the presented signal. Beatty's conclusion was that pupillary dilations reflect changes in nervous system activation due to perceptual processing and the difficulty of the task.

2.3.3. Information processing, learning and pupil size

Poock in [32] concluded that pupil diameter was related to information-processing speed. Firstly, he determined a maximum processing capacity by making the subjects press buttons corresponding to displayed numerals as fast as possible. Then he made the participants process numerals at different percentages (between 50% and 125%) of maximum capacity. When the subjects were required to process information at 75% and 100% significant increases in pupil diameter appeared. However when the requirement was raised to over 100–125% of capacity, pupillary constriction occurred.

In another study, Peavler in [33] required 14 college students to reproduce a string of digits after hearing them, varying the size of the string between 5, 9 and 13 characters. A trend toward increased pupil size with each successive digit in the five and nine digit conditions was noticed. The experiment also showed the dilation leveled off immediately after presentation of the 10th digit in the 13-digit string. These results suggested that the information processing effort was momentarily suspended at that instant. In this experiment, nine digits was approximately the short-term memory capacity of the subject, and correspond to the point of no further dilation. Even when Peavler and Poock got similar results for the first parts of their experiments (more processing load corresponded to a larger pupil size) they disagreed about what happens afterwards, when there is an overload.

3. Methodology for Website Key Object identification

In this section, we present an overview of the current methodology for WSKO extraction [4], highlighting its advantages, but also its limitations. In the next section we will describe how to incorporate pupil dilation data to improve the WSKO methodology.

The initial concept from which the whole proposed methodology was derived is the *Web Object*, defined in [21] as a *structured group of words or multimedia content that is present on a Web page, and which has metadata describing its content*. Therefore, a Website is composed of a group of Web Objects, which are displayed in a fixed structure. The metadata of each element is relevant in the sense that it could allow the computation of an objective semantic comparison between them, using a standard distance metric.

Subsequently, a subset of the Website Objects is identified as *Website Key Objects*, which specifically characterize the content of a Web page. Additionally, they attract the attention of the users, as they represent the set of salient objects. The identification of this subset represents an important opportunity in terms of the knowledge that could be captured, which can be used to understand the users' interests and information foraging habits. It must be noticed that this approach assumes the full availability of the Website content and structure and access to the activity registered in the Web logs. The methodology consists of the following steps:

3.1. Sessionalization

Given a set of Web logs for the time interval under study, a sessionalization process is performed in order to identify the sequences of pages visited by the audience. A sessionalization is basically a methodology for dividing the full set of logs into logical chunks that represent the path followed by each user. There are several ways to conduct such a task, most of them involving heuristics that handle the temporal and content-based features from the logs.

For this study, any reactive type of sessionalization could eventually be used for this purpose as long as it provides a robust estimation of the sequence of visited pages with its respective time identification. Examples of sessionalization methods include time-based heuristics, Web structure-topology based and semantic-centric methods [21].

Therefore, the input of this step is the Web log file for the chosen time under study, and the output is, for each visitor, the sequence of pages he visited, expressed by a page id and a time stamp.

3.2. Web Object identification and metadata addition

The second step is to analyze the Website and extract the set of Web Objects from each page. A *Web Object* is defined as a content entity that comprises a concept or idea. Therefore, it could be represented just by a single DOM element, such as an image or a title, or by a set of DOM elements, for example, a title combined with a paragraph and/or image, all of them sharing the same content and collaborating in giving the user a more comprehensive understanding of the content on the Web page.

Therefore, a critical question is how to identify the set of Web objects within a specific Web page, or how to group elements into truly meaningful sets. There is no definitive approach to this issue. One possibility is to extract certain semantic features from each DOM element present on the Website, and then try to group them based on a semantic similarity metric and at the same time consider spatial properties (i.e., the elements need to be neighbors).

The above approach, although straightforward, is not feasible in real world Website architectures as it is assuming that the HTML code is valid and well structured, and also that each DOM element has associated semantic properties. Unfortunately, those characteristics are rarely present on real Websites.

In this work we performed a fully human based Web Object identification, in which each Web page from the Website under study is presented to an expert (a former Web Engineer) who has a high level of affinity with the target Website, in both technical and content aspects.

The expert is asked to manually, based on visual exploration, group the DOM elements and generate a set of Web Objects for each page. Although this approach has several limitations in terms of scalability and the explicit subjectivity of the group selection, it at least provides a feasible notion of how the Website was structured in terms of the content layout. Additionally, as the expert had been maintaining the Website for a relevant period of time, he has a good estimation of how the client wants the content to be presented.

Once the group of Web Objects has been identified, they need to be associated with a concept, in order to make them comparable. Again, a scenario where each DOM element has a predefined semantic value is not assumed. Therefore, for this task a group of people from diverse backgrounds was gathered and for each Web Object they were asked to associate a group of concepts from an ad hoc fixed set. For example, if the Website under study is related to a topic such as *Economy*, the group of people need to choose from a set of Economy-related concepts. The requirement included ordering the concepts in a decreasing fashion. Therefore, the first element represented the concept the user considered to be the closest to the Web Object. The results were validated with the Web Engineer currently in charge of the Website.

Although this does not demonstrate a fully representative result, the validation performed showed that the concept association was satisfactory, as the number of object considered mislabeled by the expert did not surpass 4%.

Therefore, the input of this step is the content of each Web page, and the output is, for each Web page, the set of Web Objects. Each defined Web Object is associated to a list of ordered concepts.

3.2.1. Web Object similarity

Given the resulting set of Web Objects, each one with a concept vector associated, an edit distance was designed for comparison. Each Web Object o_i contains $|o_i|$ associated concepts, which are taken from a predefined set of M concepts, $o_i \rightarrow c_k^i, k \in \{1, \dots, M\}$. The distance between two Web Objects is defined as follows:

$$d(o_i, o_j) = 1 - \frac{L(o_i, o_j)}{\max\{|o_i|, |o_j|\}} \tag{1}$$

where $L(o_i, o_j)$ is the *Levenshtein* distance between the concept strings associated with each object. The use of an edit distance such as Levenshtein might seem counter-intuitive, as a more natural comparison should basically consider the overlap between vectors. But as the concept vectors have an explicit order, in the sense that the first element is more relevant than the second, and so on, an edit distance could take advantage of that and generate more accurate comparisons.

3.3. Time spent on Web Object

Using an eye-tracking device, it was feasible to obtain the time spent on each Web Object, as each Web Object has a fixed position on the Web page. The eye-tracking device provides a 2-D position point (x,y) associated with a time stamp (for each eye), giving a estimation of the fixations carried out by each user on the different areas of the Web page. Therefore the calculation of the time spent is simply the cumulative time the eye coordinates provided by the fixations were within the region encapsulated by the vertex of the associated Web Object.

Given the above process, now each Web Object on each Web page contains a metric of the time spent by a user. This value is computed for each user independently, allowing us to add this information to each session.

3.4. Important Web Object Vector

In other to characterize each session not only in terms of the pages visited, but also in relation to the elements that the associated user was focused on, the concept of Important Web Object Vector is defined.

Suppose a given session s_i that contains $|s_i|$ pages. Each page in $|s_i|$ contains a set of Web Objects, which now have associated a time spent value. The next step is to sum the times for each Web Object across the pages in the session (as one given Web Object could appear in more than one page, for example, certain navigational elements such as menus or headers). After this, each session will have associated a list of *seen* Web Objects. This list must be ordered in a time decreasing fashion. We define a threshold, namely the n first Web Objects and store them in the new vector called Important Web Object Vector (IOV), such as $IOV = [(o_1, \tau_1), \ldots, (o_n, \tau_n)]$, where o_i represents an object and τ_i is its associated cumulative time spent, for a particular Web session.

The above process leads us to obtain a more compact representation of the interest of the user in each session, along with a objective metric represented by the time spent. Therefore, from now, we can associate each Web user session with an IOV.

3.5. Web user session clustering

In the previous methodologies for identifying Website Key Objects, the main objective was grouping the user behavior vectors using three different techniques. The results of these techniques gave different sets of vectors, where their inner components were similar among themselves but different comparing them with the other sets. The criteria for selecting the Website Key Objects were to select the Web Objects which appeared more times in the set of vectors after applying the techniques.

3.5.1. Distance metric

To perform the necessary grouping process, it is necessary to define a distance metric. In this case, given that α and β are two IOV associated to different sessions, the following metric is proposed:

$$st(\alpha,\beta) = \frac{1}{i} * \left(\sum_{k=1}^{i} \min\left(\frac{\tau_k^\alpha}{\tau_k^\beta}, \frac{\tau_k^\beta}{\tau_k^\alpha} \right) * d(o_k^\alpha, o_k^\beta) \right) \quad (2)$$

where τ_k represents the time spent on a specific Web Object for a given session, and o_k represents a Web Object in the k position in a IOV.

3.5.2. Clustering techniques

SOFM: SOFM, the Self Organizing Feature Maps (also known as Kohonen Maps) are a type of artificial neural network that uses an unsupervised learning algorithm which allows mapping high-dimensional elements into a grid of a few (usually two) variables, called a map. These kinds of artificial neural networks are different from the classic ones in the sense that they use a neighborhood function to preserve the topological properties of input space. See [34] for a comprehensive explanation.

K-Means: This algorithm allows the grouping of data into K clusters where the objects in a cluster are more similar to other objects in the same group (homogeneous) than when compared with the objects in the other clusters (heterogeneous). This algorithm works using a *top-down* approach as it starts with a specified number of groups and later assigns the patterns to each one of them. See [35] for a comprehensive survey.

Association Rules: Association Rules is a method for finding meaningful relationships among variables in large sets of data [36]. If it is applied in the proper way, it can be used for "clustering" while attempting to understand the links or associations between the different variables or attributes of the group. For selecting the rules from all possible sets of rules well-known constraints such as minimum threshold, support and confidence can be used. The *support* of a rule ($supp(X)$) is defined as the proportion of transactions in the data set which contain the itemset. The *confidence* of a rule is defined by the equation $conf(X \Rightarrow Y) = supp(X \cup Y)/supp(X)$.

4. Pupillary dilation influence

In this section, we propose a way to incorporate the pupillary dilation data into the WSKO identification process. The main goal is to test if this addition can improve the overall effectiveness of the methodology, in terms of the average accuracy.

As explained in the previous section, the last step in the standard Website Key Object identification process is the clustering of the session represented not as simple navigational paths, but in terms of the Web Objects seen during the session and weighted by the time of the users fixations.

While there could be several ways to incorporate pupil information into this process, we chose a simple way that could allow us to understand in a clear way the influence and also visualize further and more complex extensions. Our proposal is to associate pupillary dilation activity to each Web Object present in the IOV. Then, use this new source as a group of new features for the clustering process. Therefore, our guess is that adding this additional information, the clustering step in the WSKO identification will lead to different results, which eventually could be more accurate.

In order to explore the real impact of the addition of pupillary dilation, we propose to compute the results for both approaches and then compare their accuracy against the expert-annotated data set:

- A Web behavior only-based clustering, taking into account the frequency of visits and time spent on objects (gaze-wise), which is the standard implementation of the WSKO process.
- A pupil signal extended approach, which is assumed to hold information ignored by the first approach but at the same time making a trade off on robustness as other pupil-changing factors aside from the studied phenomena are present, cognitively and physiologically (e.g. light intensity).

4.1. Pupillary dilation-Web Object association

To generate a representative signal for each Web Object, we must consider all the subjects that, during his/her session, generated a fixation on it. Therefore, an average for each subject is calculated, followed by the aggregated average for all subjects.

Every signal is preprocessed by linearly interpolating blinking and fixing offset produced by saccades. Then, it is filtered by a 2 Hz, one-pole Butterworth low-pass filter to remove noise. Experiments showed that base pupil values in response may differ greatly from subject to subject. To make signals easier to compare between subjects, the z-scored signal is used. Finally, a minimum time threshold of 500 ms spent inside the object is implemented as a way to avoid possible signal contamination by a previous object (i.e. contraction and/or dilation from a previous Web Object appearing in the next Web Object).

The result is a signal of the aggregated average of subjects for each observed Web Object where the first 500 ms are ensured to be spent inside the object and the last 500 ms, in the worst case, were spent outside, but because of the slow contraction–dilation latency observed as the pupil reaction (contraction after 500 ms object onset) the second half of the signal is still treated as part of the reaction. Following the same criteria, if a contraction was found outside a (300,700) ms window, then the signal is rejected as contaminated by the free-exploring nature of the experiment. Although a full average of every subject could have been optimal, objects are seen only by a few, and thus a minimum subject requirement is imposed, where 63 objects were observed to hold a subject count greater than five.

Each signal is then compressed into a set of five patterns: pupil contraction difference (*contDiff*) , contraction velocity (*contVel*), contraction–dilation time latency (*cdLat*), dilation velocity (*dilVel*) and dilation difference (*dilDiff*), resulting in a five-featured vector of patterns for each Web Object. Their onset frequency (*freq*) and *time* are included in the feature vector. Initial exploration shows that these two vectors are themselves separated components, where high time and low frequency objects (or vice versa) are scarcely seen, and low time/low frequency objects are a majority. A first approach will take into account only these two characteristics to review which objects fall into the high time or high frequency side, as they could be a first approach toward the characterization of WSKO, since both characteristics contribute to fixation regions which are often related to saliency maps or regions of importance in general.

5. Empirical study

In order to test if the pupillary activity influences the identification of salient elements in a Web site, an ad hoc experiment with a real Website was performed.

The main criteria used for the selection of the Website were that the intended audience could be as general as possible, hoping to provide the level of heterogeneity necessary to validate the results. Among the set of candidate Websites, the one belonging to the MBA program offered by the University of Chile was selected.[2] This Website functions basically to present detailed information about the academic program, including the description of the academic program and faculty. From the technical perspective, the Website is built on top of the Wordpress[3] content manager, which may reflect a high quality in terms of HTML output.

5.1. Web data preprocessing

The first step was to ask the Web developer to group the HTML elements of each Web page into Web objects [37]. The resulting set and the respective components of each Web Object were stored in a database, including its cumulative size and position on the page layout. A unique identifier was also added.

Subsequently, the set of resulting Web Objects was passed to several volunteers with different backgrounds. The task assigned was to associate each Web Object with concepts from a predefined list. The number of concepts that a volunteer could use was variable and the only requisite was that the list must be ordered: more relevant concepts have to be in the top positions in the list. The output of this process allowed us to obtain a concept vector for each Web Object based on the average frequency.

5.2. User behavior data extraction

For the study presented in this paper, 23 subjects were asked to participate. Each participant was equipped with an Eyelink eye-tracking device and was set free to navigate through the Website. The experiment did not have a time limit and no specific instructions were given to the subject, therefore just exploratory behavior was expected.

For each Web page visited, the subjects spent time according to their own free will. When they realized they had gotten an overview of the content or considered that there were not more interesting things to look at, they passed to the following page. No *back button* functionality was allowed in order to avoid excessive data duplication.

Once the experimental part was finished for each user, a testing procedure was performed to ensure the optimal synchronization between the Web data, represented by Web log activity, and the neuro data, represented by eye gaze activity. If the above process is successful, the final step is performed, which consists of assigning for each Web Object in each Web user session, the physiological features extracted from the eye-tracking device, which will be used as the main features for the WSKO identification.

5.3. Feature engineering and filtering

Web Objects tend to decrease exponentially in terms of subject quantity visualization (number of participants that actually generated a fixation on that Web Object) and thus a minimum subject quantity of 5 was imposed (see Fig. 2). Taking into account this restriction and the contraction window inside a (300,700) ms interval, it leads to a subgroup of 63 out of 349 of the objects mapped on the site.

Table 1 shows the correlation matrix pupil patterns as a way to observe what could be expected from a PCA reduction. A high correlation is observed between its maximum contraction and contraction velocity and between maximum dilation and dilation velocity.

Given this high correlation, pupillary signal patterns were further compressed using PCA from a 5-dimensional pupil feature to a 3-dimensional vector maintaining over 97% of the information.

As stated previously, a bias in Web Object visualization frequency was expected; certain structural Web Objects appear on most pages (i.e., banners and logos) while others only appear once (more content related). In Fig. 3a an extreme frequency distribution can be observed, where most objects are seen on average around once. Therefore, a Tf-Idf inspired approach was used to attenuate this bias, using a log-tf weighting scheme to penalize each reiterative visit on an object. This translates into a non-linear mapping of normalized frequencies, where a frequency of 1 is imposed at max value 1. Then a generic function of the following form is proposed:

$$f^* = \log(1+(\alpha-1)\times f)/\log(\alpha) \tag{3}$$

[2] http://http://www.mbauchile.cl/.
[3] http://www.wordpress.org.

where the constant α regulates the abruptness of the marginal decrease in frequency. Tf-Idf's aim is to reduce the extreme distribution in frequency, for this reason an $\alpha = 100$ is chosen to soften frequency progression. Remapped frequencies show a softer progression in their distribution which is estimated to improve clustering results, as seen in Fig. 3b.

5.4. Results and discussion

Having extracted a feasible representation of the pupillary dilation activity associated to each seen Web Object, the clustering process and subsequent ranking were conducted in order to see if the new source of data has a beneficial impact in the WSKO identification process.

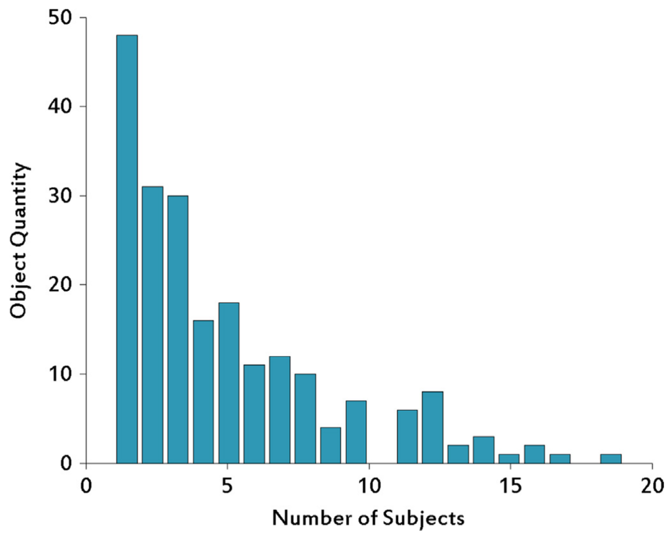

Fig. 2. Number of subjects per Web Object.

Table 1
Correlation between pupil signal features.

	time	*contDiff*	*contVel*	*cdLat*	*dilVel*	*dilDiff*	*freq*
time	1	0.0104	−0.2135	0.3022	−0.3848	−0.3158	0.2133
contDiff		1	**0.8554**	0.4487	0.1399	0.1946	0.0256
contVel			1	0.1542	0.1896	0.1891	−0.0183
cdLat				1	0.1408	0.4818	0.1222
dilVel					1	**0.8256**	−0.0586
dilDiff						1	−0.0235
freq							1

5.4.1. Clustering

We performed the clustering procedure for two configurations. Firstly, we use only gaze related features, following the state of the art in WSKO identification. Secondly, we added pupillary related features to the original process.

2-D clustering – gaze behavior approach: Under this configuration, only 2-dimensional behavioral data is used: time spent on Web Object and frequency of visualization. Therefore, our assumption is that a Web Object that has high time spent or a high frequency should be considered as a Website Key Object.

Given the data distribution and a standard *elbow method* based exploration, a 3-cluster setting was selected, where high times/high frequencies and low time/low frequencies are grouped into distinct clusters. Results tend to show coherent response in an Web Object's nature; paragraph Web Objects tend to have a high time or low time but never a high frequency. In other words, subjects tend to read a paragraph once while exploring, which is coherent with the experiment environment where subjects explored only forward into pages. In addition, high frequency Web Objects represent basically logos and menus, which have a direct appeal and practical value respectively.

We performed this clustering process for the original frequency as well for the re-weighting schema presented in Section 5.3. Therefore, two sets of candidates were obtained, 2D, with 18 WSKO and 2D+freq with 12 WSKO.

5-D clustering – pupillary reactivity inclusion: In this case, pupillary data was added to the same clustering procedure used with the gaze behavior-only. Pupillary signal is compressed into a vector of five patterns for each Web Object. To avoid the addition of poor information as a high dimension, a PCA analysis is conducted before the clustering process, as mentioned in Section 5.3, and the three resulting components are merged with the previous two components from gaze behavior and clustered in the same fashion using a 3-cluster K-means.

Fig. 4 shows the resulting clusters projected into a two dimensional space. Five cluster can be observed, each one involving a different combination of feature-value. For the purpose of this study, we were interested in two clusters, the *high frequency* cluster, represented in the figure by green points, and the *high time* cluster, represented by blue circles. As mentioned before, the resulting set of WSKO candidates is generated by merging both clusters.

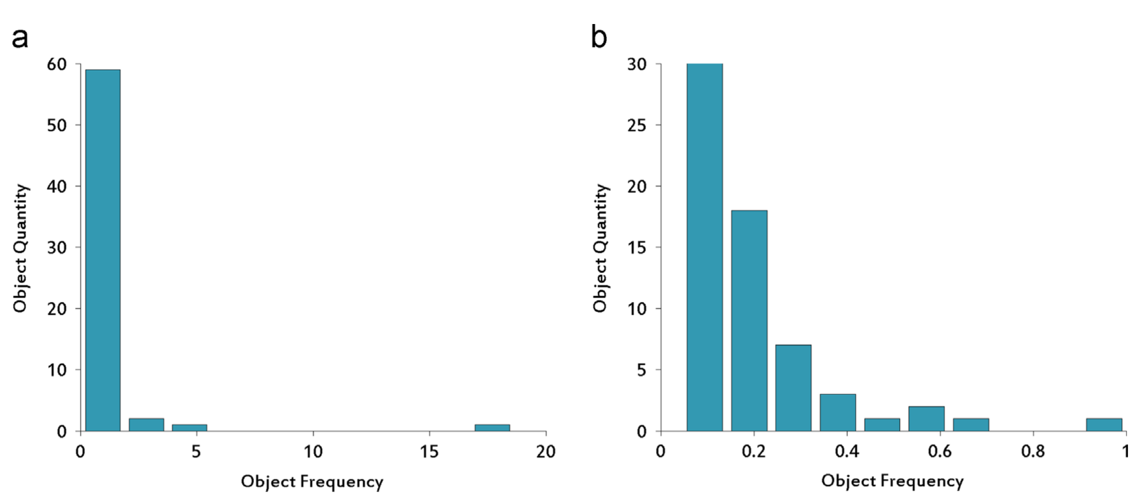

Fig. 3. Frequency re-weighting process. (a) Original frequency. (b) Modified frequency

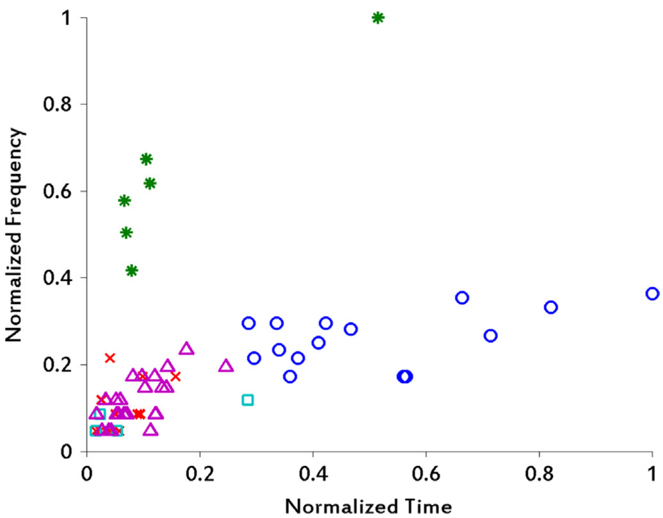

Fig. 4. 5-D clustering (Pupillary features).

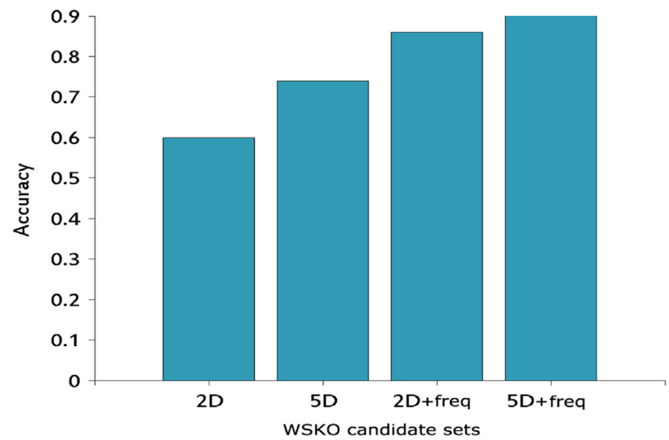

Fig. 5. Accuracy for each set of WSKO candidates.

Similar to the 2D clustering process, in this case, we also obtained sets for the original Web Object visualization frequency and the re-weighted schema, namely 5D and 5D+freq, both with 12 WSKO.

If we compare the components of each cluster, for each frequency configuration, it can be seen that the addition of pupillary features generated a transference of elements from one cluster to another. At this moment, we do not know if that transfer will affect positively the accuracy of the WSKO identification process (which is analyzed in Section 5.4.2), but interestingly, in the case of 2D, when passing to 5D the resulting set contains less elements (from 18 to 12). In the case of the frequency weighting schema, passing from 2D+freq to 5D+freq does not change the size of the resulting set (it is still 12 elements).

5.4.2. *Website Key Object identification*

Given the four sets obtained from the clustering process in the previous section, namely2D, 5D, 2D+freq and 5D+freq, the goal is now to test if those sets actually represent real salient zones of interest in a Website and, simultaneously, test if the addition of pupil activity increases that accuracy.

To perform a fair comparison, we firstly generated a golden set of *real* WSKO by asking two sources. In the first place, the Web engineer in charge of the Website was asked to label each Web Object as WSKO or not. Therefore, we obtained a notion of what should be considered *salient* from the Website point of view. In the second place, we gathered the labeling from a group of eight volunteers. With this, we aimed to obtain a representation of the salient zones for the point of view of the audience. The final set was generated based on the intersection of the two groups, resulting in 28 WSKOs.

Then, each group of WSKO candidates was compared to the gold standard by means of the level of accuracy. The results can be seen in Fig. 5, where the best configuration, 5D and weighted frequency reaches almost 90%. In the next section, we analyze these results in the context of the research questions.

5.4.3. *Research questions*

RQ1: *Does the addition of the pupillary activity improve the approach by Velásquez et al. in terms of WSKO identification?*

In the previous methodologies the analysis was based on surveys and eye tracking data, but this approach tries to explore if the inclusion of pupillary activity can improve the results obtained previously. The literature regarding pupillary activity has shown a clear correlation between pupil dilation and different kinds of activities such as mental activity [26], attitudes [38,39], perception [29,30], effective value of a stimulus [25], information processing and hess1965pupillearning [28,33]. All these behaviors can actually be related to basic exploration on a Web page, where an average user usually has to read, understand and react to certain types of images, colors and designs. We are supposing that the analysis of pupil dilation can provide some clues about which Web Objects make the user react in a more intensive way.

From the results obtained, the transition from 2D to 5D, which means the addition of pupillary data as principal analysis components to the initial gaze data, represents an increment of approximately 14% in the WSKO identification accuracy (from 60% to 74%). It must be noted that 5D retains 60% of the original elements in 2D, therefore, the addition of pupillary data can be seen a way to discover *new* WSKO (instead of just removing false positives).

In any case these results will not necessarily say anything about what kind of reactions the objects will produce, or the level of those reactions. That kind of analysis would have to be done with different equipment and is outside the scope of this research.

RQ2: *Does a frequency-based weighting filter improve the classification accuracy?*

In Web design it is usual to find some templates for large Websites, where multiple objects are presented on different Web pages within the Website, such as menus, sidebars, headers, banners and footers. There is a clear correlation between these kinds of *structural* objects and the chances for them to be observed, thus these Web Objects will have more chances of being chosen as WSKO due to the analysis that considers frequency of visualization as one of the variables. This also gives to Web Objects that are shown on just one page less chance of being selected as Website Key Objects. To avoid this bias we considered it important to include a correction to the frequency of the Web Objects, giving them weights according to the number of appearances on the whole Website, as described in Section 5.3.

We performed a comparison applying the frequency weighting to the two configurations of features. From Fig. 5, the increment in the accuracy for 2D is 23% reaching 0.83 in the case of 2D+freq. Along with this increase in the accuracy, it can be seen that the number of WSKO candidates decreased, from 18 to 12. This means that the weighting of visualization frequencies allowed the reduction of false positives by basically removing elements, which represents a remarkable result.

In the case of 5D, when passing to 5D+freq a increment of 15% can be observed. Interestingly, in this case both 5D and 5D+freq have 12 Web Objects, which means the addition of the frequency weighting increases the accuracy by replacing elements.

Therefore, the use of the frequency weighting schema benefits the overall process, but depending of the nature of the features, it discriminates the Web Objects in a different way.

5.5. Threats to validity

In this section, we discuss the results in terms of their applicability and overall validity.

External validity: One of the most important aspects at the time of designing a Website is the users. For this reason every Website has different goals and use technologies. A Website designed for kids between 6 and 10 years old will probably have several colors and images, and much less text. On the other hand, an online newspaper will have many text areas, maybe some small images and large headlines. In this research the analysis was performed on the Website of an MBA program offered by a public university, and according to the Web administrator, the scope of it is the people interested in getting information about the program (courses, teachers, methodologies, etc.) for applying to it. In particular, these people are mainly professionals of different areas between 25 and 45 years old, with at least three years of experience in their areas. In this sense, the Website was created using more technical information and diagrammed using a formal design and plain "formal" colors, such as blue and white. These kinds of settings are also reflected in the Web Objects shown, which follow the same scheme. This makes each Website unique, and for the same reason, the results obtained here are only valid in this context and should not be applied directly on other Websites. In spite of that, we believe that certain structural Website components which are common to multiple other sites, such as footers, headers, and menus, can be compared to the results obtained here, by making the appropriate differentiation. Those comparisons are outside the scope of this research.

Additionally, as we performed the experiments using only one Website, the level of generalization of the results could be seen as limited. We acknowledged that weakness and consider that it is necessary to perform sets of experiments on the different Websites with different characteristics, such as layout and content type. Nevertheless, we consider that the Website under study represents an average informative Website, and given that, our results might reflect a general behavior.

Internal validity: Measuring the effect of the Web Objects based on a physiological metric such as the visual gaze dynamics was the main objective of this research, and in this sense, we are trying to identify whether there is a meaningful relationship. The classic process of visiting a Website involves a series of factors which are difficult to control and also depend on each user. For this reason most of the internal validity threats are related to the way the subjects interact with the Website during the experiment process.

When a user explores a Website, he generally tries to accomplish some kind of task depending on what he wants (looking for specific information, trying to download a certain file, checking location, etc.) and this decision directly affects which Web Objects will be presented and visualized. In this paper, we tried to recreate the process of visiting the Website but without assigning any particular task to the subjects. In this sense, subjects were free to check all the Web Objects available on every page at their will, without giving specific relevance to some of them. This behavior can affect the results because the user is responding to the Web Objects just by the way they are presented, and not necessarily for the information they provide for accomplishing a task. In that sense, the user is not *foraging* information, but *exploring* the content.

Another important variable that can affect the internal validity of the results is the group chosen for the experiment. Even when they were selected among those within the target scope of the Website, while trying to meet all the required features, there is a slight chance that they are behaving in a different way than expected. The site tries to offer a MBA, but the subjects in the experiments are regular people who may or may not be interested in that academic program.

6. Conclusion and future work

In this work, a major re-design of the WSKO methodology is proposed and evaluated. In the first place, we incorporated pupil dilation as an explanatory variable that allowed a more robust definition of the group of Web Objects that can be classified as WSKO. Although there is still room for improvement, and we acknowledge the limitations of the empirical study conducted, the process of validation of the results led us to hypothesize that pupil dilation is in fact a factor that should be considered.

For future work it is important to consider other kind of variables that can help us to improve the understanding of user behavior on a Website. It is proposed to reproduce the experiment with a larger set of users from a more heterogeneous sample in order to test the robustness of the methodology in a realistic setting. Additionally, we consider necessary to test different types of Websites, in terms of their content, as controlling that variable could allows us to segment users response in terms of its dependency to the content.

The analysis of pupil dilation showed it to be a good variable for analysis of the user reactions regarding a Web page, but this does not consider what kind of emotional reaction the Web Objects or the design produces on the user, such as positive, negative or neutral emotions. Therefore, a Web Object that was classified as WSKO can only currently be perceived as *relevant* to the user, but it is unknown if its relevance was caused by a good or bad connotation.

To improve the analysis towards the identification of the emotional impact of WSKO, it could be necessary to explore how the brain reacts to the pages through the analysis of brain waves using EEG. This could be helpful for designing Websites oriented toward producing certain kinds of emotions or for guiding the user to certain aspects of the page. In the same way, using pupil dilation it could be possible to understand which kinds of decisions a given Web Object could trigger, such as changing pages or going back to a previous page among others. Combining these two approaches could be useful for understanding what kind of Web Objects is relevant based on the emotions that are being generated and also for developing decision-making models based on physiological features.

Acknowledgments

The authors would like to acknowledge the continuous support of the Chilean Millennium Institutes Complex Engineering Systems (ICM: P-05-004-F, CONICYT: FBO16) and Biomedical Neuroscience Institute ICM P09-015-F; the Fondef IDeA project (CA12I10061) entitled, AKORI: Advanced Kernel for Ocular Research and Web Intelligence.

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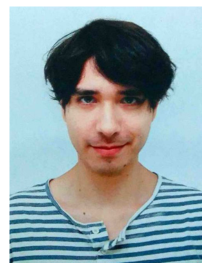

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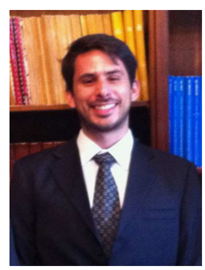

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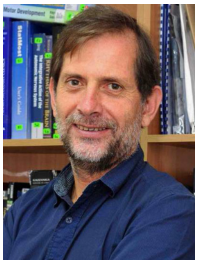

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