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TOWARDS HUMAN-INFORMATION SYSTEM INTERACTION MODELS DERIVED FROM EYE-TRACKING DATA

Introduction

Eye-tracking has been employed in usability testing of interactive information systems for more than a decade. The main use of eye-tracking has been limited typically to examining temporal patterns of eye-gaze locations. This kind of data and its visual representation can reveal interesting aspects of user interaction with information systems and help to identify usability problems. There is, however, much more can be learned from eye-tracking, including specific mental states of users during interaction. To learn user mental states, we propose creating intermediate constructs from eye movement data and then correlating them with higher-level constructs such as the user's task type and task difficulty, cognitive load, and level of the user's knowledge. This approach to processing eye movement data from user interactions with information systems provides a high-resolution user-centric view of the process. It is also a novel methodology to investigate task, individual differences (e.g. knowledge and cognitive abilities), and interactions with information systems.

Motivation and Our Approach

Our research in human-computer information retrieval (HCIR) aims to improve *understanding* of human information search mediated by information systems. The goal is to *enhance* search user interfaces and learn how best to adapt information systems to support the user in achieving their goal.

Information retrieval (IR) systems that do not take account of the user or their task provide less than optimal support. If users would indicate which documents

they found useful during a search, then a representation of that document, that is some selected words from the document, could be added to the user query in order to allow the search system to find documents that are more likely to be useful to the user in their task. This procedure of selecting words from documents likely to be useful to the user has become one of the most important elements in improving information retrieval systems and is now a core part of all of the search engines. These systems take a user's query and run the search. From the results of that search a number of terms are selected from the highest ranked documents and added to the query. Then the expanded query is run again and those results are returned to the user. This procedure is called pseudo-relevance feedback (PRF) and is used by all of the major search engines. The "pseudo" in PRF comes from the recognition that the highest ranked documents that supplied the terms may not in fact be relevant to the user. If a system could have some other mechanism that better identified documents useful to the user, then the performance of the IR system could be further improved. Since users will not typically supply explicit indications of document usefulness, the idea of learning implicitly the documents that are useful has been a significant research thread for IR. One approach that has received a lot of attention is to discover which documents are useful from observations of user behaviors during information search. A behavior could be clicking on a link to reach a document, a revisit to a document, the time of viewing the document, mouse movements, and so on. The general idea in this research is to make a model from these behaviors that makes predictions of document usefulness for a new behavior observation [Kell05].

Another source for implicit information about user interactions with information systems is eye tracking. Data collected by eye trackers has been used in IR as an additional evidence for information relevance. The focus has been on eye fixations, for example to indicate which items are considered in ranked search results pages [BrHo08; PaHe07], or in identifying words useful for relevance feedback [BuDe08; LoBr11]. In contrast, we use eye-tracking data to calculate objective measures of a user's cognitive processing related to reading and interacting with text.

Two important discoveries from reading research explain why eye movement-based approaches can reveal user mental states during interaction with an information system. First, eye movements are cognitively controlled [FiGi03] and directed by the processing needs of a task [TrBa03]. Second, the duration of observed fixations indicate current mental state of acquiring information because the eyes remain fixated during the lexical processing period independently of the stimuli, for example even if the word is removed [FiGi03]. The next saccade takes place only after lexical processing is completed. It is possible that the user

could be looking but not really seeing the word and so engaging the machinery that does the lexical processing. Recent research has established that such 'mindless reading' can be detected (e.g. [ReRe10; ShNu12]).

These two facts mean that observations of fixation properties are also direct observations of at least the user's immediate state of processing the information. One can infer other mental states from these direct measurements of processing states. For example, familiar word meaning is acquired faster than unfamiliar meanings. This is an implicit indication of the user's level of domain knowledge. So, it is possible to infer something about user knowledge levels from observations of reading eye movements under assumptions about language features involved in the mind's representation of concepts.

Methodology

We model aspects of a user's interactive (text-based) information search using a reading model inspired on the E-Z Reader model [RePo06]. We implemented a simple, line-oriented reading model influenced by the E-Z Reader. The E-Z Reader model is a cognitively-controlled, serial-attention model of reading eye movements. It takes word identification (i.e. it is not a sentence processing model), visual processing, attention, and control of the oculomotor system as joint determinants of eye movement in the reading process. Our algorithm (Figure 1) considers eye-fixations long enough (>=113ms) for users to identify words (semantically) to select those fixations that likely to result in word meaning acquisition. We use temporal as well as spatial features of lexical fixations and classify them into two reading sequence states: reading text in a line (called a reading state), and reading isolated words (called a scanning state) and calculate state transition probabilities between the two states. [CoGw11-1] provides implementation details.

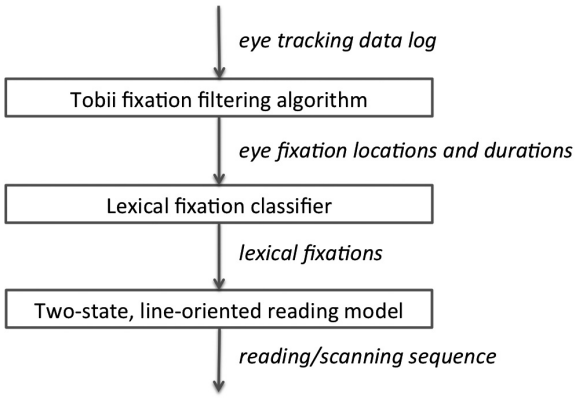

Fig. 1. The main components and the flow of processing in our reading model algorithm

Cognitive effort measures

Several measures based on reading fixation sequences have been developed. Studies of reading employ these measures but they have not been construed by others as cognitive effort, per se. The measures are:

1. *Lexical access duration excess (LADE)*: fixation duration in excess of the minimum required for lexical processing. Fixation duration is an indicator of the cognitive processing required to establish the meaning of the word, and the meaning of the word in context. The mean minimum time to acquire the meaning of a word is 151ms [RePo06]. We use a conservative figure of 113ms as an absolute minimum time for processing a word based on the mean minimum time for the familiarity check [PoRe06]. We define the lexical access duration excess (LADE) as the additional observed fixation duration beyond this familiarity check minimum.
2. *Regressions: the existence and number of regression fixations in the reading sequence*. A regression fixation is a fixation that, in left to right reading, returns to a portion of the text already processed. We operationalize a regression measurement as a count of the regression fixations in a single reading sequence consisting of at least four fixations.
3. *Perceptual span*: the spacing of fixations in the reading sequence. Perceptual span reflects the spacing of the fixations in the horizontal dimension while reading and describes the amount of text one takes in as a unit. We measure the mean perceptual span in a reading sequence as a cognitive effort feature. Since regression fixations may occur, a reading sequence can have several left to right subsequences. The reading/skimming distinction made by Buscher and colleagues [BuDe08] is similar to our definition of mean perceptual span, although we classify reading sequences in a different way.
4. *Reading speed*: defined as the length of text acquired per unit time. Reading speed is the ratio of the amount of text processed (the reading length) to the processing time. Reading speed is a function of the duration of the individual fixations in the reading sequence, the spacing of the fixations (perceptual span), and the regressions in the reading sequence.

We use transition probabilities between reading and scanning states and the above measures that reflect some aspects of cognitive effort in reading to characterize differences in reading between tasks, interfaces, and users with diverse levels of cognitive abilities.

Validation of the methodology: Evidence from three user studies

In two controlled Web search user studies, the eye-tracking cognitive effort measures have been shown to correlate with designed and perceived task difficulty. Some characteristics of information search tasks are correlated with differences in reading-state transition probabilities. This confirms the intuition that different tasks induce different reading strategies. Finally, using the results from the third study, we demonstrate a correlation between the eye-tracking derived cognitive effort measures and users' self-assessed domain knowledge.

Study 1: Cognitive effort and task difficulty

A user study (n = 32) was conduced to investigate the effects of task characteristics on information search behaviors used journalism students performing realistic journalism information search tasks. The journalism domain was selected because the same task can be associated with any topic and this supports generalization of the study results. Four tasks were identified by interviewing journalism faculty and practicing journalists. The tasks were designed to vary by characteristics that were expected to affect search behavior [Li09]. These characteristics included: complexity, defined as the number of necessary steps needed to achieve the task goal (e.g. identifying an expert and then finding contact information), the task product (factual vs. intellectual, e.g., fact checking vs. production of a document), the information object (was processing a complete document or only a document segment required), whether the search target is specifically identified (named), and the nature of the task goal (specific vs. amorphous). The tasks and their categorization are described in [CoGw11-2].

Our reading model was used to identify sequences of eye fixations as 'reading' or 'scanning'. A scanning instance is an isolated lexical fixation. We used this classification of eye fixation sequences to fashion a state model (an example for one task is Figure 2) of the user's engagement. The state model transition probabilities may be understood as reflecting a personal or task-induced bias on the strategy to process the page. Figure 3 shows there were significant task effects on the scan to start reading and the end reading to scan transition probabilities. This suggests users adapted their information acquisition and processing strategy for different types of tasks.

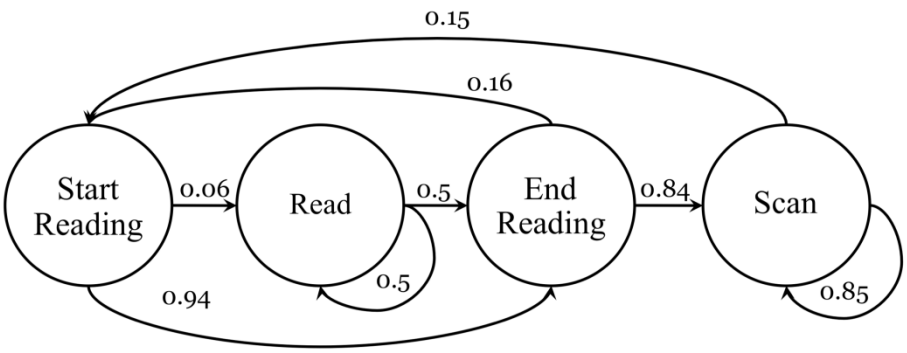

Fig. 2. An example of a reading state model for a task in the user study

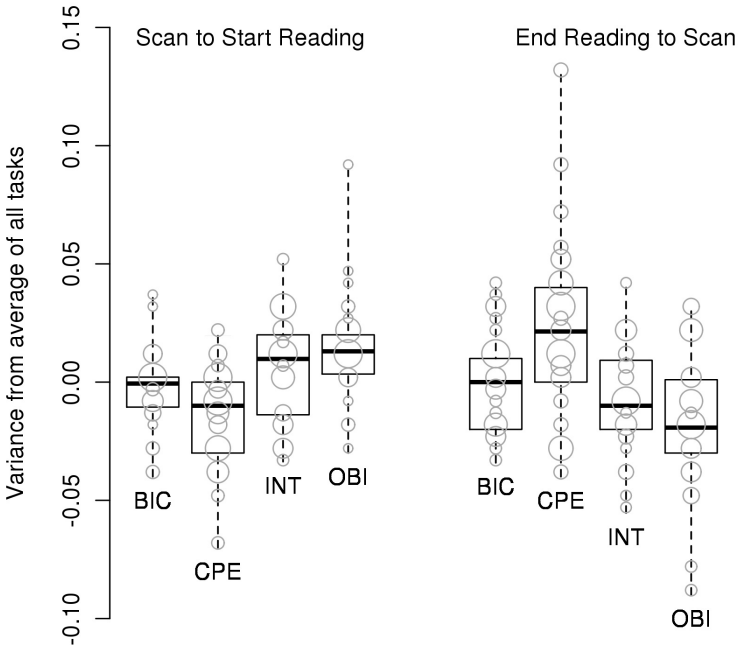

Fig. 3. Journalism search tasks: Task effects on reading state transition probabilities. The size of circles represents the distribution of the number of participants for each task

Turning to the analysis using the cognitive effort measures of the reading sequences shows there are correlations with the user subjective task difficulty assessments and with other objective measurement of task effort, such as time on task, etc. Figure 4 provides a model of the analysis framework.

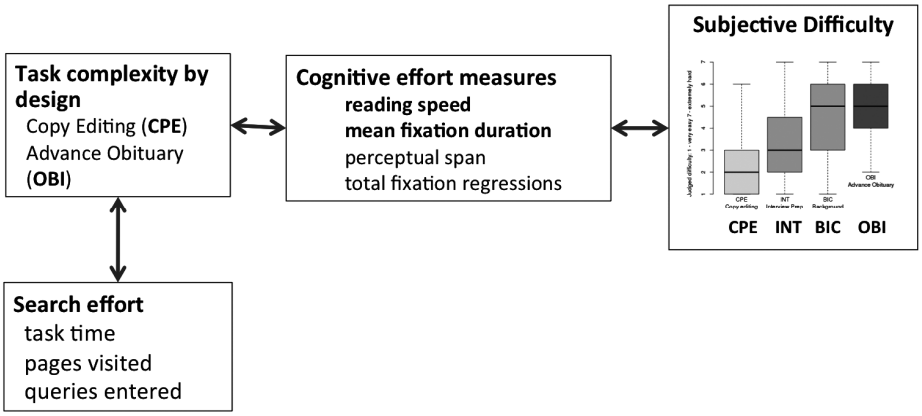

Fig. 4. Analysis framework showing the designed task complexity in the user study and the relationships between the cognitive effort measurements, subjective task difficulty, and the other objective task effort measurements

The cognitive effort measures correlate well with user subjective task difficulty assessments and other measures of effort in a task (Tables 1 through 3). For example, the CPE task was subjectively the easiest, took less time to complete, etc. and had the greatest perceptual span, fewest regressions, highest reading speed and lowest LADE. The correspondence between these high level task measures and the cognitive effort measures is not perfect but a consistent story overall emerges.

Table 1

Behavioral measures for tasks

Task	Mean subjective task difficulty (sd)	Mean task time [minutes] (sd)
BIC	4.53 (1.76)	17.95 (6.16)
CPE	2.31 (1.28)	9.42(6.63)
INT	3.31 (1.57)	11.63(5.94)
OBI	5.25 (1.37)	12.52 (5.45)

Table 2

User search effort measures for tasks

Task	Number of content pages		Mean number of queries (sd)	Mean number of unique pages visited (sd)
	Total	Saved		
BIC	1161	271	24.62 (12.39)	25.72 (8.57)
CPE	513	212	7.81 (5.35)	10.41 (7.09)
INT	1101	262	11.28 (6.4)	21 (11.46)
OBI	950	288	20.78 (11.87)	19.59 (10.89)

Table 3

Cognitive effort measures for tasks

Task	Mean regressions per page	Mean perceptual span [px]	Mean total reading length [px]	Mean reading speed [px/ms]	Median LADE (ms)
BIC	3.89	81.40	2566.96	0.4437	198.68
CPE	4.77	81.59	2780.39	0.4957	184.15
INT	3.40	79.12	2239.43	0.4578	203.00
OBI	3.02	77.86	1981.75	0.4239	199.20

For task difficulty, there was a clear distinction between CPE (copy editing) and the other tasks. By both the subjective assessment and objective task effort measures (time on task, pages visited, etc.) CPE was the task that required the least effort. This is unambiguously reflected in the eye movement pattern cognitive effort measurements. The tasks were designed to vary in several dimensions that impact task completion requirements. OBI and CPE were the least similar tasks overall. One can see that OBI was unambiguously judged the most difficult task and most of the cognitive effort measures distinguish it from the other tasks, especially CPE.

In summary, the cognitive effort measurements derived from the eye movement data appear to correlate well with both the subjective task difficulty and task session effort. Further, the cognitive effort measurements distinguish between the individual tasks.

Study 2: Understanding search user interfaces

Another user study employed the cognitive effort measures to gain a detailed understanding of how users worked on the same tasks in different user interfaces. We wanted to know how the addition of an overview tag cloud affected user actions during search. It seems reasonable to think a tag cloud can help people navigate to document(s) that are more likely to be relevant. To investigate this we observed eye movement behaviors in two interfaces, one with and one without a tag cloud derived from the search results (Figure 5).

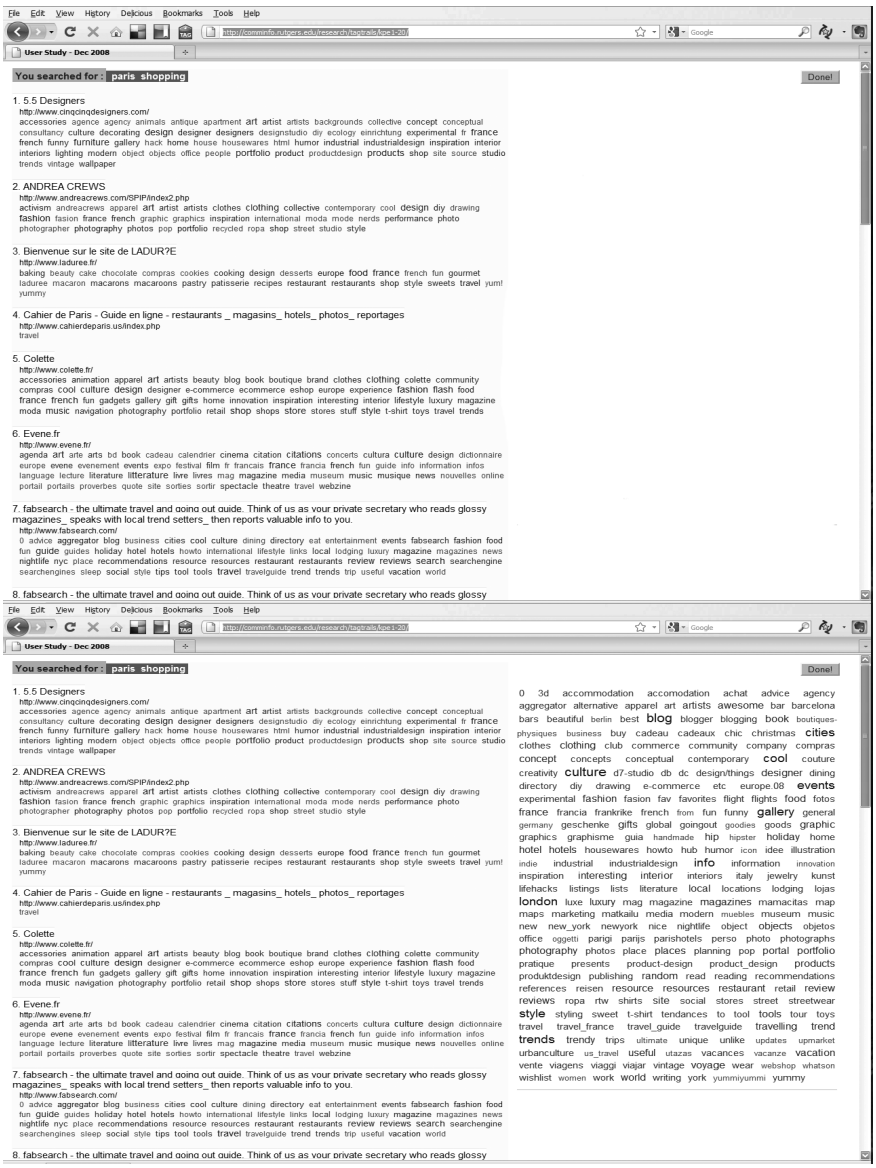

Fig. 5. Two user interfaces from study 2. Top: List (L) interface and bottom Overview+List (O+L) interface

The documents used in study two were related to topics on travel, sightseeing and shopping in London and Paris selected from the Delicious social bookmarking site. The tags were the ones assigned by the Delicious users to these documents.

Travel, sightseeing and shopping were selected as everyday search topics familiar to the general public. Task scenarios were constructed to present realistic situations where the participant was searching for information to help a friend who

is traveling. All participants started each task from the same search results list. Users looked for information within these results. They could narrow or expand results by clicking on tags or by removing tags from the list of words that acted as a query. The selected tags were used to retrieve the documents. After finding the information they would compose a short message advising their friend of the results of their search, for example the name of an inexpensive hotel near to Heathrow airport. The tasks were designed to have different levels of complexity.

The eye fixation cognitive effort measures were calculated for each sequence of reading and the results compared within users for the two interfaces. We found the UI with the tag cloud allowed users to work faster. The eye tracking data provided a detailed comparison of how much effort was expended in each of the two interfaces. Table 4 provides the results.

Table 4

Significant effects of UI on eye movement measures

Eye movement measures	L vs. O+L UI
Number of fixations	524 vs. 167***
Reading length [000' pixels]	40 vs. 12.4***
Total fixation duration [seconds]	174 vs. 60.3***
Reading vs. scanning [in proportion of all sequences] (for list part of UI only)	0.42 vs. 0.36***

Non-parametric tests Wilcoxon: *** p <.001.

The cognitive effort measures also permitted a detailed understanding of how effort is allocated within the UI. For example, we found that in the UI with the tag cloud most reading effort was devoted to processing the search results. The ratio of number of fixations in the search results list to the overview tag cloud was 2.89 (W(35), $p<0.001$). The total reading length (scan path length in pixels for each reading sequence) ratio was 2.95 (W(35), $p<<0.001$).

These cognitive effort measures not only provide evidence that the tag cloud helped, but also provide rich insight into the amount of cognitive effort and its characteristics – for example whether the average time to acquire word meanings while processing the search results is reduced after processing the tag cloud. It happens that the effect of the overview tag cloud seemed to be quite powerful, as 41 eye fixations on the tag cloud reduced the number of fixations on the search result list from 451 to only 104. Apparently, the presence of the clickable overview tag cloud helped participants to find the right terms for queries faster and to find the needed information faster.

This study demonstrated the use of eye tracking data to generate a model of reading and objective user performance measures (cognitive effort) that were then used to obtain explain differences in interaction with two interfaces.

Study 3: Detecting user domain knowledge

Another user study (n = 40) examined domain knowledge effects on search behaviors. Participants with differing levels of knowledge of genomics self-rated their knowledge of 409 concepts from NIH MeSH, a comprehensive biomedical controlled vocabulary. These self-ratings were normalized and used as a representation of their level of genomics knowledge. Participants were then asked to search and collect documents relevant to each of four research tasks. These tasks varied in difficulty, but were all difficult search tasks when compared to more typical search tasks. The details of the study design and calculation of domain knowledge are given in [CoGw12].

The cognitive effort measures were calculated from the logged eye-fixations. Two regression models learned to see if using the cognitive effort measurements as independent variables could classify participants by knowledge level. One model was a simple linear regression. The other model was a decision-tree ensemble model, random forests [Brei01]. Figure 6 shows the overall flow of the analysis in this experiment.

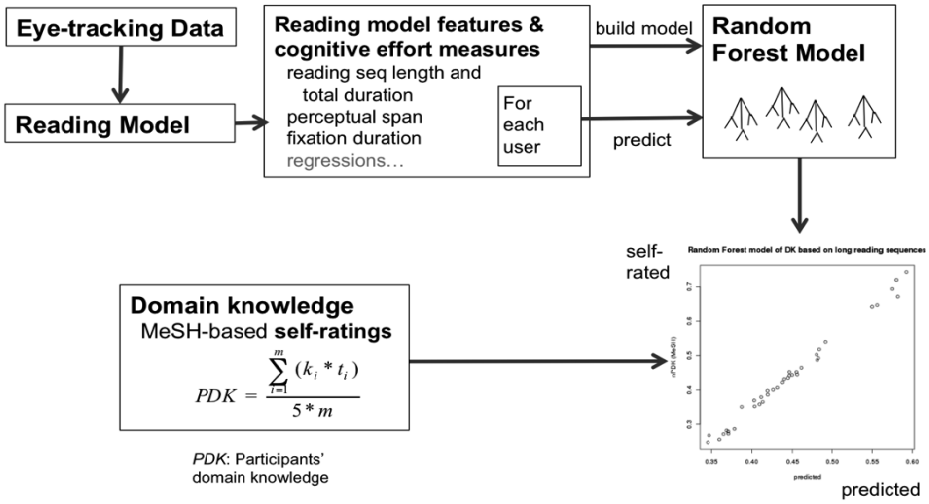

Fig. 6. Modeling domain knowledge using random forests

The results [CoGw12] show that the linear model gave reasonable discrimination between the high and low domain knowledge groups. After removing non-native English speakers (n = 14), the model results were better for the high knowledge group, but deteriorated somewhat for the low knowledge group. The random forest model performed much better and when the non-native English speakers were removed the model was able to classify all of the participants cor-

rectly into high- and low-knowledge groups. These results provide evidence for the ability of the cognitive effort measures to capture salient aspects of differences in the reading-based information acquisition process due to a user's knowledge of their task and domain.

One complexity in modeling interactions with an interface and an information system is the conditionalization of interaction due to varying levels of user knowledge. This may affect the use of resources in the interface, selection of items, search strategies, and strategies to process the information presented by the system. All of these factors are associated with interface design choices and lay at the heart of questions about how best to adapt the system to the user and their immediate need. Eye tracking-based cognitive effort measurement can allow inference of the user's state of knowledge and trigger modification of the system or its interaction with the user to improve the overall performance of the UI and the system during the task session.

Discussion

We motivated our work by describing importance of obtaining implicit feedback from users engaged in interactive information retrieval. Traditionally, the emphasis of information retrieval research was on using user behavior as an indicator of document relevance [Kell05] that could be incorporated as pseudo-relevance feedback and used in query expansion or in document re-ranking. More recently, eye fixations were used to indicate which items are considered by users in ranked search results pages or to identify words useful for relevance feedback [BrHo08; PaHe07; BuDe08; LoBr11].

In contrast, our work uses eye-tracking data to calculate objective measures of a user's cognitive processing related to reading and interacting with text and shows that these measure are good implicit indicators of several aspects of human-information interactions. Specifically, we used results from three controlled Web search user studies to demonstrate that reading model parameters (such as, reading-state transition probabilities and the frequency of reading-states) correlate with differences between search user interfaces and with some information search task characteristics, and that eye-tracking derived cognitive effort measures correlate well with: designed and subjective task difficulty, users' self-assessed domain knowledge, and differences in interaction with search interfaces (search result list and overview tag cloud + search result list).

Conclusion

The objectives of this work are to inform theories and models of human-computer information retrieval and to develop information systems that better support users in their tasks. Our approach is to learn more about users using information systems without asking them and while they are still engaged in their tasks. What we learn will be eventually included in algorithms embedded in information systems that will adapt to user. Eye tracking provides a rich dataset for this effort. Representation of the eye movement behaviors as measurements of cognitive effort associated with the information acquisition process have been shown to allow for deeper understanding of how users work within information system interfaces and to predict mental states germane to the information task, such as perceived difficulty and the user's level of domain knowledge.

At the fundamental level, eye tracking is appropriate because it is a direct observation of the user's interaction with information. The reading model methodology and cognitive effort measures are based on many years of empirical research in cognitive psychology. They are domain independent because the content of the text document is not used, and are largely culturally independent. The algorithm we use for processing the eye-movements can be adjusted to different languages, orthographic systems, and reading patterns (i.e. left to right, top down, etc.) by changing model parameters. Calculating the cognitive effort measures is easily accomplished in real time because simple calculations are applied to the eye tracking data stream, which consists of three numbers: the fixation duration and its location coordinates. A couple of the cognitive effort measures that require identification of the entire reading sequence, such as perceptual span and reading length, can be accomplished as soon as the reading sequence is completed. The result is that eye movement analysis can be conducted in real time using the immediate eye position and caching just a few seconds of fixation data to ensure capture of extended reading sequences. The analysis can be continuously updated and the resulting stream of reading sequence representations filtered for important cognitive effort events.

Implications

Appling and extending our eye-tracking based method has a potential for refining and extending theories and models in human-computer information retrieval. For example, it can be used to validate significance of search task characteristics (such as those proposed in [Li09]).

A prediction about the state of the user takes less than 40 ms using a standard computer where the stream of eye fixations is input to an existing model, e.g. a random forests model. This enables real-time assessment of cognitive effort and system detection of user characteristics in just a few seconds, including level of domain knowledge and task characteristics. That is fast enough to permit a system to seamlessly adapt support to information searchers in their immediate state.

Application of our work is today only possible in research settings because eye trackers are expensive and used mainly ass research tools. However, there are reasons to think that devices with eye tracking capabilities may come into widespread use. A consumer laptop prototype with camera-based eye-tracking technology and a gaze interaction interface was demonstrated at the recent Consumer Electronics Show (CES 2012) by Lenovo and Tobii, a Swedish producer of eye-tracking solutions. Google will soon market Web-connected glasses expected to incorporate electrooculography eye position sensors. Olympus and Oakley are also ready to introduce such smart glasses to the consumer. If the eye position sensors have sufficient resolution, such augmented reality glasses would be a suitable real time input for our system.

As noted above, calculations of cognitive effort measures from eye fixation data streams is easy to accomplish and models can be used to make real time predictions of the user's current mental state. These predictions can be a basis for a system to adapt to the user in several ways. For example, if the cognitive effort measurements predict the user will assess the task as difficult, the system might intervene to provide memory aids in the interface, for example automated note taking. When the user issues a query to a search engine the system can use the cognitive effort measurements on each of the documents processed by the user to predict which of them were useful, extract the most informative terms, and add those terms to the query that is sent to the search engine.

Limitations and recommendations for future work

The studies presented in this chapter were conducted with a limited set of search tasks. Future work should extend the types of examined user tasks. Reading states identified by our reading model take into account reading each line of text separately. While this approach is appropriate for the analyses presented here (we used aggregated measures of reading and scanning states), in the future, we will extend our model to identify reading sequences that span multiple lines of texts and to parameterize the model with the number of text lines read. Our reading model and the cognitive effort measures were created based on the knowledge of human text reading, and thus they do not cover looking at and

processing of images. The use of an eye-tracker carries with it limitations inherent in this technology (the accuracy and precision of the hardware [Tobii11-1]) and the associated algorithms (eye-tracker fixation detection algorithm). In the work presented in this chapter, we used Tobii T-60 eye tracker [Tobii11-2] manufactured by Tobii Technology AB.

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MODELE INTERAKCJI CZŁOWIEKA Z SYSTEMAMI INFORMATYCZNYMI BAZUJĄCE NA OKULOGRAFII

Streszczenie

Okulografię (eye-tracking) stosowano do badania użyteczności interakcyjnych systemów komputerowych od ponad dekady. Główne zastosowanie eye-tracking ograniczało się do badania temporalnych zmian kierunku patrzenia. Ten rodzaj danych i ich wizualna reprezentacja pozwalały odkryć interesujące aspekty interakcji użytkownika z systemem informatycznym i pomagały w zidentyfikowaniu problemów z użytecznością. Jednakże eye-tracking może dostarczyć dużo więcej informacji. Na przykład dzięki tej technice można identyfikować stan umysłu użytkownika w czasie interakcji z komputerem. W artykule zaproponowano stworzenie i użycie pośrednich zmiennych uzyskanych na podstawie ruchu oka i skorelowanie ich z bardziej ogólnymi aspektami, takimi jak: typ zadania użytkownika, cognitive load (wysiłek umysłowy) oraz poziom wiedzy użytkownika. Takie podejście do przetwarzania pomiarów ruchu oka z interakcjami z systemem informatycznym daje dokładniejszy obraz interakcji. Proponowana metoda jest nowym podejściem do badania zadań użytkownika, różnic między użytkownikami (np. w poziomie wiedzy czy też różnic kognitywnych) i interakcji z systemem informatycznym.