Investigating User Behavior in Document Similarity Judgment for Interactive Clustering-based Search Engines

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***Abstract*—This paper investigates the behavior of users judging the similarity of documents in order to examine the user's feedback cost for interactive document clustering. Modern web search engines employ linear-style SERPs (search engine result pages). In order to make use of information on continuously growing web, various search engines for the next generation have been studied, among which clustering-based search engines are expected to be promising. It is also important to introduce interactive user feedback mechanism into search engines. The aim of this paper is to study the effective interface design that is suitable for interactive clustering-based search engines. An experiment is conducted with 21 test participants, who were asked to judge the similarity of document pairs based on three conditions: viewing snippet, topic terms, or original text. Those conditions are compared in terms of judgment time and accuracy with ANOVA and chi-square analysis. The typical judging behaviors of the participants are also investigated by eye-tracking system. The results will contribute to the design of interface for interactive clustering-based search engines for the next generation.**

***Index Terms*—web search interfaces, interactive clustering, document similarity judgment, eye-tracking**

I. INTRODUCTION

This paper investigates the behavior of users judging similarity of documents. Recent years with the growth of information, Web search engines has become a very important applications that can help our information access. However, modern search engines have room for improvement, in order to make use of information on continuously growing Web. Therefore, various search engines have been studied and developed for the next generation.

Most of the modern search engines are designed based on a query, and user can find desired pages from SERPs (search engine result pages). Compared with such engines, some new types of searching performance has been developed, which have more advanced functionalities. For examples, some engines such as "Baidu Zhidao"[1] employ a FAQ like search facility. Users can pose their questions to the system and let other people to answer it. Some other search engines just like "Yippy"[2] divide the searching results into several clusters, from which users can choose the cluster close to their searching purpose.

In our opinion, modern search engines have two points to be improved. One is the limitation on the style of SERPs. That is, information about retrieved pages, such as the title, URL, and snippets, is linearly ordered in a SERP. Therefore, when a query is ambiguous and has several meanings, web pages of various topics are contained in a SERP in a mixed manner. For example, when we input a term "Olympic" as a query, various topics, such as independent Olympic Game, forthcoming game, summary of winter and summer Olympic Games, various records of successive games, will be contained in the SERPs. From existing SERPs, it is difficult to discriminate such topics and find required pages. In order to solve such a problem, one promising approach is to employ clustering algorithm, such as the above-mentioned Yippy Search.

Another point to be improved is insufficient feature of user feedback mechanism. Obtaining feedbacks from users are very important for improving search engine's performance through interaction. In the field of document retrieval, relevance feedback [1] has been studied as feedback mechanism. It obtains the result of user's relevance judgment of documents as the feedback for improving the retrieval performance.

Regarding the web search engines for the next generation, this paper focuses on interactive clustering-based search engines. By introducing user feedback mechanism in clustering-based search engines, its potential is expected to be increased.

[1] http://zhidao.baidu.com/
[2] http://search.yippy.com/

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Introducing feedback information from a user to clustering process can be done by constrained clustering [2]. It uses two kinds of constraints; must-link that indicates two documents connected with the link must be in the same cluster, and cannot-link that indicates two documents having the link cannot be in the same cluster. By converting the user feedback into those links, the feedback mechanism can be incorporated into clustering-based search engines.

When obtaining feedback from users, the workload of users providing feedback should be considered. Although much feedback information improves the performance of systems (i.e. search engines), it forces heavy burden on users. In order to solve this tradeoff, the concept of Minimal User Feedback (MUF) [3] has been proposed. The MUF employs two approaches: minimizing the quantity of feedback information and minimizing the cost of generating each of feedback information (i.e. relevance judgment for a single document). A related work with the former approach is active learning [4, 5], in which a learner actively gathers training data effective for learning.

The aim of the paper is the fundamental study of interface design for interactive clustering-based search engines, which relates with the latter approach of the MUF. The effectiveness of a Web search engine is not only determined by its retrieving mechanism such as ranking algorithm and crawlers, but also by the design of interface and interaction with users, such as the design of SERPs.

When user feedback mechanism is introduced in clustering-based search engines such as the Yippy Search, the primitive task of users is not to judge a relevance of web pages as in the case of existing document retrieval, but to judge the similarity of web pages. We call such a task "document similarity judgment" in this paper. This paper studies the effect of providing information (clue for the judgment) on the user behaviors in document similarity judgment. The study on users judging relevance of objects has been investigated as introduced in Section 2. However, to our best knowledge, the study on users judging similarity of objects has not been investigated.

In this paper, test participants are asked to judge the similarity of two documents. Given a pair of news articles, a participant judges whether those articles relate with the same topic or not. As the clue for judging similarity, three kinds of information: original text, snippets, and terms, are mutually provided. As less work has been done for studying similarity judgment, it is not clear what terms or snippets are effective for the judgment. In this paper, we suppose that information identifying the difference and commonality of documents is effective. Therefore, common and specific terms / snippets are presented to test participants in a separate manner.

The judgment accuracy and judgment time are compared between these 3 conditions (text, snippet, term). The result shows participants viewing terms could judge the similarity of documents more quickly than viewing other conditions, whereas the improvement of accuracy with experience was observed when a snippet or original text is presented.

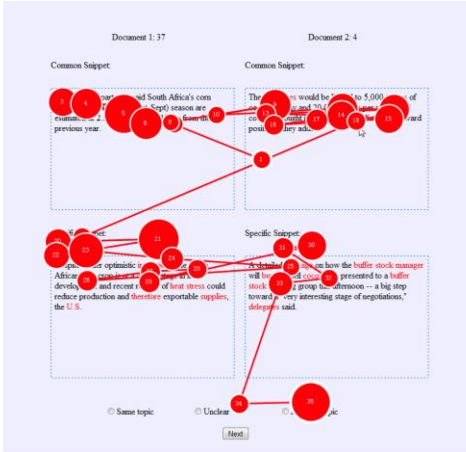

Figure 1. A screenshot of gaze plot by T60 Eye-Tracking System

Behavior of test participants in judging document similarity are also recorded using eye tracking device. By analyzing AOI (area of interest) and focusing time, typical viewing behavior is investigated.

This paper is organized as follows. The studies of user behavior in relevance judgment are summarized as the related work in Section II. Section III describes the outline of experiment, which includes the used document set and algorithm for generating clues for judgment. Experimental results are shown in Sec. IV.

II. User Behavior in Relevance Judgment

As noted in Section I, relevance judgment and similarity judgment are essential tasks for a user to provide feedback information. Compared with similarity judgment, much work has been done for studying users behavior in judging relevance of documents, which include users' viewing behavior in SERPs and web pages [6, 7, 8] and study on the effect of snippet on relevance judgment [9, 10, 11]. Among them, Chen et al. compared accuracy of relevance judgment and judgment time between the condition of providing snippet and that of providing original text [11]. Most of the studies does not only investigate judgment accuracy and judgment time, but also analyze users' behavior by using eye-tracking systems.

An eye-tracking system can record user's eye movement on a computer screen. This paper uses T60 from Tobii technology to investigate the user behavior in document similarity judgment. It can record eyes movement and focusing area (AOI) on the screen. The focusing time is also recorded. By using the Tobii's accessory software Tobii Studio, the recorded data can be visualized. Figure 1 shows a gaze plot, which shows the trajectory of focusing point. In the gaze plot, the size of node represents the focusing time. Figure 2 is called a heat map that is also visualized by the Tobii Studio. A heat map is a graphical representation of data where the accumulated focusing time is represented as colors. The heat map can be used for displaying areas of a Web page that are frequently scanned by readers [9, 10]. The most frequently focused areas are highlighted by red colors.

Figure 2. A screenshot of heat map by T60 Eye-Tracking System

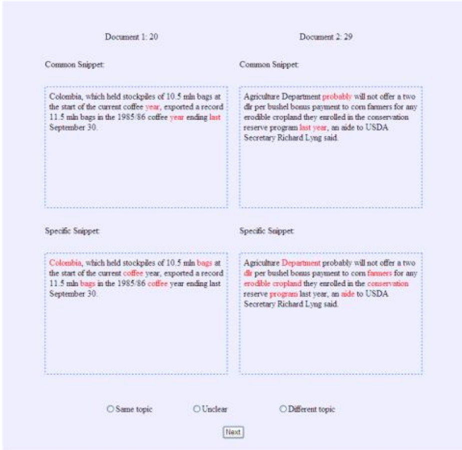

Figure 3. A screenshot of the experiment system

Such eye-tracking systems have been widely used for studying users' behavior in viewing Web search results. Cutrell [9, 10] has investigated the effect of task type, snippet length, and the position of the best result in MSN SERPs on users' viewing behavior. Interesting results were obtained, such as that snippet length has different effect between navigational and informational tasks. That is, for informational task, longer snippet improved click accuracy while reducing the task time, but opposite effect was observed for navigational task. This result was explained based on the analysis of eye-tracking record that user performing informational task tended to rely on snippets.

Rodden [7] has explored the relationship between mouse movements, and eye movements when performing a search task with using Google. Various interesting patterns are observed, such as keeping the mouse still while reading and using the mouse as a reading aid.

Lorigo et al. [6] has investigated users' search and evaluation behavior based on the analysis of scan path recorded by using eye-tracking system. The results have shown that users tended to make decision on performing new search before viewing entire page of retrieved result, and that they tended to reexamine top 1 and 2 results frequently.

III. OUTLINE OF EXPERIMENT

This paper investigates users' behavior in similarity judgment. The task of test participants is to judge the similarity of two documents. Given a pair of documents, they are asked to judge whether those documents relate with the same topic or not.

For the experiment, we implement an experiment system that is written in VB language as ASP pages. Figure 3 shows the screenshot of the experiment system, which can be accessed with ordinary web browsers. In these pages, information about 2 documents is arranged side by side.

As noted in Sec. III.B and III.C, two kinds of topic terms (snippet): common and specific terms (snippets) are presented. The common terms (snippets) are displayed in the upper part of the screen, and specific one is displayed in the lower part. Topic terms are highlighted with red when snippet is displayed. The document pair is extracted randomly from 42 documents. In the rest of this section, a document set used in the experiment and the method for extracting topic terms and that for generating snippet are described.

A. Document set

The documents and topics are selected from Reuter Test Collection[3]. It includes 21578 documents with 135 topics. In the experiments, we prepared the document set by selecting a few topics and randomly picking up the corresponding documents. If the document of different topics is obviously different, test participants can judge the similarity of documents without carefully reading displayed information. Therefore, topics that are to be used in the experiments should relate with each other. Based on this consideration, we selected the following 3 topics, which are overlapping each other, i.e., several documents belong to two of those topics: Coffee (Topic 1), Cocoa (Topic 2), and Corn (Topic 3).

Fourteen documents that belong to only one of those topics are collected from each topic, and total 42 documents are used in the experiment.

B. Extraction of topic terms

Terms that represent the topic of the document are supposed to work as a clue for judging similarity of documents. In particular, the terms indicating the difference and commonality between documents should be presented to a user. Based on this consideration, we classify the topic terms into common and specific terms, which are extracted with the following two steps:

Step 1: Extraction of topic terms from a document
Step 2: Extraction of common and specific terms

In step 1, given a set of documents *D* (42 documents used in the experiment), terms that have high TF-IDF values are extracted as topic terms. Among various definitions of TF and IDF, we employed the following equations.

[3] http://www.daviddlewis.com/resources/testcollections/

$$TF_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} . \quad (1)$$

$$IDF_i = \log \frac{|D|}{|\{d : t_i \in d\}|} . \quad (2)$$

Where $n_{i,j}$ is the number of occurrences of the considered term (t_i) in document d_j, and the denominator of Eq. (1) is the sum of the number of occurrences of all terms in document d_j. The denominator of Eq. (2) shows the number of documents in which the term t_i appears. It should be noted that we calculate TF−IDF score for only the terms appeared at least once in *D*. To be more exact, all of the terms in *D* are extracted and the TF-IDF values are calculated except the terms that are contained in a stop word list. In the experiment, we employed the stop word list available from Wikipedia[4].

In step 2, for a pair of documents that are to be compared, the topic terms that occur in both of the documents are selected as common terms, whereas the terms exclusively occur in either of the documents are selected as specific terms.

C. Snippet generation

One of the most important features of modern search engines is a snippet, which is a fragment of a document that represents its contents. In particular, the snippet generated based on the topic can help users to make a judgment easily on whether to read the corresponding documents or not. This merit is supposed to be valid for similarity judgment.

Based on the same consideration as noted in Sec. III.B, two types of snippets, common and specific snippets, are employed in this paper. The snippets are generated by the following steps:
Step 1: Extraction of topic terms (Sec. III.B).
Step 2: Score calculation for each sentence.
Step 3: Extraction of a set of sentences as a snippet.

In step 2, the score of a sentence is calculated based on the TF-IDF values of specific/common topic terms that are contained in the sentence.

In step 3, a set of sentences with the highest score is selected as a snippet. The snippet that consists of the sentences containing specific (common) terms is called specific (common) snippet.

IV. EXPERIMENTAL RESULTS

In the experiment, 21 participants including 18 graduate / 2 undergraduate students and 1 researcher (19 males and 2 females) in engineering field took part in the experiment. A participant is asked to judge 3 document pairs for each type of information (snippet, text, term). A pair of documents is generated randomly from the document set containing 42 documents as described in Sec. III.A.

The experimental results are analyzed by two approaches. First, the performance of participants' similarity judgment is compared among 3 types of information in terms of judgment accuracy and judgment time. After that, the behavior of the participants in performing the experiment is analyzed based on the record of eye-tracking system.

TABLE I.
EXPERIMENTAL RESULT IN THE 1ST TRIAL

	Text	Snippet	Term
AVG (s)	73.31	40.07	36.41
STDEV (s)	40.00	27.62	27.80
Correct	12	11	10
Mistake	9	10	11

TABLE II.
EXPERIMENTAL RESULT IN THE 3RD TRIAL

	Text	Snippet	Term
AVG (s)	58.54	43.59	32.27
STDEV (s)	41.87	24.02	19.46
Correct	17	16	11
Mistake	4	5	10

A. Performance of similarity judgment

When a user performs similarity judgment in an actual application, the judgment has to be repeated several times. Therefore, user's adaptability is one of important factors for evaluating the type of providing information. In the experiment, a participant judged the similarity of documents 3 times for each type of information. In order to consider the participants' adaptability, we separately analyzed the results in the 1st and the 3rd trials.

Table I and II show the experimental results in the 1st and the 3rd trial, respectively. These tables contain average judgment time (AVG) and its standard deviation (STDEV), and the number of correct answers and mistakes. The columns correspond to the type of information.

The difference of snippet, text, and term in judgment time is in the 1st trial is analyzed using one-factor repeated measures analysis of variance (ANOVA). As a result, we found statistically significant differences in the mean judgment time among snippet, text, and term ($F(2,40) = 16.52$, $P = 5.9E-06$).

In the case of the 3rd trial, the assumption of equality of variance was rejected. Therefore, we conducted nonparametric test (Kruskal Wallis Test) and confirmed the difference is statistically significant ($\chi 2 = 7.023$, $P = 0.030$).

As for the difference between the 1st and the 3rd trials, p-value of the 1st trial is much smaller than 3rd trial. We think that in the 1st trial, participants did not get used to the experiment including the type of information, which affected the variance.

In order to examine the effectiveness of each type of information, multiple comparison tests are conducted. In the case of the 1st trial, assumption of equality of variance could not be rejected. Therefore, Tukey's test and Fisher's LSD is used. In the paper, * and ** indicate the significant level of 5% and 1%, respectively. Table III

[4] http://en.wikipedia.org/wiki/Stop_words

summarizes the result. The result shows that the participants could judge the similarity of document using snippet and terms more quickly than reading original text.

As already noted, the assumption of equality of variance was rejected in the case of the 3rd trial. Therefore, we conducted nonparametric tests: Scheffe test and Steel-Dwass test, of which the results are shown in Table IV. In this case, only the difference between text and term is statistically significant. From both the results of the 1st and the 3rd trials, it is shown that providing terms is more effective in terms of the time cost of similarity judgment.

A chi-square analysis on the number of correct answers and mistakes as shown in Table I are performed in order to investigate the effect of type of information on the accuracy of similarity judgment. Although we found no significant difference among 3 types of information in both of the 1st ($\chi2$=0.382, P=0.826) and the 3rd trials ($\chi2$=4.672, P=0.097), we can see the tendency that the difference in the 3rd trial is larger than the 1st trial. In particular, the judgment accuracy in the 3rd trial when snippet and text are provided gets improved from the 1st trial. However, the judgment accuracy when terms are provided is low both in the 1st and the 3rd trials.

We suppose this result indicates that snippets and original text are easier for the participants to adjust than terms. In order to consider it in more detail, typical judging behavior of the participants is investigated in Sec. IV.B.

B. Analysis of behavior in similarity judgment

By analyzing the eye-tracking data, we found that the position and topic of documents affected participants' viewing behavior. We also found the viewing behavior that is specific to the case when terms are presented. These findings are described in the rest of this subsection. It is noted that all of the 3 trials for each type of information per participant are analyzed in this subsection.

1) Effect of document position on participants' viewing behavior

Figure 4-6 show the distribution of AOI per participant, in which focusing time is accumulated for right-hand and left-hand document areas, respectively. It is noted that among 21 participants, 6 participants were excluded from these analysis because of stability problems with the eye tracking, leaving us with 15 participants.

These figure show that participants spent more time on looking at left-hand document area when either text or snippet is presented. This tendency is stronger when text is presented than snippet. Figure 7 is the heat map that shows this tendency when snippet is presented.

We think this tendency can be described by two assumptions about our behavior when reading documents. First, it is supposed that we usually read a document from left to right. Second, when we compare two things, we use one as a basis and try to find the difference from another one. As a result, we suppose participants read the left document first and used it as a basis.

TABLE III.
MULTIPLE COMPARISON TEST IN THE 1ST TRIAL

Level1	Level2	P-value (Tukey)	p-value (LSD)
Snippet	Text	0.0042**	0.0015**
Snippet	Term	0.9287	0.7152
Text	Term	0.0014**	0.0005**

TABLE IV.
MULTIPLE COMPARISON TEST IN THE 3RD TRIAL

Level1	Level2	P-value (Scheffe)	p-value (Steel-Dwass)
Snippet	Text	0.5393	0.4264
Snippet	Term	0.3112	0.2206
Text	Term	0.0307*	0.0341*

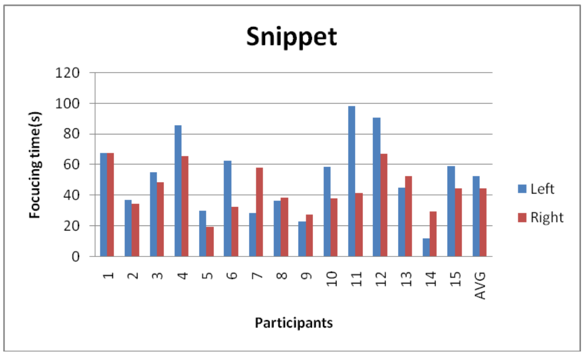

Figure 4. AOI distribution per participant (Snippet)

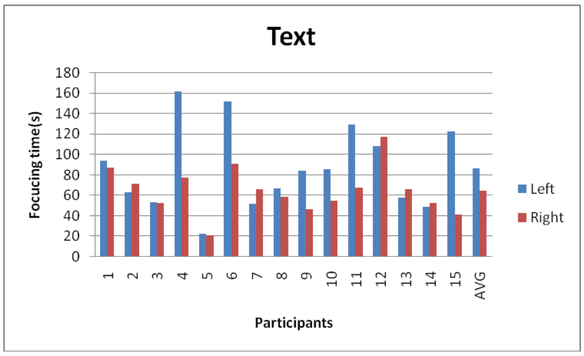

Figure 5. AOI distribution per participant (Text)

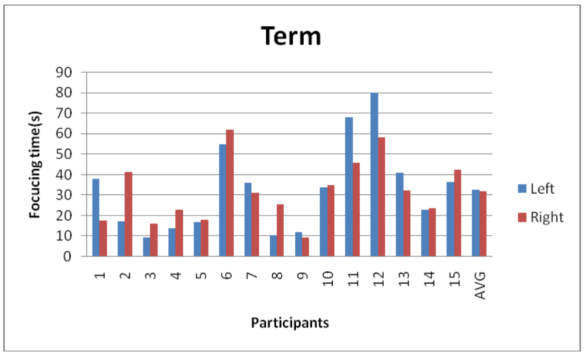

Figure 6. AOI distribution per participant (Term)

Figure 7. Heat map of typical behavior of viewing snippet

Figure 8. More focus at specific snippet in different topic conditions

TABLE V.
SUMMARY OF FIRSTLY-GAZED AREA

	Text	Snippet	Term	Sum
Left	42	39	32	113
Right	3	6	13	22
Sum	45	45	45	135

TABLE VI.
EFFECT OF TOPIC ON VIEWING BEHAVIOR

Topic	Snippet		Term	
	Common	Specific	Common	Specific
Same	22	5	19	12
Different	7	11	4	10

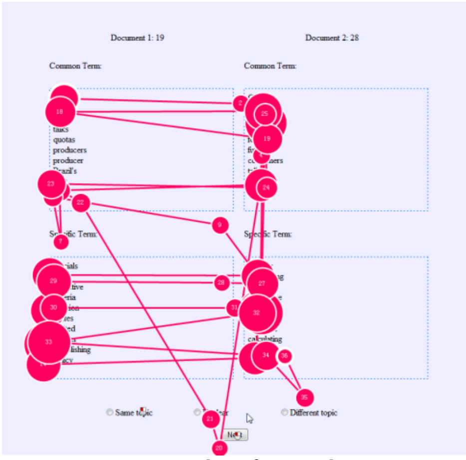

Figure 9. Frequent switches of AOIs when viewing terms

In order to examine this assumption, we analyzed which document area (right-hand or left-hand) the participants gazed first. Table V shows the frequency of gazing at right-hand / left-hand document areas per type of information. From the table, we can see the same tendency as Fig. 4-6, i.e., participants viewing text were the most likely to gaze at left-hand document area first, and those viewing snippet were second most likely to gaze at it first.

2) Effect of topic on participants' viewing behavior

Table VI shows the number of participants who focused on the corresponding (common or specific) area more frequently than another areas. It is counted in two categories: when documents of the same topic are presented and those of different topic are presented.

The table shows that in the same topic condition participants more frequently looked at common snippet / terms than specific ones. On the contrary, in the different topic condition, specific snippet / terms were more frequently focused by participants than common ones. Figure 8 shows typical heat map when documents of different topics are presented. It can be seen that the participant more gazed at specific snippet (lower part) than common snippet (upper part).

From the result, it is supposed that participants first assume whether given document pair relate with same topic or not, then examine the assumption by reading the corresponding information. That is, participants would carefully read specific terms / snippet when they assume the documents relate with different topic from each other. This result suggests participants need different kind of information according to assigned task. In that sense, separately providing common/specific information (snippets and terms) as employed in the paper is effective for supporting the task of similarity judgment.

3) Viewing behavior specific to terms condition

Figure 9 shows a gaze plot of viewing behavior that is specific to the case when terms are presented. The figure shows that the participant frequently switches AOIs between left-hand and right-hand document areas. This behavior was frequently observed when terms are presented. On the contrary, as shown in Fig. 10 and Fig. 11, such switching behavior was less observed when text or snippet is presented.

In order to investigate this tendency in more detail, we calculated the number of "switches": a switch occurs when participants changed AOI from left-hand to right-hand documents or vice versa. Table VII shows the average switching frequency that is counted per type of information. It shows that participants most frequently switched when terms are presented.

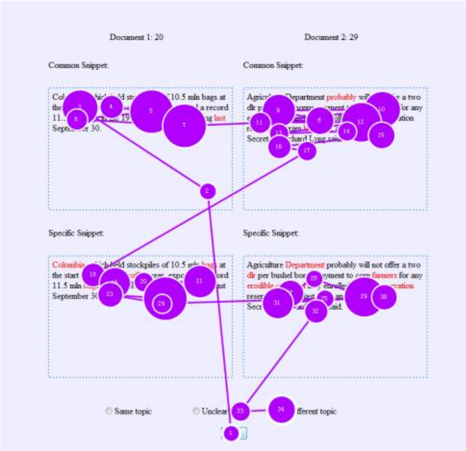

Figure 10. Fewer switches when viewing snippet

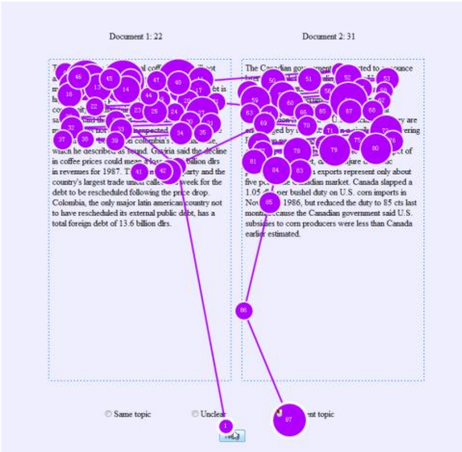

Figure 11. Fewer switches when viewing text

TABLE VII.
AVERAGE SWITCHING FREQUENCY

	Text	Snippet	Term
Average frequency	4.49	7.06	12.34
STDEV	3.28	3.54	6.82

It seems that each term can be examined independently, whereas participants have to read a sequence of terms when snippets or original text is displayed. We think such difference between terms and others is one of the reasons that participants reading terms can judge the similarity of document more quickly than other condition as shown in section IV.A. On the other hand, the improvement of judgment accuracy with experience was not observed when terms are presented. This implies that the context formed by a sequence of terms is important to grasp the contents of a document.

Although it is beyond the scope of the paper, the fact that term and snippet have different merits from each other would contribute to the design of an interface from MUF viewpoint. That is, both of the similarity judgment time and judgment accuracy would be improved by highlighting terms more clearly, such as by using larger fonts than other terms.

V. CONCLUSIONS

This paper investigates the behavior of users judging similarity of documents. The aim of the investigation is to obtain the hint for minimizing the cost of users judging similarity of documents, which is an essential task for users when performing interactive document clustering.

An experiment system was implemented, with using which 21 test participants were asked to judge the similarity of given pair of documents. Regarding the clue for the judgment, 3 types of information: original text, snippet, and term, are compared. The judgment accuracy and judgment time are analyzed, and the result shows that presenting terms is the best in terms of time cost, whereas judgment accuracy when snippet or text is presented improved through experience.

The behavior of participants was also recorded by T60 eye-tracking system. Analyzing the recorded data found typical viewing behaviors that can be the evidence of the difference between term and other 2 clues.

Our future work includes the development of interactive clustering-based Web search engine. The obtained result will contribute to realization of interface that can minimize the user's feedback cost for document similarity judgment.

ACKNOWLEDGMENTS

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