Understanding Viewing Pattern in e-Learning VOD Systems*

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***Abstract* - Recordings of lectures (Web lectures) and their usage for support learning have become increasingly popular. Most of the Web lectures are usually available in streamed formats. In this paper, we investigate what information can be gained from analyzing the users' interactions with such streams. Specifically, we have conducted a large-scale study of students' VOD (Video On Demand) behavior by analyzing the seeking data collected from a deployed e-Learning VOD system. The analysis shows that common viewing patterns among the students' VOD behavior can be identified. We also give an interpretation what causes the patterns. This work shows that as limited data collected from streams is, it is nevertheless a valuable source of information.**

Index Terms - Web lectures, Seek, VOD, Viewing Pattern.

I. INTRODUCTION

Recordings of lectures (Web lectures) and their usage for support learning have become increasingly popular. While first investigations date back to the seventies, advances in Web and multimedia technology and faster networks have resulted in an increasing amount of Web lectures becoming available. Web lectures are often available in streaming formats, i.e. students watch the lectures using a Web based player, instead of downloading them and watching them using a desktop player. When a web lecture is streamed, the streaming server can collect data about the behavior of the student watching the stream. This paper investigates seeking data, i.e. on which time point and to where students are likely to perform a seek action while watching the stream, more precisely the question what the seeking data can tell us. Are there typical viewing patterns? What are they?

The paper is structured as follows. The next section (Related Work) puts our work in context and shows the value of analyzing seeking behavior. Session 3 provides an overview of the VOD system used in our survey. We then describe our survey (Session 4), including the data formats and the methodology. Session 5 then presents an in-depth analysis of the collected data and reveals our discovery of the viewing patterns. Session 6 makes a further discussion of the data, discusses the relationship among the students' VOD behavior, students' performance and the teacher quality. Session 7 provides a conclusion of the paper.

II. RELATED WORK

Research on the usage of recorded lecture materials has been undertaken since long. For instance, Gibbons et al, 1977, showed that distant students who watched recordings along with a facilitator outperformed students who attended the live lectures [1]. Seminal work has been undertaken by Abowed and Brotherton in the eClass/Classroom 2000 project (Brotherton, 2004) [2]. The eClass system was designed to enable students to do efficient note taking. Students could access the recordings via a timeline, by clicking on a specific slide (which would start the recording starting at the point when the slide was displayed), and also by clicking on elements of a displayed slide. Since the lectures were recorded and easily accessible, students were freed from the need to take notes that captured the complete content of the lectures. Thus, the rationale was, students could focus on those points specifically relevant for them. The eClass project was analyzed in a detailed study that covered access behavior over a period of three years. Their analysis provided important information for streaming optimization (e.g., that the first five minutes of a video are most heavily accessed), but also on when students access videos (not surprisingly, a peak in access occurs around the exam dates). Also investigated was the pattern of interaction, e.g., whether students prefer to use access via slides or the timeline.

A large amount of existing work on analyzing navigation behavior focuses on technical issues with the goal of modeling/simulating/forecasting workload of the media servers (Padhye 1999, Almeida 2001, Costa 2004). Zupancic (2002) analyzes audio recordings of lectures (e.g., the typical lengths of sessions).

Fewer researches have investigated navigation patterns from a more pedagogical viewpoint. For instance He (2000) has used navigation data to formulate design guidelines [4].

Research on Social Navigation in Web lectures (Mertens 2006) has shown that the users' interactions with a video yield valuable data. They report that visual cues showing the viewing history of prior users influence the viewing behavior of current users [5].

The major difference from our research to most prior work is that we investigate user interaction with a video stream that does not offer advanced navigation. Obviously, advanced

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navigation functionality, in particular using slides, enable a more efficient navigation and in the eClass project were the preferred mode of interaction. However, such functionality requires post-processing and the according software. But today a significant amount of Web lectures (such as the MIT OpenCourseWare,http://ocw.mit.edu/courses/audio-video-courses/) are only available in the "primitive" form of a single video stream, without the possibility of advanced navigation, e.g., by slides.

III. Introduction of The VOD System

The VOD system used in our survey is deployed by the School of Continuing Education of Shanghai Jiao Tong University. The users of the system are the students from the school, about 30,000 persons in total. Most of them have full time job and receive continuing education through the Internet at home.

The VOD system is a typical client/server architecture based system. The server holds the Web lectures given by teachers, and students use web browsers to open a web page which contains an Active-X control to watch the lectures. A progress bar is placed in the page, which can be used to seek to any part of the lectures by users.

Figure 1 is the playing page of the VOD system:

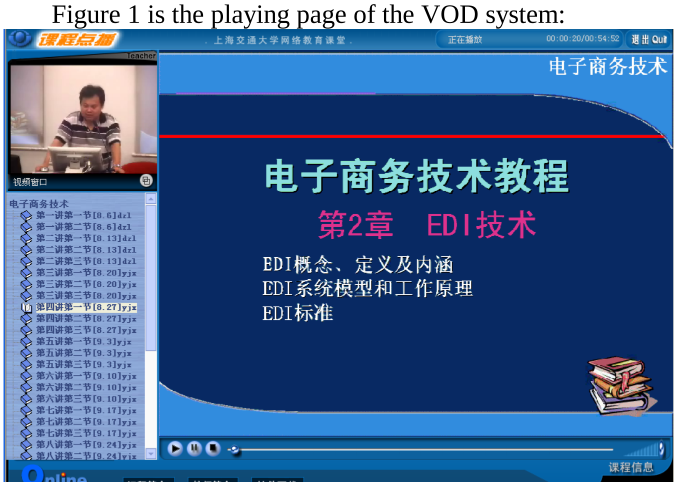

Fig. 1 Playing page of the VOD system

IV. Methodology

Our study focused on studying users' behavior, specifically the users' seek patterns as given in the seeking data. Thus, the data we intend to collect is all about the seek actions of the users. Because the VOD system is deployed in a university context and used as the main tool for the students, we had to assure that collecting the data would not disrupt the users' access to the system. We opted for the following solution.

Our survey system is based on JavaScript and Ajax. We patched the original system with a set of simple scripts to record the users' behavior on a server. When the users use the progress bar to perform a seek action, our scripts are activated. The information of this seek action is transferred to our server using the technology Ajax where it is stored in a database. In this way, we make a minimal modification to the original system and do not have any disruption to the normal access to the system.

TABLE I
Format of the Collected Data

SessionID	UserID	Seek-From -Time	Seek-To-Time	ResourceID	Record-Timestamp

The data we collected has the format as shown in Table I. A session is started when a user begins to watch a video and ends when the user watches a second video or closes the player. In a session, a typical user does not just watch a video sequentially, but rather skips parts of the video and jump to a new position. These jumps are stored as parts of the session. Each session has a unique session ID which is generated randomly. Every user also has a unique user ID (their student ID). The Seek-From-Time means that the time of the video when the user uses the progress bar to seek. The Seek-To-Time means the time of the video which the user jumps to. Each video has a predefined and unique resource ID. According to this resource ID, we can retrieve more information about the video, like the length, video content and etc. Record-Timestamp is the time this seek action has been recorded, which approximates the time when this seek action happens.

For example, the data in Table II describe a user's viewing session. At time 1, user u123 starts to play the video. After viewing 10 minutes of the video, the user performs a seek action, and jumps to the 25th minute of the video. After the user has watched until minute 28, he jumps back to minutes 15. Then the user continues to watch the video until minute 35, when the session closes as he starts to watch a second video or closes the player,.

TABLE II
An Example of the Collected Data

SessionID	UserID	OldTime	NewTime	ResourceID	RecordTime
SE23	u123	START	NONE	RE01	1
SE23	u123	10	25	RE01	11
SE23	u123	28	15	RE01	14
SE23	u123	35	END	RE01	34

V. Analysis of the Data

Our survey started on 2010.5.12 and ended on 2010.7.12, thus lasted for 2 months. It covered a non-exam period (5.12~6.12) and an exam period (6.13~7.12). In these two months, we collected information from 2992 students. This amounts to 49434 sessions and recorded 282502 seek actions in total, which corresponds to about 5 sessions per user, and about 5 seek actions per session.

The students watched 4883 video files in total; the length of these videos varies from 40 minutes to 90 minutes. The average time the user spent on one video file is about 25 minutes.

We make a more detailed analysis of the data, as shown below:

A. *Distribution of the time when users join the system*

Figure 3 is the histogram of the time when the users join the system. We can see from the figure that the time most users join the system concentrates in the interval between 19:00 and

22:00. This is consistent with the demographics of the users of this system, as most of them have daytime job and are only free in the evening. But there is still something interesting in this figure. Some students watch the videos as early as 6 am. We can guess that these students are really hardworking.

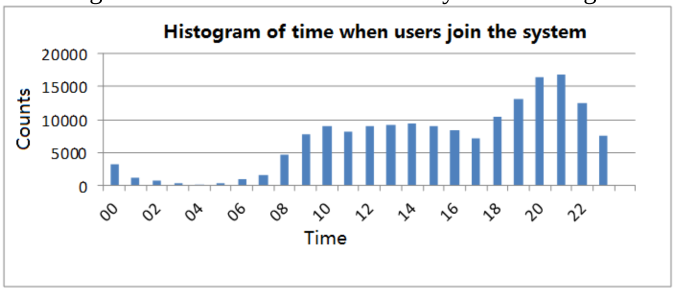

Fig. 3 Distribution of time when users join the system

B. *Distribution of the jump spot*

Figure 4 shows the distribution of the jump spots of all the videos. The jump spots have been normalized according to the video lengths. As we can see, in the early stage, there's a high probability that the user will seek. And this probability drops while the time proceeds. In the middle stage [20%~90%], the probabilities that the user will jump are almost the same. In the late stage (90%~100%], the probability drops again. This result is just almost the same as what we have expected. The initial part of the videos may be neither interesting nor important, for example, some logos or copyright notice, thus the students have a high probability to skip this part. Another reason is that instead of watching the entire video in one time, they watch the video in several turns. So they may just skip the initial part and continue to watch the left part. In the analysis in part E, we can see that this user behavior pattern may be attributed to the attendance rules of the school. There is not anything special during the middle stage of the videos, so the probabilities that a seek action will be performed are almost the same, this is well represented in the figure. But in the late stage, the users have viewed the previous part of the video and have little left in the following part, thus there is no need for the users to perform a seek action to jump forward or jump backward. So the probability drops in the late stage.

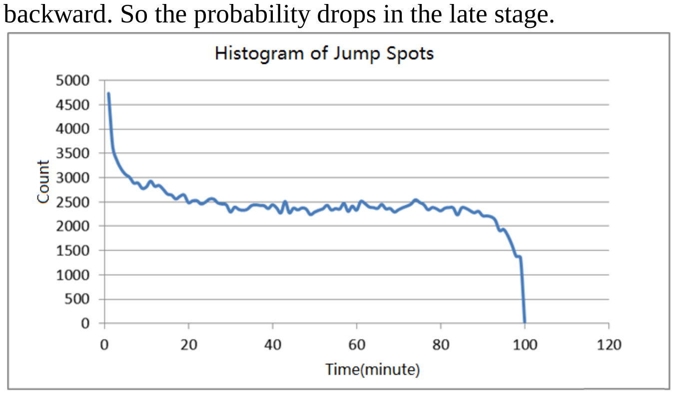

Fig. 4 Distribution of jump spots

C. *Popularities of the Web lectures*

The popularities of the Web lectures are not even; the most popular one is hundreds times frequently viewed than the least popular one. One reason for this is that the enrolled student number of each course is not the same. After reviewing the contents of the most popular Web lectures, we find that these lectures are all about examinations. Not surprisingly, as most students cram for exams, the system gets the most use ground the time of exams.

This finding is the same as the finding discovered by the Brotherton (2004). In their survey, the accesses of the learning tool eClass had peaks around the exam dates [2].

D. *Distribution of the jumps in the media*

Figure 5 shows the distribution of the jumps in the media. A negative number means user seeks backward and a positive number means that user seeks forward. As we can see from this figure, the jump distances appear to be clustered around zero, which means that the users do not do a long seek when a seek action happens, mainly about -5 to 10 minutes. Brotherton (2004) also found a similar result. But in their survey, 50% of the media jumps are to a point more than 10 minutes forward or backward from the current point of the media [2], while in our survey, only about 25% of the jump distances are more than 10 minutes. Maybe the reason behind is the system used to perform the survey. eClass is slide based and offers advanced navigation information, while our system is stream based and does not offer any advanced navigation information. When users of our system are not interested in some parts of the videos, because they do not have advanced navigation information, instead of seeking far away, they prefer to seek gradually, possibly because they do not want to miss any important part of the videos.

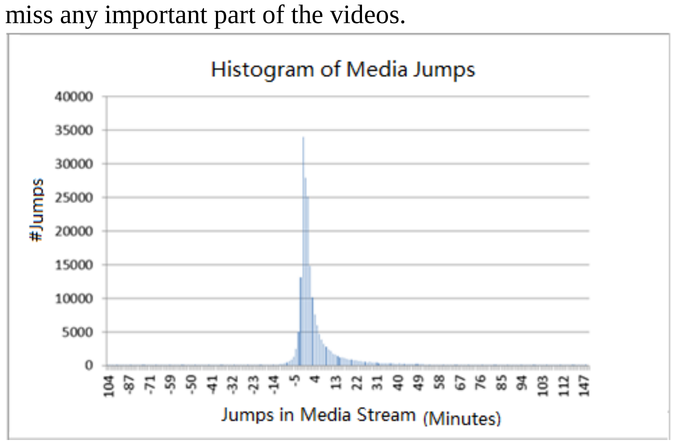

Fig. 5 Distribution of jump in the media

Brotherton (2004) found in their analysis that counts of the forward jumps were 1.7 times more than that of the backward jumps [2]. In our analysis, the proportions of the forward media jumps and the backward media jumps are about 0.7 and 0.3 respectively. Both results are basically consistent with each other.

E. *A more detailed analysis of the jumps in the media*

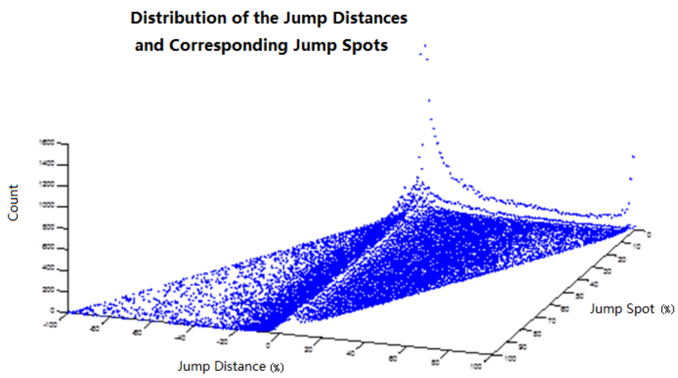

Fig. 6 Distribution of the jump distances and the corresponding jump spots

Our survey aims at analyzing the users viewing pattern by analyzing the jumps in media. One important fact is the jump distances, and the other is the jump spots. We have analyzed them separately in the previous section. In this section, we will analyze them jointly. We plot the jump spots and the corresponding jump distances on to one graph, as shown in Figure 6. This figure is a histogram of jump spots and corresponding jump distances, shown in a 3D way.

We can see that when viewing the initial part of the video, there is a high probability that the users will directly jump to the end of the video. This is because of the attendance rules designed by the school. The school counts for the attendance when the students watch the video for once, no matter how long they spend on it. Thus in order to get the attendance credit cheaply, some students just open the video, and jump to the end. This finding suggests a need to revise of the attendance rule.

We do the same analysis of the data in the exam period and the non-exam period. We plot the two graphs as shown in Figure 7 and Figure 8.

We can see that in the exam period, the probability that users would directly jump to the end of the videos when viewing the initial part is much smaller than that in the non-exam period. This suggests that in the exam period, the students watch the videos more seriously, and not just for the attendance credit. This is a further explanation of the significance that examination and scores to the students.

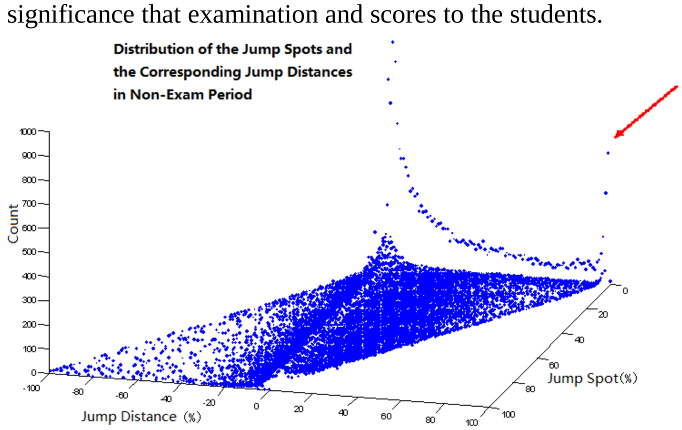

Fig. 7 Distribution of the jump distances and the corresponding jump spots in none-exam period

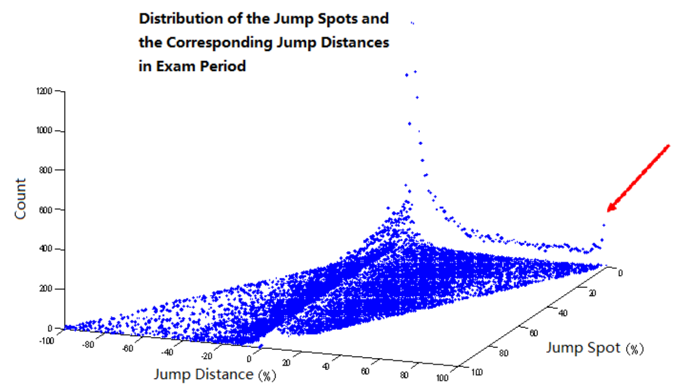

Fig. 8 Distribution of the jump distances and the corresponding jump spots in exam period

F. Categorization of the access sessions

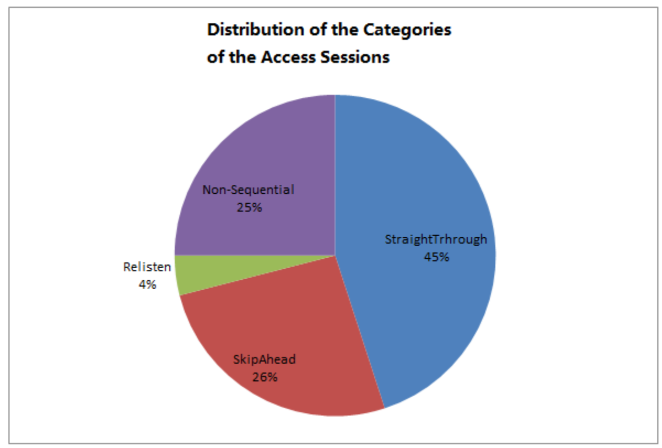

Fig. 9 Distribution of the categories of the access sessions

We employ the terminology defined in Brotherton (2004) to categorize the interaction with the video stream:

1) StraightThrough: a study session plays media, but has no media jumps.

2) SkipAhead: a study session has only forward jumps in the media

3) Relisten: a study session has only backward jumps in the media

4*)* Non-Sequential: a study session has both forward and backward jumps in the media.

The distribution is shown in Fig 9. Not surprisingly, the proportions of StraightThrough is dominant, Brotherton (2004) [2] also had a similar discovery.

VI. Further Discussion

The analysis above discovers some patterns from the overall seeking data. But are all these patterns consistent with the patterns in a specific lecture? We do the same analysis of the top 10 lectures respectively, and find that the patterns discovered from the overall seeking data are also exhibited in each lecture, which means that the users have common behavior patterns while they are using the VOD system.

The goal of this paper is to analyze the seeking data, and determine what the seeking data can tell us. In order to unearth more from the data, we analyze the relationship between the students' performances (final scores) and their VOD behavior, and students' VOD behavior and the teacher quality, expecting that if a student spends more time on the Web lectures, perform less seeking forward actions but more seeking backward actions, which suggests that the student takes the Web lectures more seriously, would have a higher score. We were also expecting that if less seeking forward actions had been performed in a course, then the quality of the teacher of this course was better. But after analyzing the data, we could not find the relationship among them. The students' performances do not have a relationship with their VOD behavior, which suggests that Web lectures VOD may be not the dominant learning tool for the students. Actually, the students have many learning tools in the school, like receiving the live broadcasting of the lectures or go to the classroom directly. In our opinion, students who carefully work with textbooks can also have a good score without viewing the Web lectures. Because the students do not take Web lectures as their dominant learning tool, their VOD behavior of course cannot reflect the teacher quality.

VII. Conclusion

In this paper, we present a large-scale survey of students' VOD behavior by collecting jump data from a deployed VOD system. We described and evaluated the measurement tools we developed for this purpose. We then reported the statistical data from the survey and make an in-depth analysis. By analyzing these data, we find that there are common viewing patterns among the students' VOD behavior. There is a high probability that the students will jump in the initial part of the video. Jump distances are clustered to zero. Exams and scores are important to students, their VOD behavior on somehow is according with the rules of the score and the exam. We also discovered that the users' VOD behavior had no relationship with their performance and teacher quality, partially because the VOD system is not the primary learning tool for the students.

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