Structural Analysis of Video-Audience-Watching Preference

Chonthorn Ariyapitipan,and Kingkarn Sookhanaphibarn
BU-Multimedia Intelligent Technology Laboratory,
School of Information Technology and Innovation
Bangkok University, Thailand

***Abstract*—This paper presents a systematic approach for video-audience-watching content analysis. Our analysis technique is based on audience preference that they will click Like while watching a video clip. The principal component analysis is applied to extract the content structure of a video clip. The hierarchical clustering technique also is used to segment a video content as time slots. The analysis and clustering are based on the audience opinion. In our experiment, the approach is set to teaching video content for 22 4-year students in Bachelor degree. The analysis results show the three principal structures that can represent three principal video-audience-watching preference styles.**

***Index Terms*—Routine-structure analysis, Singular Value Decomposition (SVD), Principal Component Analysis (PCA)**

I. Introduction

A video is widely used in e-learning systems because it can draw students attention more than other teaching media. It is obvious that the student concentration and the video length are associated. Analyzing a video content based on user preference can improve the effectiveness of teaching material because the analyzed results will be used to video summarization. This proposed technique will support the strategy of student-centered teaching.

In the previous work [1], they presented a systematic video summarization by expert voting scores. They use a straightforward method as follows. First, the video frames are scored by a expert group. Next, these assigned scores are averaged to produce a singular value for each frame, and lastly, the highest scored video frames alongside the corresponding audio and textual contents are extracted to be inserted into the summary. Under this straightforward method, the resulting video summary is a set of most highest voting video frames.

For a teaching video, we developed a video playing tool that let users click Like at particular content. To summarize the video content, we applied the Eigendecomposition technique to extract principal components. Then, the video content was segmented by using the obtained principal components. The segmented contents are based on the students like. This paper presents a video content summarization by using Eigendecomposition technique.

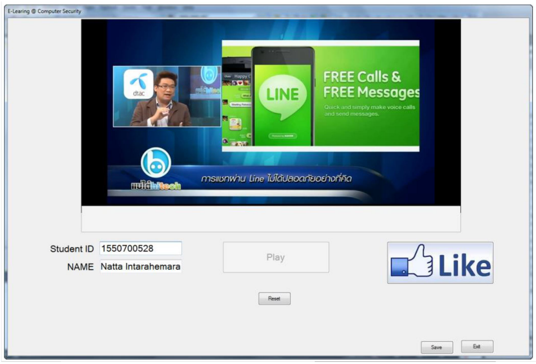

Fig. 1. Video playing tool.

A. Eigendecomposition

Eigendecomposition is adapted in many applications as follows: As Eagle and Pentland [2] concluded, the behavior structures become more apparent when the behavior is temporally, spatially, and socially contextualized, the visitor circulation in the museum space will be dominated by a set of primary structures.

Eigendecomposition was firstly used for analyzing the daily routine structure of people where the structure will relate to time and place of everyday life as introduced by Eagle and Pentland [2]. Singular Value Decomposition (SVD) were extracted to present the primary routine structure because normally behavior is temporally, spatially, and socially contextualized. Eigendecomposition has been also utilized in other applications like the game-virtual-space analysis, and campus-space analysis.

Sookhanaphibarn [3] introduced an eigenbehavior-based method to extract the primary behaviors of players's movements. The primary pattern was a repeating and common structure of the players' movements to the same virtual place (in-game). The technique was applied to a Massively Multiplayer Online Game (MMOG) for identifying the locations where players go to receive a service, such as, a quest or assistance.

Eigenplaces was firstly used by [4] who applied eigendecomposition to extract the discriminant features from the time-series data. The location data was collected from the students' mobiles for almost three months. They categorized the location based on wireless access points. The resulting eigenvectors were another called eigenplaces referring to applications in network planning, traffic an tourism management, and even marketing.

978-1-7281-3575-5/19/$31.00

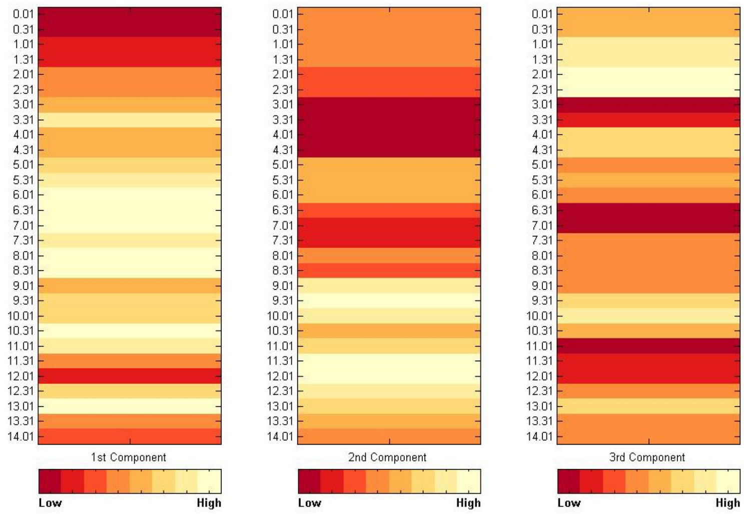

Fig. 2. Three principal components of video contents from 22 viewing students where the brightness shade means high volume of Like-clicks, and the vertical axes are video playing time.

II. Proposed Methodology

A. Data Collection Tool

We developed a video playing tool as shown in Fig. 1 that a student can click Like button while watching a video. The student name and ID was also required. All the viewing time and the frequency of Like clicks are manually saved by the student as he/she consented. The student can immediately stop watching with exit button.

B. Algorithm

Given a set of like-click associated with video content, our segmentation algorithm consists of the following steps:

1) Set a row vector $\mathbf{x} = \{x_1, ..., x_p\}$ as a binary vector of one audience-like viewing content, where p is the number of time-slot in a viewing video.
2) Construct a data matrix $\mathbf{X} = \{x_{ij}\}$ where $1 \leq i \leq n$ and $1 \leq j \leq p$ as a binary matrix consisting of the set of all data vectors, one vector per row, where n is the number of row vectors.
3) Extract a set of eigenvectors $\mathbf{V}$ of $\mathbf{X}^T\mathbf{X}$ by calculating SVD.

$$\mathbf{X} = \mathbf{U} \cdot \mathbf{\Sigma} \cdot \mathbf{V}^T \tag{1}$$

4) Compute the significance score that is correlated with the percentage of power in the data matrix $\mathbf{X}$ captured in the rank-k reconstruction.
5) Indicate a set of primary eigenvectors v_i with a desired significance score.
6) Parition the content with the set of primary eigenvectors.

For Steps 1-2, the association matrix is $\mathbf{X} = \{x_{ij}\}$ where an entry represents the like-click of i^{th} student viewing at the j^{th} particular content. In other words, each column vector corresponds to the popularity for a content as well as each row vector corresponding to an association vector for a time slot.

III. Experiment and Result

In our experiment, participants were 22 undergraduate students in School of Science and Technology. They were 15 male and 7 female and their ages were between 21-26 years old. Their GPA was 2.96 in average. All participant watched a video clip with a length of 13.02 min. This video was as a part of teaching material in subject of computer security. There were paper-based pre-test before and post-test after watching the video. Three principal components (or eigen-vectors) of video contents from 22 viewing students are shown in Fig. 2. For visual representation, the brightness in each bar is associated with high volume of Like-clicks. The segmentation of video content can be achieved by using top primary components at least one.

IV. Conclusions

This paper introduces how to use eigendecomposition for summarizing video content. Like-clicks during video viewing can used for identifying a degree of student attention and content interesting.

References

[1] K. Darabi and G. Ghinea, “Video summarization by group scoring,” in *2014 International Conference on Multimedia Computing and Systems (ICMCS)*. IEEE, 2014, pp. 112–116.

[2] N. Eagle and A. S. Pentland, “Eigenbehaviors: Identifying structure in routine,” *Behavioral Ecology and Sociobiology*, vol. 63, no. 7, pp. 1057–1066, 2009.

[3] K. Sookhanaphibarn, R. Thawonmas, F. Rinaldo, and K.-T. Chen, “Spatiotemporal analysis in virtual environments using eigenbehaviors,” in *Proceedings of the 7th International Conference on Advances in Computer Entertainment Technology*. ACM, 2010, pp. 62–65.

[4] F. Calabrese, J. Reades, and C. Ratti, “Eigenplaces: segmenting space through digital signatures,” *IEEE Pervasive Computing*, vol. 9, no. 1, pp. 78–84, 2009.