SDPS-2014
Printed in the United States of America, June, 2014

PSYCHOLOGICAL, MATHEMATICAL, AND PEDAGOGICAL ANALYSIS OF VIDEO STREAMS FOR MEASURES OF STUDENT ENGAGEMENT

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ABSTRACT

The increasing use of multimedia in and out of the classroom is in part due to the recognition of critical roles it plays in the learning process. Video media has the potential to capture and focus student attention on information relevant to the academic subject in ways that other media do not. The phenomenon of student engagement is a beginning point in an extended process of student learning, and without engagement, student learning will be limited. We have initiated preliminary studies to explore student engagement through video media in a freshman level earth science course. In these studies, we find, not unexpectedly, that in a large sample of video snips, there is wide variation in the frequency with which students recall video at a later time. Why are some video snips recalled with greater frequency? These findings, and the questions they raise, suggest that a complex web of variables will need to be disentangled to better understand this initial phase of student learning. If associations could be discovered between videos that are recalled with higher frequency and objective measures of information encoded in the digital video streams, then this association could potentially provide a way to identify in advance videos that are more “memorable”. The selection of videos by predictive criteria, as well as criteria for generating good educational videos, may therefore contribute to enhancing student engagement and thus academic performance.

INTRODUCTION

Student engagement is a critical variable in such diverse educational issues as attendance, graduation rates, and overall academic success (Thatcher, 2014). As with any other human-related behavior, student engagement is a complex phenomenon that spans many axes of understanding, from academic to social environments. The National Survey of Student Engagement (NSSE, 2014) has surveyed over 1,000,000 students since 2000 for information at the macro level about student activities and participation, and provides institutional and faculty guidance on best practices. Studies of student engagement vary widely in their focus, from attitudes about the importance of faculty behavior and attitude towards positive undergraduate outcomes (Umbach and Wawrzynski, 2005), to content mastery in specific courses (Redish and McDermott, 1999). In a review of the literature, Handlesman et al. (2005) found “...general agreement that engaged students are good learners and that effective teaching stimulates and sustains student engagement…”.

What factors play significant roles in engaging students in an educational setting? Particular components of student engagement have been generally recognized - attendance, attention, student interactions with peers and the teacher, and, in general, the participation in “active learning” (Hacker and Niederhauser, 2000; Thatcher, 2014). “Active learning” means in general the participation of the student in a focused activity. Many educators advocate for replacing a “traditional” lecture dominated by the instructor in a one-way delivery channel by multiple channel delivery with active learning (Center for Research on Learning and Teaching, 2014).

Among the diversity of channels through which students receive and interact with information is digital video. Digital video use in the academic environment has significantly increased with the growth of online video archives (e.g., YouTube) and the build-out of internet and technology infrastructure required for classroom video viewing (Kaufman and Mohan, 2009). As a consequence, questions about how best to select and use digital video in the classroom have proliferated (e.g., Brande and Arslan, 2013), and some general guidelines have been developed (e.g., Clark and Mayer, 2011; Derry, 2005; Mayer and Moreno, 2003). Of particular relevance to studies of video multimedia use is the dual-channel theory of multimedia learning proposed by Mayer and Moreno (2003). They propose that because visual and auditory sensory input arrives through two distinct “channels”, and that channel capacity is ultimately limited, under some conditions, cognitive processing may be reduced, thus impeding learning.

Results of research in the cognition and psychology of meaningful learning indicate the importance of three significant factors: 1) selective organization and integration of images and text; 2) an environment of reduced cognitive load (e.g., fewer ideas, distractions, unrelated images and text); 3) generation of self-explanations (Sorden, unpublished).

Because of the increasing recognition of the potential of digital video for enhancing student engagement and learning, we have recently begun to explore the availability and applicability of what we consider to be pedagogically relevant video to an introductory (freshman level) earth science course. We have found that among the vast YouTube archive, an increasing number of channels are accumulating geoscience video content, much of which is applicable to common topics covered in our course. Might short digital video snips viewed throughout a course lead to greater student engagement and performance? And if so, how might one more effectively and efficiently select video for the potential gains we would like our students to achieve? We are certainly unable to answer this broader question at the present time. Rather, the studies we report herein are of a preliminary and much more restricted nature.

a) Do students recall within a specified period of time instructional video snips with different frequencies? That is, are some videos, “more memorable”, recalled to a greater degree than others?
b) If some videos are more memorable, can we design future studies to generate objective properties of the video stream data that correlate with student retention and recall?

Our focus is on a student’s ability to recall video snips previously viewed during classroom instruction. Therefore, our definition of student engagement is the number of videos a student recalls and records on an examination within a specified period of time, of all those previously viewed.

MATERIALS AND METHODS

Discovery and Selection of Video

Discovery: A domain expert (Brande) searched YouTube for geoscience content relevant to topics discussed in his introductory earth science course. Video discovery on YouTube was an extended process, as the vast majority of videos retrieved from relevant searches were judged unsuitable for classroom presentation (significant factors that excluded video included, among others, unreliability of source channel, poor quality and insignificant factual content). Videos for potential inclusion were viewed and judged from reliable source channels (e.g., government agencies, scientific organizations, educational and non-profit institutions, individual researcher laboratories, major news organizations). Other significant criteria for potential inclusion were: a) short length (<3 minutes), b) factual content that aligns with predetermined lecture material, c) higher quality video display (=>640x480 pixel resolution), and d) overall attractiveness to foster student engagement (arbitrarily determined by the instructor - Brande).

Thirty one (31) videos were selected for viewing during lectures throughout a period of approximately six weeks. Video titles and their URLs are given in Table 1.

Preparation of video for classroom viewing: Links to most videos selected for classroom viewing were processed through www.ezsnips.com, an online software service (Brande and Arslan, 2012) designed to play a YouTube video via a specially constructed, web browser-compatible URL (sniplink). The sniplink was attached as a hyperlink to an object on a PowerPoint slide in the lecture presentation.

Playing the video in the classroom: At the appropriate time during the lecture, the instructor simply clicks the slide object to which the sniplink was attached, and within a few seconds, the YouTube video begins playing in a new browser tab, automatically opened by the PowerPoint hyperlink call. Some YouTube channels display banner advertisements at one or more points during the playing of a video. Due to terms of conditions imposed by YouTube, these banner ads are not to be suppressed. The instructor at the podium is able to quickly (<3 seconds) click off a banner ad that appears. At this time, we are unable to determine if there is any significant impact of these interruptions by partial ad display on student engagement.

Metric of student engagement based upon memory recall: A simple metric of student engagement was defined as the number of videos recalled from the previous period of lecture and study, approximately every 2 to 2.5 weeks. Three closed book examinations were administered. At the end of each examination, a section was provided in which students could enter a list of videos they recalled watching during the previous lectures. This section was incentivized with a bonus point for the list of recalled videos previously viewed. The requested list did not require exact titles or precise details, only enough description to enable the instructor to identify the specific video being referenced. Each video in the list written by each student was matched by the instructor to the video title played during a previous lecture. The number of times each video was identified was recorded (Figure 1, Table 2).

Correlation of student engagement with examination score average:

An hypothesis was advanced about whether or not student recall frequency (Figure 2) is related to the average of a student’s examination score (Figure 3). Because of visual deviations of the data (Figure 3) from an expected bivariate normal distribution, both non-parametric (Spearman’s coefficient of rank correlation), and parametric (product-moment correlation coefficient) tests were performed. We note that studies have found the parametric statistical test of the product-moment correlation coefficient robust under a wide range of non-normality (Fowler, 1987).

Image Processing

Two video snips were selected for exploring the nature of mathematical functions of the digital video data (Figure 4; "Dust Devil in Desert", hereinafter "Dust Devil" and "China Wall for sport", hereinafter "China Wall"). The two snips record similar environments (desert southwestern United States), and similar inclusion of people in sport-like circumstances and activity (bicycling, all-terrain vehicle riding). Furthermore, we selected these two video snips in anticipation of determining the difference in degree, if any, to which these videos were recalled by students (results and discussion, below), and the correlation, if any, with objective, mathematical features.

As noted, our second, and longer term, goal is to discover correlations, if any, between cognitive signatures of student engagement (e.g., degree of recall from memory) while viewing instructional video and objective (computational) properties extracted from the data file of the video stream. It is clear that the number of possible features for extraction from a digital video file is infinite, both in the spatial and temporal domains.

Therefore, we must make choices that limit our investigation to particular metrics that we believe to represent features of cognitive significance in psychology. In this exploratory study, we have chosen a small set of spatial and temporal functions simply to test whether or not these functions vary to some degree among video data streams from what we subjectively judge to be somewhat similar videos. Among spatial functions, we computed average frame brightness, deviation of intensity, contrast, and other texture features (Haralick et al., 1973). In the temporal domain, we evaluated the amount of motion based on optical flow (Horn and Schunck, 1981) and the percent of non-stationary pixels in the image. Some of those features are also used in video quality evaluation and compression (Sonka et al., 2014). Spatial and temporal functions used for feature extraction are listed and described below. All video frames were first converted from RGB to gray levels before functions were computed, and results displayed on normalized scales.

Selected functions:

Median intensity is based upon a conversion of the pixel-level Red-Green-Blue (RGB) data to gray level via the following function - 0.2989 * R + 0.5870 * G + 0.1140 * B (Shapiro and Stockman, 2001).

Interquartile intensity is the range from the 75th percentile to the 25th percentile of the gray level intensity distribution.

Edginess is our term for describing the frequency of image edges in each frame. The value of edginess is determined from dividing the total number of edge pixels by the frame size (number of pixels in a single frame of the video). Edge pixels were determined from the algorithm in Canny (1986).

Entropy is a measure of information, calculated here from the frequency distribution of the pixel matrix p (Gonzalez, et al., 2009) by $E = -\sum_i p_i \log_2 p_i$.

Colorfulness was computed as the sum of the standard deviations of the frequency distributions from each of the Red, Green, and Blue channels.

The next four texture features are based on the computation of the gray co-occurrence matrix $g(i,j)$ (Haralick et al., 1973).

Contrast was computed as $\sum_{i,j} |i-j|^2 g(i,j)$.

Correlation was computed as $\sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)g(i,j)}{\sigma_i \sigma_j}$, where μ_i, μ_j are row and column averages of g, and σ_i, σ_j are standard deviations.

Energy was computed as $\sum_{i,j} g(i,j)^2$.

Homogeneity was computed as $\sum_{i,j} \frac{g(i,j)}{1+|i-j|}$.

Non-stationary pixels – computed as $\frac{1}{N}\sum_{i,j} |I_{k+1} - I_{k+1}|$, where N is a total number of pixels, I_k is the current frame, and I_{k+1} is the following frame.

Total motion – computed as the sum of the magnitudes of vectors that represent optical flow (Horn and Schunck, 1981).

RESULTS

Subjective student recall data

A total of 31 videos (Table 1) were played during lectures and viewed by approximately 50 students throughout this study. The instructor matched student responses to the video titles, and compiled the frequency distribution given in Figure 1. A total of 347 instances of individual video recall were recorded by students over all three examinations (Table 2). One video ("Animation of river sediment") was not recalled by any student.

The association of the number of videos recalled by each student is plotted against the student's average examination score over the three tests (Figure 3). The parametric product-moment correlation coefficient was found to be statistically highly significant computed, r = 0.49 (n=49, p<0.001, 1-tailed). The coefficient of determination, R^2, was found to be 0.24.

Objective image analysis

The YouTube video snips were downloaded using DVDVideoSoft's YouTube Download Free Studio. The video feature extraction was carried out using an in-house developed code in MATLAB (Mathworks, Natick, MA).

Measures of spatial features (per frame) are shown in Figure 5. Measures of temporal features (per frame) are shown in Figure 6.

No statistical studies based on the selected image analysis functions were possible in this preliminary study, as only one video was selected from each group (highly remembered, least remembered) for their exploratory use.

Statistical studies will commence with the acquisition of image processing data from multiple videos in each group.

DISCUSSION

Today, there are more opportunities for students to be engaged in the academic classroom because of changes in "best practices". Many of these more recent changes devote more time to interactive activity and less time to the traditional one-way lecture delivered by the instructor. The explosive growth and accessibility of video on the web, specifically on YouTube, has given instructors a tool for the fast and effective delivery of digital video to web-enabled classrooms. There is a general recognition that video is an important component of effective pedagogy, but certainly not the only one (Clark and Mayer, 2011).

We are especially interested in the degree of memorability of instructional video because of this medium's ability to document phenomena and bring dynamic processes from nature and the laboratory into the lecture classroom with information that potentially enhances student learning. From our perspective, what makes some earth science videos more memorable than others? Are there any factors that would help to identify in advance the more "memorable" videos? If so, could such factors be used to predict student engagement, and more importantly, student performance? Are the students who recall and record more videos simply the better students, i.e., students who tend to score higher on the examinations?

Videos selected for the course (Table 1) obviously vary in an unlimited number of ways. We hypothesized at the beginning that students would not recall each video with equal frequency. This seemed intuitively reasonable considering the variability of a large number of factors within the videos. Among them would be psychological and cognitive factors such as salience (which would include absence or presence of people and their activities in the videos) and visual factors such as color, foreground/background separation, time of occurrence and gradients of flow (action). We did not, *a priori*, hazard a guess as to *which* videos we thought would be recalled with greater frequency.

Our data may be used to investigate in more detail student responses. The frequency with which students recalled videos they had seen in lecture during the preceding period is given in Table 2 and Figure 1.

As expected, we find that not all videos are equally memorable to all students. Could it be that students whose examinations scores are higher on average than lower scoring students remember more videos? The variation of the number of videos recalled with the average examination scores for each student is given in Figure 3. It is obvious visually that the correlation is quite weak - in fact, R^2=0.24. In this case, about 75% of the variance is <u>not</u> explained by the correlation. We conclude that the ability of the student to achieve a higher score on average is not a dominant factor in explaining the number of videos recalled.

We have not collected, nor are we able to analyze, the innumerable other human factors that may control the number of videos a student recalls under these experimental conditions. However, with a sample size of about 50, it is also reasonable to assume that many of the factors (especially those that are subjective) are random with respect to their interactions, and therefore combine to cancel directional effects.

Thus, we have begun to explore the potential for objective measures to differentiate highly memorable videos from others. As previously noted, there are an infinite number of ways in which digital video streams from highly memorable videos might differ from those less memorable. To begin the exploration of objective methods and metrics, we have chosen a set of 11 mathematical functions and applied them to two videos from among our sample that have been judged to be similar in a number of ways (but are obviously different in many other ways). "Dust Devil" and "China Wall" (Tables 1, 2, Figure 4) are both set in a desert landscape of the southwestern United States, and both show people in active motion. These videos were chosen before any student response data were collected, and it was surprising to us that these two videos differed substantially in their recall frequency. "Dust Devil" was the fourth most memorable video, recalled 23 times by students, while "China Wall" was recalled by less than half this frequency, 9 times.

Different types of information, spatial and temporal, may be computed from the matrix of digital data from each frame of the video. Spatial measures are computed from single frames, while temporal measures are computed from changes that occur between adjacent frames in the stream. Results of a spatial analysis of the first 200 frames of each video are shown in Figure 5, and for temporal analysis, in Figure 6. It is obvious that these two videos, recorded by different people, at different times, in different places, of different subjects, should produce spatial and temporal metrics that differ to some degree. For example, note that for "Dust Devil" (Figure 4, top; Figure 5, left), contrast averages about 0.1 (all measurements expressed on a normalized scale), and for "China Wall" (Figure 4, bottom; Figure 5, right), contrast variably decreases to about 0.3. Other variables are not so different. For example, median intensity is similar, around 0.5 to 0.6 for each video. Colorfulness is about 0.4 for each video. Entropy is about 0.6 to 0.7.

Comparisons similar to that discussed for spatial variables may be made for temporal variables. Figure 6 shows patterns of temporal change in the number of non-stationary pixels, and the total motion for each pixel location, derived from an optical vector flow analysis. "Dust Devil" (Figure 6, left) exhibits a segment of greater total motion from one frame to another between approximately frame 60 and frame 120. The pattern of total motion for “China Wall” (Figure 6, right) does not exhibit a similar segment of motion within the equivalent video segment.

The visual analysis just described is not to be interpreted as objectively statistically significant in any way, especially as students viewed during lecture a longer video segment. Furthermore, we are not proposing that any of these objective measures of the digital video stream are either psychologically significant, or otherwise a cause of the difference in memorability exhibited by these two somewhat similar videos. Our purpose here is simply to explore the possibility of applying mathematical functions to the analysis of videos that we already know to be of different memorability to students under the specified conditions.

However, this preliminary analysis does point the way to further studies that could lead to valid statistical hypothesis testing. For example, with a larger selection of videos, we will be able to accumulate multiple videos of high and low recall frequency. From such a collection we could build a sample of sufficient size for statistical hypothesis testing. For example, we may find that, as a group, highly memorable videos differ from low memorable videos in the degree of motion, or of higher contrast, or in any other of these, or other variables we explore.

If such objective and significant differences are found, it would be of considerable interest to test whether or not videos that prove to be highly memorable can be predicted prior to classroom use. And if such an analytical process could be demonstrated, then a more efficient and effective use of digital video in classroom instruction may be possible. This would be a desirable and positive step in the development of tools and techniques for enhancing student learning with video multimedia.

CONCLUSIONS

Student engagement may take many different forms, and increases in student engagement are an important component of learning and performance. The incorporation of digital video snips in a lecture centered course has been designed to test students for variation in recall frequency, a proxy for student engagement. Students were given an incentivized bonus question if they could recall videos within a period of approximately 2.5 weeks after viewing. Of a sample of 31 videos viewed by students, one video was not recalled by any student. Of the 30 videos that students recalled at least once, the number of times individual videos were recalled ranged from one to 27. Although there is a statistically significant correlation between the number of videos a student recalled and the average overall examination score, the percentage of variance unexplained in the correlation is about 75%, thus pointing to, potentially, many other variables that may account for differences in video recall frequencies among students.

An analysis of spatial and temporal mathematical properties of two videos selected for higher recalled frequency and lower recalled frequency show both differences and similarities in various measures, including contrast, homogeneity, edginess, total motion, and other properties. Future statistically based studies may identify image and video properties that associate with differential recall frequency.

These preliminary results provide guidance for the design of further experiments to discover and determine potential correlations between subjective assessments by students (of the degree to which videos are memorable, and thus remembered to a greater degree), and objective and as yet undiscovered quantitative properties of the digital video streams. If such correspondences could be identified and quantified, we believe this process would provide a better way to select video for instructional content, provided the video also satisfies academic requirements for the instructor and course. The selection of more memorable digital video could then be tested for enhancing student engagement and performance.

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FIGURES AND TABLES

Title	EZSnips URL
PBS - Ken Burns Dust Bowl trailer	http://www.ezsnips.com/uDekicwH_Z4dS
Asian Dust Transport Computer Model	http://www.ezsnips.com/IiLVZ9MVvQQhm
Dust Devil in Desert	http://www.ezsnips.com/BGLoJcvnXTU3I
Movement of sand in wind tunnel	http://www.ezsnips.com/Xg35ZwKR5VysZ
Wind-blown sand on dunes	http://www.ezsnips.com/_TrebvU1U_fSr
Dust (suspension) storm, Mali, West Africa	http://www.ezsnips.com/OfCDdclmCeCuB
Natural Angle for Dry, Loose Sand	http://www.ezsnips.com/hnIohUAaHmnO_
China Wall for sport, Glamis, Calif.	http://www.ezsnips.com/v8aJzSdZC6i4a
Sandboarding on Namibian Dunes	http://ezsnips.com/iCqA_sXa65ORI
The Hadley Cell	http://www.ezsnips.com/TUkNEqz-zmDOg
Mud settling in tube	http://ezsnips.com/9ZdoRfV91OeJU
Animation of river sediment flowing into delta	http://www.claseshistoria.com/bilingue/1eso/relief/imagenes/rivers-sediments.swf
Sand blowing across dunes	http://www.ezsnips.com/aZK9L2i0aOfxT
Sand ripples in wave tank	http://www.ezsnips.com/G_U-I6OJroHXG
More sand ripples in wave tank	http://www.ezsnips.com/BJb_MRGos4J89
Laboratory mudcrack formation	http://www.youtube.com/watch?v=mTEDmYnw2bs
Living coral reef	http://www.ezsnips.com/eTQMTNxSRcq6H
Alabama Marble Quarry	http://ezsnips.com/LwnTBHREvMFzI
Creme Marble Quarry - Spain	http://ezsnips.com/9nRu8wXkA1_yT
Global Ocean Ridge System	http://ezsnips.com/xEUwr6eGPrtep
Hydrothermal Vent "black smoker"	http://www.ezsnips.com/M7FAZ3J7EevXZ
Regional and Contact Metamorphism at a Subduction Zone	http://www.ezsnips.com/AF0eSvmto8au9
Grand Canyon history in a sandbox	http://ezsnips.com/C_TNqmu7BiufU
Geology at Siccar Pt, Scotland	http://ezsnips.com/gExMRm9OkcfNi
Bill O'Reilly - Where'd the Moon Come From?	http://www.youtube.com/watch?v=UyHzhtARf8M
Origin of Earth's Moon	http://www.ezsnips.com/qrLa_ZcDx0M3S
Sources of Water on Earth	http://ezsnips.com/6qeTKwOz90Ias
Experimental Headward Erosion	http://ezsnips.com/kCihRMlTAMhOG
Stream Loads	http://ezsnips.com/0bwcrcrxXgstS
Braided Stream	http://ezsnips.com/3_yit0EWbhbkk
Managing the Mighty Mississippi	http://ezsnips.com/gpGQzCBCSk_K9

Table 1. Video titles included in this study, and their web links

Video Snip Title	Count	% of Total
Mud settling in tube	27	7.8
Alabama Marble Quarry	25	7.2
Natural Angle for Dry, Loose Sand	25	7.2
Dust Devil in Desert	23	6.6
Creme Marble Quarry-Spain	20	5.8
Sandboarding on Namibian Dunes	20	5.8
Global Ocean Ridge System	19	5.5
The Big Whack - SWRI Canup Simulation	18	5.2
Dust (suspension) storm, Mali, West Africa	15	4.3
The Hadley Cell	14	4.0
Living coral reef	13	3.7
Grand Canyon history in a sandbox	12	3.5
More sand ripples in wave tank	11	3.2
Sand ripples in wave tank	11	3.2
Regional and Contact Metamorphism at a Subduction Zone	10	2.9
PBS - Ken Burns Dust Bowl trailer	10	2.9
Managing the Mighty Mississippi	9	2.6
Experimental Headward Erosion	9	2.6
Laboratory mudcrack formation	9	2.6
China Wall for sport, Glamis, Calif.	9	2.6
Geology at Siccar Pt, Scotland	8	2.3
Wind-blown sand on dunes	7	2.0
Stream Loads	4	1.2
Bill O'Reilly - Where'd the Moon Come From?	4	1.2
Hydrothermal Vent "black smoker"	4	1.2
Movement of sand in wind tunnel	4	1.2
Sand blowing across dunes	3	0.9
Asian Dust Transport Computer Model	2	0.6
Braided Stream	1	0.3
Sources of Water on Earth	1	0.3
Animation of river sediment flowing into delta	0	0.0
Grand Total Count:	347	

Table 2. Counts of videos recalled by students on examinations

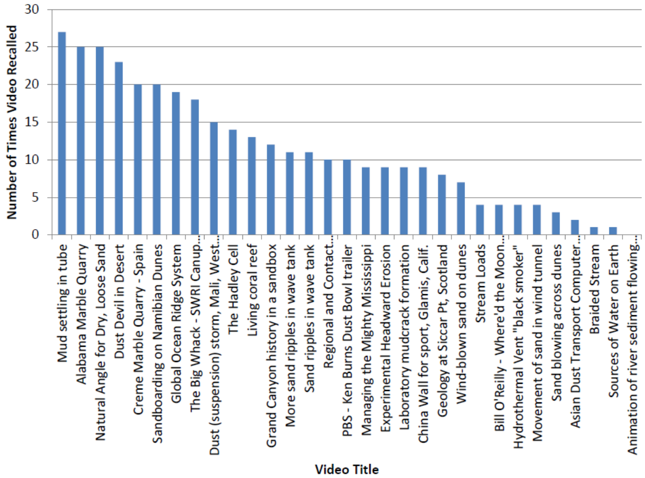

Figure 1. Frequency of recall for a selection of short videos shown during lecture periods.

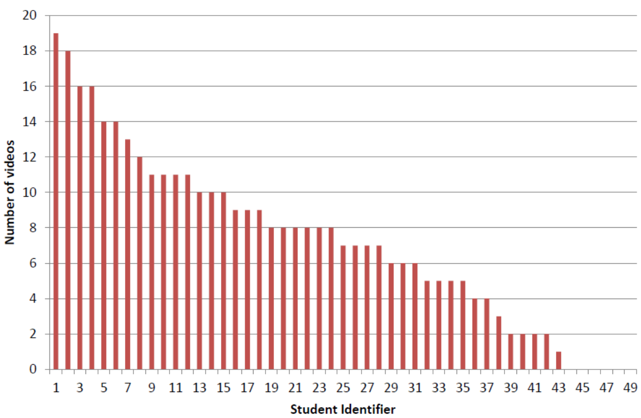

Figure 2. Number of videos recalled by each student

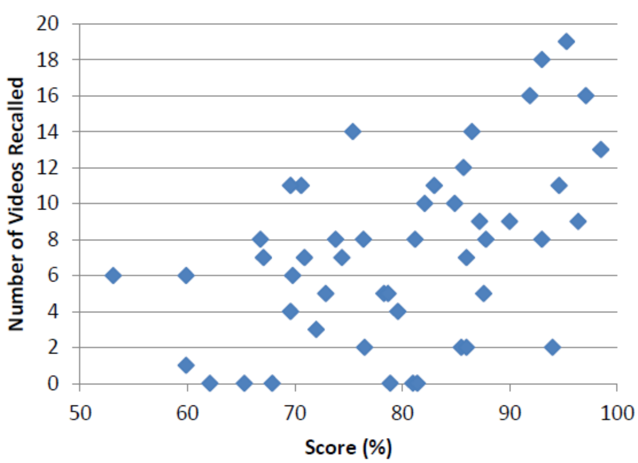

Figure 3. Variation of the number of videos recalled with test score.

Figure 4. Video sequences from two snips shown to students. Top – "Dust Devil in Desert", Bottom – "China Wall for sport, Glamis, Calif."

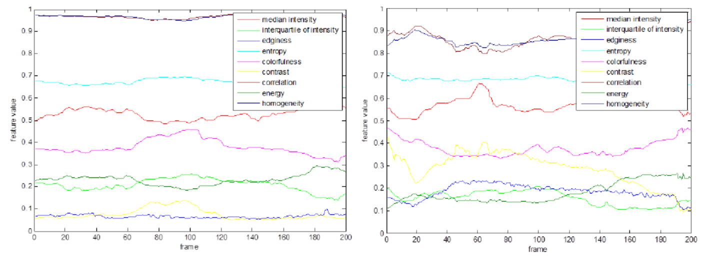

Figure 5. Values of spatial variables (on normalized scale, per frame) for two video snips. Left – "Dust Devil in Desert", Right – "China Wall for sport, Glamis, Calif."

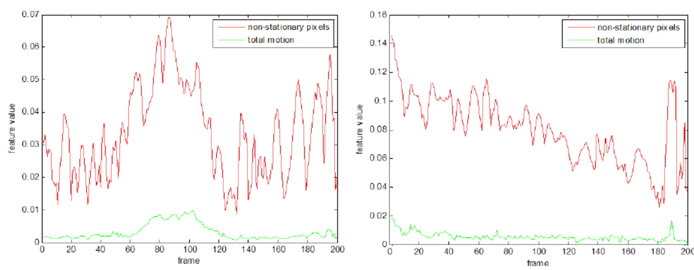

Figure 6. Values of temporal variables (on normalized scale, per frame) for two video snips. Left – "Dust Devil in Desert", Right – "China Wall for sport, Glamis, Calif."