THE VisOR SYSTEM: TESTING THE UTILITY OF USER INTERFACE COMPONENTS FOR FEATURE BASED SEARCHING IN VIDEO RETRIEVAL SOFTWARE

by
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A Master's paper submitted to the faculty
of the School of Information and Library Science
of the University of North Carolina at Chapel Hill
in partial fulfillment of the requirements
for the degree of Master of Science in
Information Science.

Chapel Hill, North Carolina

January, 2004

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Advisor

Richard Gruss. The VisOR System: Testing the utility of user interface components for feature-based searching in video retrieval software. A Master's paper for the M.S. in I.S. degree. January, 2004. 52 pages. Advisor: Gary J. Marchionini.

This study uses a test video retrieval system, VisOR, to assess the value of user interface components that provide feature-based searching on automatically-extracted visual and auditory features. In particular, the study attempts to find a) whether sliders that allow users to adjust the relative weights of individual features improve performance on search tasks, b) which features prove the most useful in conducting normal search tasks, c) whether feature-based searching is difficult for the typical user, and d) whether color and brightness-based searching enables users to find exact-match shots especially quickly. Seventeen subjects completed 14 search tasks each. For a), it was discovered that the weight sliders had no significant effect on performance. For b), it was found that keywords, Indoors/Outdoors, and Cityscape/Landscape proved most useful. For c), user questionnaires indicated no special difficulty or frustration. For d), it was found that users who regularly use color and brightness components for searching consistently found exact-match shots more quickly than others.

Headings:

Indexing – Video recordings

Information Retrieval

Information Systems – Special subjects – Video recordings

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I. Introduction

The availability of consumer digital video products has brought about massive increases in the production of both professional and amateur digital video. According to the Canon Consumer Digital Lifestyle Index (Local sales, 2003), sales of digital cameras that use the Digital-8 and miniDV formats grew by 1041% between 2000 and 2003, far outpacing cameras that use traditional analog formats like Hi-8, VHS, VHS-C, and Super VHS-C. Two of the most popular digital video cameras, the Canon ZR65MC and the Sony DCR-TRV350, start at less than $450 each. Quality video editing software, which used to cost thousands of dollars, is also now within the reach of typical consumers: Apple's Final Cut Pro sells for about $900 and Adobe Premier is only about $600. Affordable 64-bit PC architectures like the Apple G5 reduce and, for some tasks, eliminate the long latency traditionally associated the computationally intensive video editing and compression. Also, reliable IDE hard drives can be purchased for about $1.00 per gigabyte, making available the large amounts of storage necessary for large video files.

All of these factors contribute to the thousands of hours of digital video being produced every year. Digital video is rapidly becoming the medium of choice for entertainment, education, and communication, and much of the footage being produced could potentially be of historical and cultural importance. Digital librarians are starting to face the challenge of organizing, cataloging, indexing, and annotating large digital video collections. Some initiatives include the Internet Archive (http://www.archive.org/movies/), the Open Video Project (http://www.open-video.org) , and the Informedia Project (http://www.informedia.cs.cmu.edu/). As digital librarians gain expertise in managing large video collections that might be distributed on multiple servers and use large databases, they can offer a valuable service by providing individuals with the tools they need to manage their own personal collections that simply reside on hard drives. The role of the librarian is certainly changing in the digital age, and one new responsibility is to help create software that will enable people to be their own librarians and effectively manage their expanding personal digital collections.

To promote the development of tools for cataloging and retrieving digital video, the National Institute of Standards and Technology has added a video track to its TREC workshop, where several organizations can test their video retrieval systems in a competitive atmosphere: “The goal of the conference series is to encourage research in information retrieval by providing a large test collection, uniform scoring procedures, and a forum for organizations interested in comparing their results” (Text Retrieval Conference). Many universities and organizations, whether they participate in TRECVID or not, have groups working on some aspect of this problem, either discovering algorithms for automatically segmenting videos into shots, developing metadata for describing characteristics of shots, or constructing user interfaces for efficient browsing and searching.

This study uses the TREC Video Track framework to test the effectiveness of VisOR (Visually Oriented Retrieval), a new software package that allows users to search for videos by keywords and nine different low-level visual and auditory features, and allows users to adjust the relative importance of those features. In particular, this study attempts to answer these questions:

1) Will the ability to adjust the relative weights of low-level features in a query improve recall on search tasks?

2) Which of these features will be most useful in typical search tasks?

indoors/outdoors
cityscape/landscape
people
faces
human speech
instrumental
text overlay
color
brightness

3) Will users find it difficult to formulate queries using low-level features?

4) Will the addition of weight sliders make a system too complicated or frustrating for users?

5) Will the ability to search by keyframe hue or brightness values reduce the time required to find specific shots?

II. Related Work

Several software projects have incorporated automatically-detected low-level features into a video search interface. The earliest features have been those extracted from individual keyframes using methods of Content-Based Image Retrieval (CBIR). CBIR systems--including QBIC (Petrovik, 1996), VisualSeek (Smith, 1997), Virage, Photobook, Netra, and Blobworld (Carson, 1999)--all use some combination of color, texture, and shape to index a digital image, and then apply a comparison algorithm such as cosine distance, simple difference, or Euclidean distance to match two images. Various weightings of low-level features have been tried, but no system offers a fully satisfying search, primarily because from a user's perspective, similarity is understood conceptually rather than visually. An image of a fox, for example, is conceptually similar to other foxes, regardless of color, shape or texture. Conversely, a picture of an automobile, even if it matches the color, shape and texture of the fox perfectly, will not be similar. Santini (2001), for similar reasons, argues that any general-use tool for image retrieval must incorporate some form of semantic information. Low level features are useful, however for making very broad conclusions about the content of an image: whether is it indoors or outdoors, whether is a landscape or a cityscape, or whether it contains a human face. The Informedia Project at Carnegie Mellon (Christel, 1999), successfully uses low level image features to identify a human face, but can only extract accurate semantic data by using video OCR on superimpositions.

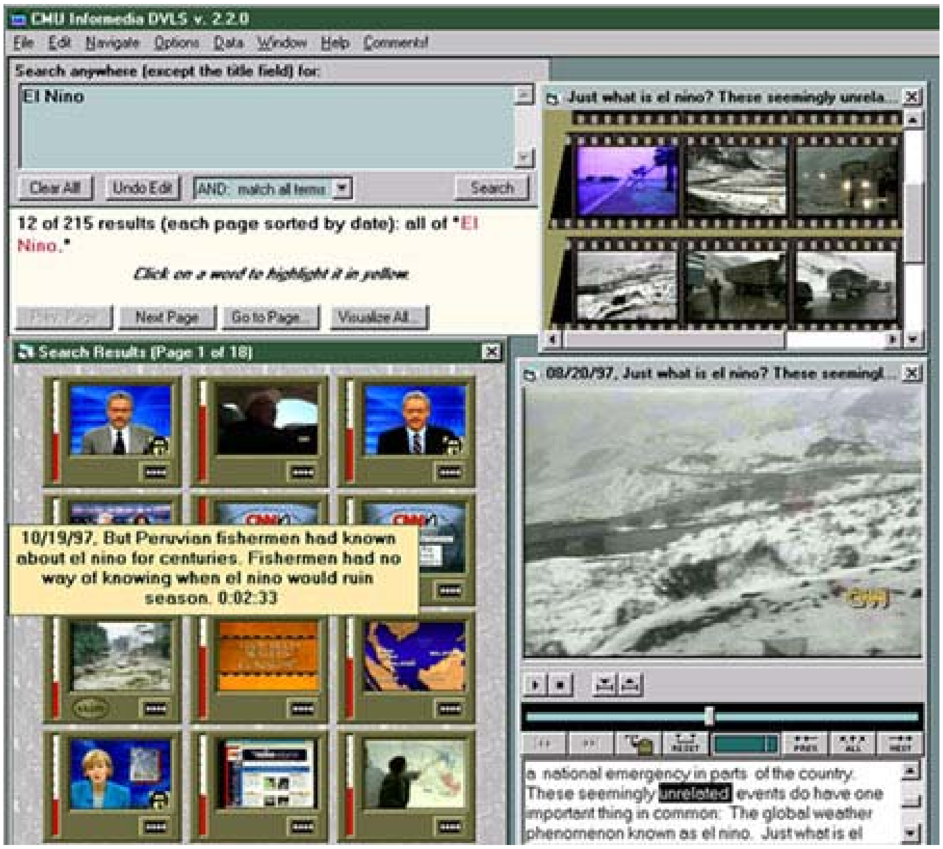
Although highly experimental and limited, several intriguing studies have attempted to interpret video content using only automatically extracted low-level features. The system IRIS (Image Retrieval for Information Systems) (Alshuth, 1996) uses neural networks to train systems to recognize objects in videos. The theory is that the objects in the individual frames, which might be of interest even though they would never be mentioned in the title or video description, could be recognized, and the names of those objects stored in ASCII text in a database. Colombo (2001) used low-level features to identify cuts, fades, dissolves, cutting rate, rhythm, shot size, focus, tilt, flashback, flashforward, lighting, color and sound, and was able to accurately classify commercials into four different moods—practical, utopic, critical, playful. The research in this area is still new but very promising, challenging Dimitrova's (1995) belief that semantic video retrieval is a myth. However promising this area of inquiry is, though, it is still confined to highly specialized genres, and is still impracticable for large, variegated video collections. A reasonably useful video retrieval tool should allow users to combine low-level features according to their own judgment of what is appropriate to the task, rather than attempt to make broad genre guesses based on those features.

How exactly to create an effective interface using those features, however, is not straightforward. Christel (Christel et al., 2002) formulated some basic principles of user interface design:

1) People want slider bars to move around in a video
2) People want some way to move smoothly from a sample clip to an entire video.
3) People want to be able to initiate new searches quickly.
4) People want text descriptors even on highly image-driven interfaces

The Informedia Project (Christel et al., 2002) has also experimented with a variety of interface components, including VIBE, timeline digests, and map collages. VIBE takes a query consisting of several keywords and creates a plot in which each word is a corner and small boxes, which represent relevant video segments, are positioned according to the words they include. The user can drag the words around to regroup the videos and can select a region by holding down the mouse button and drawing a box. Timeline digests, which work best for news video, position the relevant segments along a timeline. Map collages allow the user to click on a geographical region of interest and retrieve videos pertaining only to that area. The Fischlar Browsing system (Lee, 2000) allows the user to scan organized key frames for a single segment. The user is provided with a set of key frames arranged in a multi-tiered hierarchy. Only the widely-spaced first level frames are showing at first, but by clicking a frame, the user can expand a section to see more frames. At any point in the browsing, the user can click on a frame and start the video playing at that point. The Open Video Project's stated aim in designing user interfaces was to provide users with 1) overviews 2) the ability to search by title, 3) smooth transitions from overview to preview, 4) a variety of fast previews, and 5) convenient access to supplementary video information (Geisler et al., 2001).

There are several tools currently in development for marking up and browsing digital video. The Informedia Project at Carnegie Mellon uses speech recognition to create transcripts that temporally align with extracted key frames to create "video paragraphs." The interface allows for keyword searches that produce a result set of relevant shots (Figure 1). The keyword search field is in the upper left corner, and the search results are in the lower left corner. When users select a result, the video is loaded in the lower right corner and a storyboard aligned with text transcript appears in the upper right. This interface is effective for finding small numbers of shots on the same topic, but it does not allow the user to search by visual characteristics. The results field displays fewer than 20 shots, so scanning large numbers of candidate shots is not possible.



Search anywhere (except the title field) for:

El Nino

12 of 215 results (each page sorted by date): all of "El Nino."

Click on a word to highlight it in yellow.

Search Results (Page 1 of 18)

Just what is el nino? These seemingly unrela...

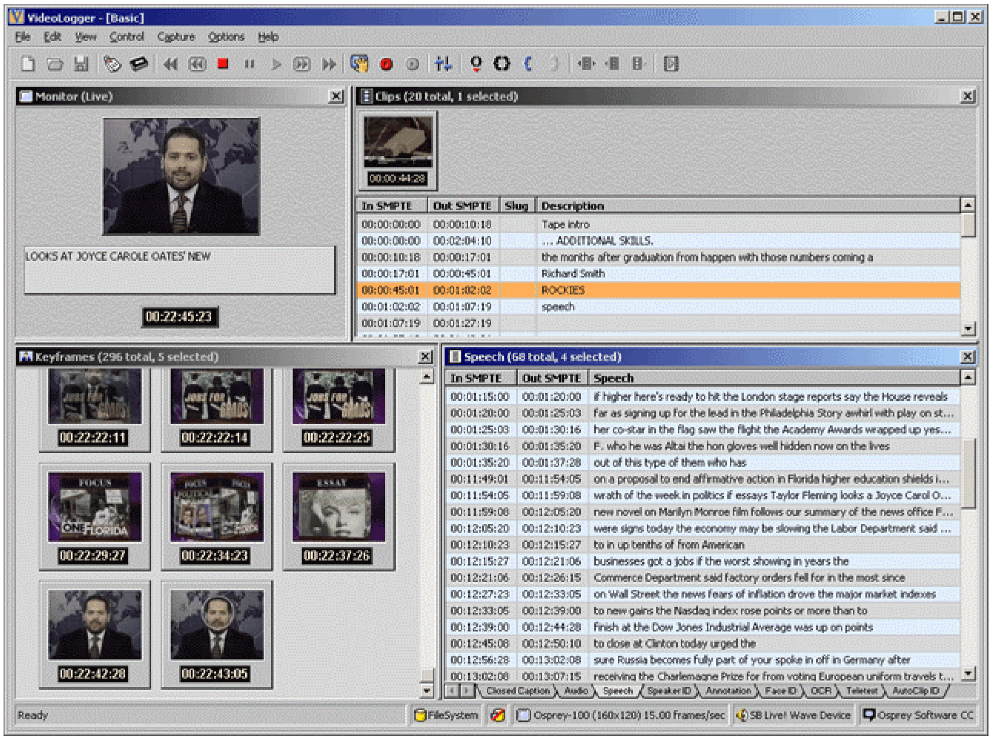
08/20/97, Just what is el nino? These seemingl...

10/19/97, But Peruvian fishermen had known about el nino for centuries. Fishermen had no way of knowing when el nino would ruin season. 0:02:33

a national emergency in parts of the country. These seemingly unrelated events do have one important thing in common: The global weather phenomenon known as el nino. Just what is el

Figure 1. Informedia.

Virage's VideoLogger is principally a tool for indexing (Figure 2). Like Informedia, it uses speech recognition to create a transcript that is aligned with timestamps. Users can also extract key frames manually and add their own annotations. Also like Informedia, this tool is effective in providing conceptual access to the content of the video collection, but it does not allow any visually-oriented access. Also, manual keyframe extraction and annotation is time-consuming and becomes less feasible as video is produced more quickly. A system that can use automatically-extracted features to allow for flexible searches might be more useful in the long term.

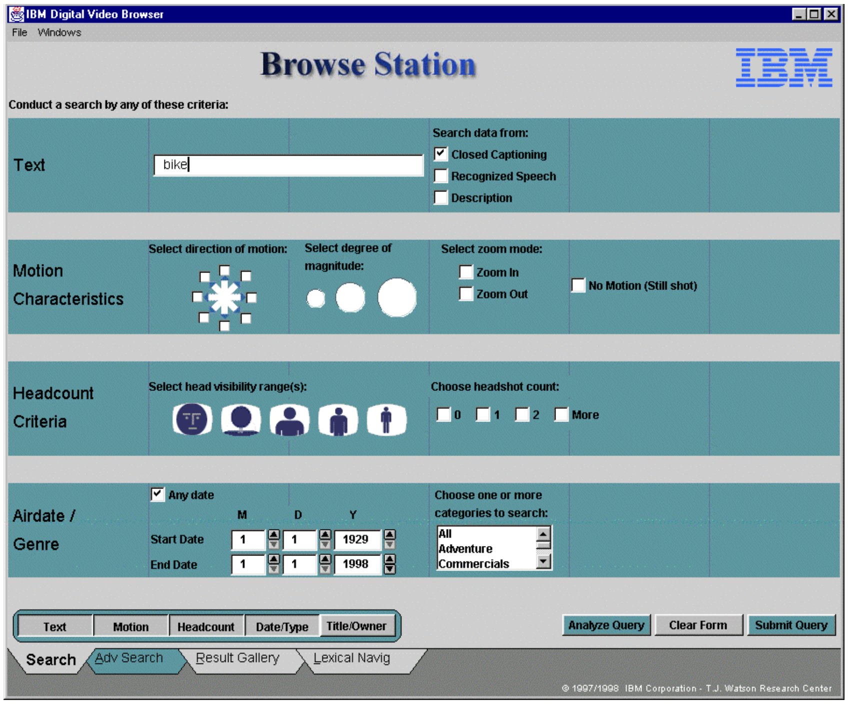


In SMPTE	Out SMPTE	Slug	Description
00:00:00:00	00:00:10:18		Tape intro
00:00:00:00	00:02:04:10		... ADDITIONAL SKILLS.
00:00:10:18	00:00:17:01		the months after graduation from happen with those numbers coming a
00:00:17:01	00:00:45:01		Richard Smith
00:00:45:01	00:01:02:02		ROCKIES
00:01:02:02	00:01:07:19		speech
00:01:07:19	00:01:27:19		

In SMPTE	Out SMPTE	Speech
00:01:15:00	00:01:20:00	if higher here's ready to hit the London stage reports say the House reveals
00:01:20:00	00:01:25:03	far as signing up for the lead in the Philadelphia Story awhirl with play on st...
00:01:25:03	00:01:30:16	her co-star in the flag saw the flight the Academy Awards wrapped up yes...
00:01:30:16	00:01:35:20	F. who he was Altai the hon gloves well hidden now on the lives
00:01:35:20	00:01:37:28	out of this type of them who has
00:11:49:01	00:11:54:05	on a proposal to end affirmative action in Florida higher education shields i...
00:11:54:05	00:11:59:08	wrath of the week in politics if essays Taylor Fleming looks a Joyce Carol O...
00:11:59:08	00:12:05:20	new novel on Marilyn Monroe film follows our summary of the news office F...
00:12:05:20	00:12:10:23	were signs today the economy may be slowing the Labor Department said ...
00:12:10:23	00:12:15:27	to in up tenths of from American
00:12:15:27	00:12:21:06	businesses got a jobs if the worst showing in years the
00:12:21:06	00:12:26:15	Commerce Department said factory orders fell for in the most since
00:12:27:23	00:12:33:05	on Wall Street the news fears of inflation drove the major market indexes
00:12:33:05	00:12:39:00	to new gains the Nasdaq index rose points or more than to
00:12:39:00	00:12:44:28	finish at the Dow Jones Industrial Average was up on points
00:12:45:08	00:12:50:10	to close at Clinton today urged the
00:12:56:28	00:13:02:08	sure Russia becomes fully part of your spoke in off in Germany after
00:13:02:08	00:13:07:15	receiving the Charlemagne Prize for from voting European uniform travels t...

Figure 2. VideoLogger, from Virage.

VideoVista, from IBM, performs automatic segmentation and automatic feature extraction, and offers a sophisticated search interface (Figure 3). Users can search by faces, text metadata, or motion characteristics. Although the system does provide searches on visual features, there are only two, faces and motion, and it is unclear how useful a motion feature would be.



Text: bike

☑ Closed Captioning

☑ Any date

Start Date 1 1 1929

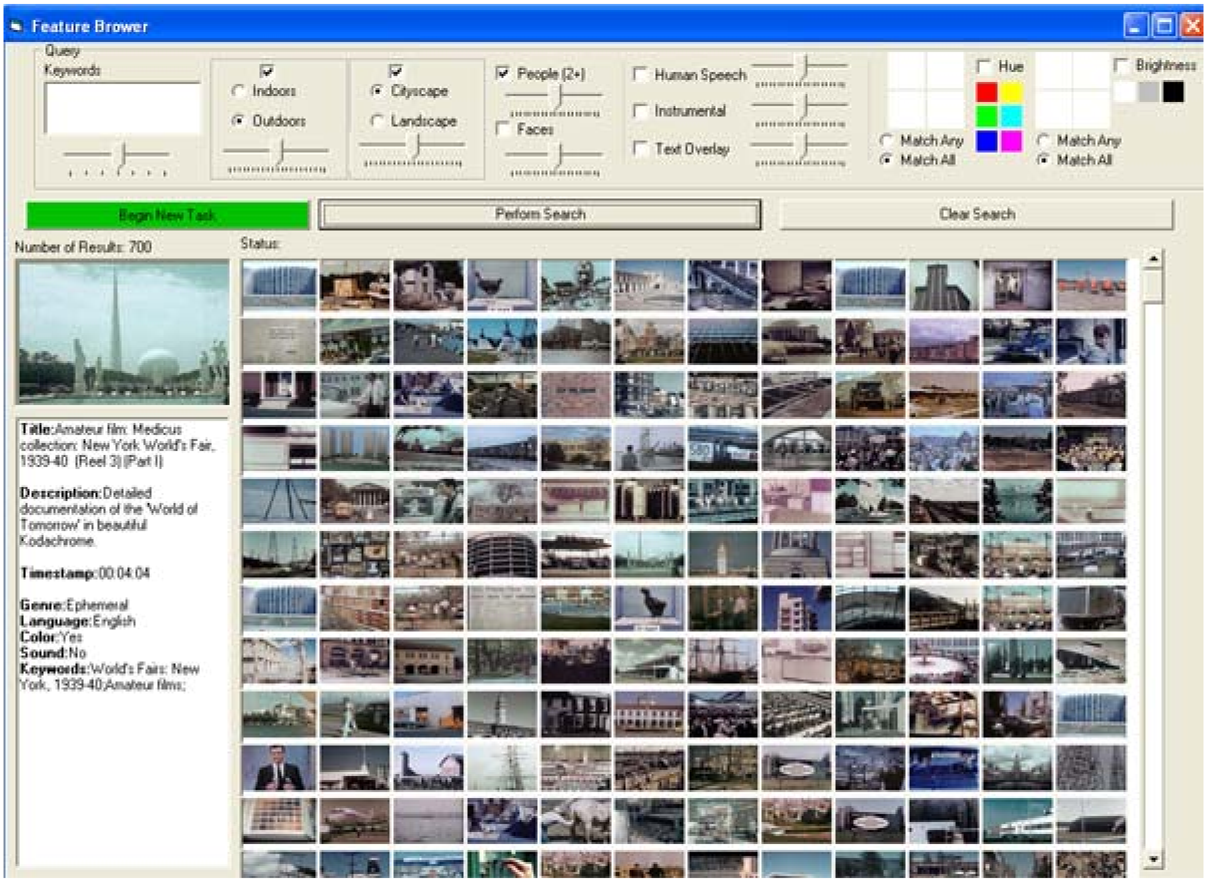
End Date 1 1 1998

Figure 3. IBM's Video Browser.

All of these tools allow users to enter queries using combinations of text and visual features, but none of them allow users to adjust the relative importance of the features. Feature weighting in video retrieval is analogous to term weighting in text retrieval. Numerous studies have investigated optimum term weighting in text retrieval (Greiff, 2002; Jin, 2001; Kwok, 1996), but no studies have tested whether allowing users to manually adjust the weights of low-level feature data will improve performance in retrieving digital video.

III. Description of VisOR

VisOR is a standalone application with a Visual Basic front end and a MySQL back end.



☑ ○ Indoors ● Outdoors

☑ ● Cityscape ○ Landscape

☑ People (2+)

☐ Faces

☐ Human Speech

☐ Instrumental

☐ Text Overlay

☐ Hue ○ Match Any ● Match All

☐ Brightness ○ Match Any ● Match All

Number of Results: 700

Title: Amateur film: Medicus collection: New York World's Fair, 1939-40 (Reel 3)(Part I)

Description: Detailed documentation of the 'World of Tomorow' in beautiful Kodachrome.

Timestamp:00:04:04

Genre: Ephemeral
Language: English
Color: Yes
Sound: No
Keywords: World's Fairs: New York, 1939-40;Amateur films;

Figure 4. VisOR, Tier 1 and 2

The key principle governing the design of the interface (Figure 4) is that a large amount of information needs to be displayed in a small space. Counting the keyword field, ten features can be included in queries, each requiring its own input component. The color and brightness components require extra space because they allow a user to specify values for the four quadrants of a keyframe, and also to specify whether all quadrants must match or only some. There are over 14,000 shots in the test collection, so most queries will return hundreds of relevant shots that have to be displayed in the most compact way. In addition to feature and result set elements, it is also necessary to fit buttons for performing a search and for clearing the search options. While these buttons have to use minimal space, they also have to be large enough to be easily clicked from anywhere on the screen, since they would be used more frequently than any other interface component. The greatest challenge is to arrange all of these elements so that they are tight without being cluttered or confusing.

To make the best use of screen real estate, the interface offers a 3-tier approach to the videos:

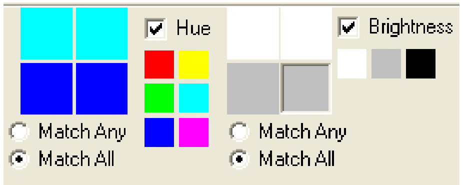
Tier 1:

The user begins a search with the feature options arrayed across the top. An earlier version positioned the feature options on the left, but this caused the main result set thumbnail frame to be tall and thin, which made it more difficult to scan. It was suspected that people tend to scan back and forth along horizontal lines (possibly the result of conditioning through reading), and this suspicion was confirmed in informal observation: subjects typically ran either their finger or the mouse button over the thumbnails in a horizontal sweep. A thumbnail field that is tall and thin, because it requires more frequent vertical retrace, is less efficient than one that is short and wide.

The left-to-right arrangement of the feature components reflects a hypothesis of their relative usefulness and how obtrusive they would be if they were not used. People are accustomed to entering text into a search engine, so a large keyword field was appropriate to have in the upper left corner. The Indoors/Outdoors and Cityscape/Landscape components describe the general setting of a shot, rather than some specific item within the shot, so they seemed the most applicable. All shots are either indoors or outdoors, and if they are outdoors, they are either Cityscape or

Landscape. By default, these two components are grayed out (disabled). Cityscape and Landscape are mutually exclusive, and if the component were not disabled, the user would think he was required to designate one or the other. The user can activate the components by clicking the checkboxes above them. The People and Faces components are grouped together because they are related features. The close proximity also forces the user to recognize that there is a difference between the two: "Face" means a shot has a close up of a recognize person, whereas "People" simply means that there is at least one human being in the shot. The Human Speech, Instrumental, and Text Overlay components are placed on the right because they seem to be the least useful, Human Speech because nearly every shot has a person talking in it, and Instrumental and Text Overlay because they are so specific.

The Color and Brightness components are exiled to the far right not because they might be less useful, but because they require a lot of space and would be too obtrusive further to the left when they are not needed.   The four boxes together represent a preview of the keyframe for a shot, and provide a means for the user to enter a rough query-by-example sketch. To assign a color value to one quadrant of the keyframe, a user clicks on a box to specify it, and selects one of the 6 colors. The box turns that color. The user can then specify with radio buttons whether all quadrants of a candidate keyframe must match, or at least one. The brightness component operates the same way, except there are only three levels of brightness (Figure 5).



○ Match Any
● Match All

☑ Hue

○ Match Any
● Match All

☑ Brightness

Figure 5. VisOR Color and Brightness components

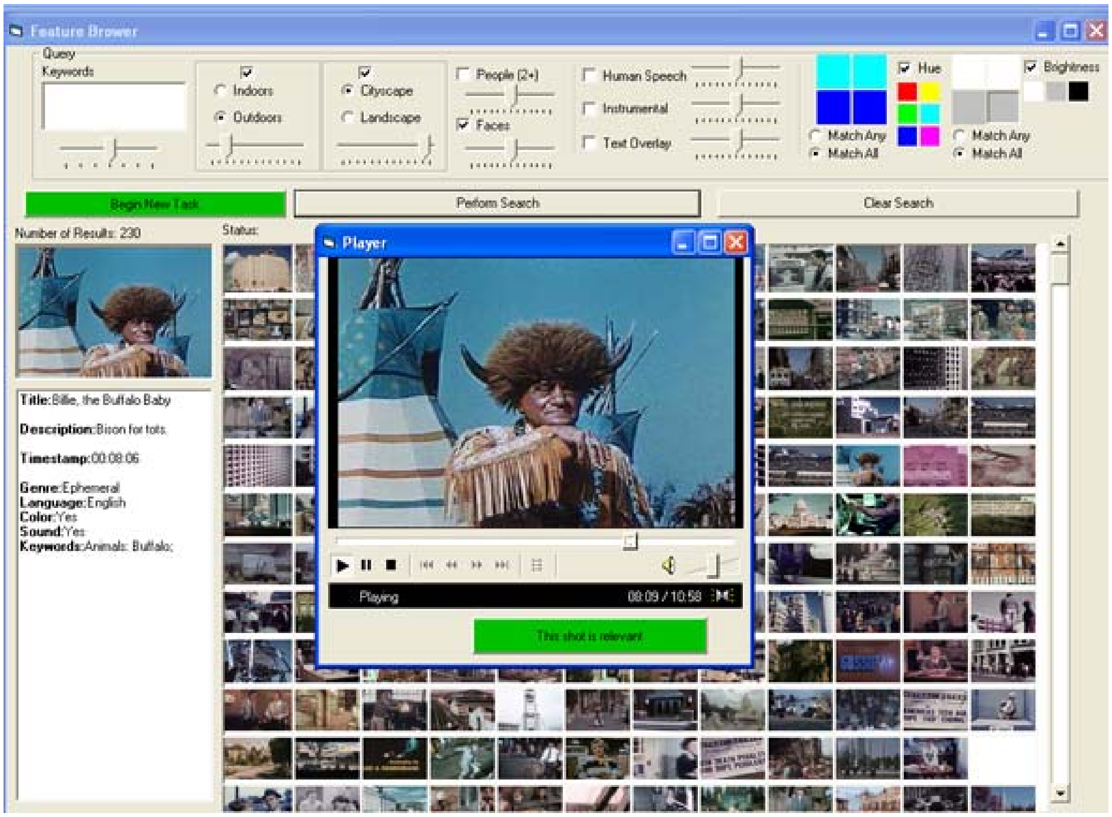
Users can enter any combination of keywords and features. After the query is run, thumbnails of each candidate shot appear in the main image frame, which can accommodate up to 144 images without scrolling. Result sets are limited 700 to keep the system operating quickly and dynamically. The small thumbnails (60 pixels x 41 pixels) allow the user to scan several candidate images rapidly and eliminate any that are plainly not relevant. The user cannot discern everything the thumbnail images, especially the dark ones, but can make out enough of the shape and texture to identify promising candidates. When a shot looks as though it might be relevant, the user can move to Tier 2 to get further information about the shot.

Tier 2:

When the mouse hovers over a thumbnail, a larger preview image appears in a panel at the left with basic text descriptors of the video in which that shot appears. Text descriptors include the title, description, keywords, genre, language, and sound (whether the video has sound or is silent). The text box is large relative to the other screen elements, occupying the same amount of space as 24 thumbnail images, because studies indicate that users find text beneficial in judging candidate shots (Christel, 2002). The text is set apart against a white background to make for easy skimming. The preview image, at 200x 136, is three times the size of the thumbnail, but still substantially smaller than the full 320x240 of the videos themselves. In the original design, the preview keyframe and text information appeared in a popup window directly over the cursor, the rationale being that this would minimize eye movement. This caused irritating unintentional popups as the mouse was returned to the query section of the interface, however, so the design was modified. Also, by having the preview picture and text description on the left, users are free to drag the mouse over the thumbnails, which they tended to in the study even when they were not looking at the preview. In Tier 2, the user can make out most of the visual detail of the shot and can gain a conceptual understanding of the video that is home to the shot.

Tier 3:

If a shot looks promising based on the thumbnail, the preview image and the text descriptors, users can click on the thumbnail to view the entire full-size video cued that shot (Figure 6). The video player allows the user to pull a time slider back and forth to move to other places in the video, in accordance with Christel's (2002) recommendation. The player can be repositioned anywhere on the screen, but it opens next to the text descriptors box so that the user can study the text more closely while the video plays. If the user wants to return to the original shot to which the video was cued when it started playing, he can read the timestamp from the text descriptors box.



Keywords

☑ ○ Indoors ● Outdoors

☑ ● Cityscape ○ Landscape

□ People (2+)

☑ Faces

□ Human Speech

□ Instrumental

□ Text Overlay

○ Match Any ● Match All

☑ Hue

☑ Brightness

○ Match Any ● Match All

Number of Results: 230

Status:

Title: Billie, the Buffalo Baby

Description: Bison for tots

Timestamp:00:08:06

Genre: Ephemeral
Language: English
Color: Yes
Sound: Yes
Keywords: Animals; Buffalo;

Playing 08:09 / 10:58

Figure 6. VisOR, Tier 3.

The 3-tier approach to retrieval appears to be a good compromise between presenting too little data about too many videos (too extensive) and presenting too much data about too few videos (too intensive).

The interface is supported on the backend by a database consisting of a single table of 14522 rows (one for each shot), because further normalization resulted in substantially longer latency due to intensive join operations (see Appendix D for a more detailed description of the table and data types). The feature data was automatically extracted and provided by IBM, MSRA (Microsoft Research-Asia), CMU (Carnegie Melon University), or DCU (Dublin City University) for use in the 2002 TREC Video Retrieval Track (available at http://www-nlpir.nist.gov/projects/t2002v/t2002v.html). All of the features, with the exceptions of faces, color and brightness, are represented in the database (Table 1) as floating-point rationals that describe the probability (0-1) that that feature occurs in that shot. The faces feature is represented as the number of faces in the shot.

Feature	Data Source	How Represented
Indoors	IBM	0-1
Outdoors	IBM	0-1
Cityscape	MSRA	0-1
Landscape	MSRA	0-1
People	IBM	0-1
Faces	CMU	Number of faces in the shot (0-6)
Human Speech	DCU	0-1
Instrumental Sound	DCU	0-1
Text Overlay	IBM	0-1
Hue	Gruss	HMMD hue value average for each quadrant: 0, 60, 120, 180, 240 or 300
Brightness	Gruss	HMMD max value average for each

		quadrant, quantized into 4 bins: 0, 50, 160, 200.

Table 1. How features are stored in the database.

The color feature is represented as the hue value in the HMMD color space, which describes hues as degrees along a continuous wheel from red (0°) to yellow (60°) to green (120°) to cyan (180°) to blue (240°) to magenta (300°) and back around to red (360°). Each quadrant of the shot keyframe has a hue value derived by calculating the mean hue for all pixels in that quadrant and taking the nearest value divisible by 60. The brightness value for each quadrant is derived by taking the average Max(r, g, b) for all pixels in the quadrant and assigning whichever of 0, 160, or 200 is closest.

When a user selects features, an SQL query is generated using the following rules:

1) For any feature that is selected, return all values where the probability in the database is greater than .5.

2) If any keywords are entered, use MySQL's built-in full-text search feature. When a word is entered in the keyword field, only videos whose title, description, or keyword set contain that exact word appear in the result set. There is no thesaurus or stemming, and there are no text transcripts.

3) Conjoin all selected features with "AND".

4) If "Match Any" is selected with the hue or brightness features, use "OR" between the quadrants but "AND" between color and the other selected features.

5) Order the results using the following rules:

    a. Take the full text value for the keywords returned by MySQL and multiply by the keyword slider value, which ranges from 1 to 7 and defaults to 4. The MySQL full-text search uses a form of Inverse Document Frequency to assign relevance to a record, as described in the user manual:

        > Every correct word in the collection and in the query is weighted, according to its significance in the query or

> collection. This way, a word that is present in many documents will have lower weight (and may even have a zero weight), because it has lower semantic value in this particular collection. Otherwise, if the word is rare, it will receive a higher weight. The weights of the words are then combined to compute the relevance of the row (MySQL manual).

The relevance score returned from the MySQL full-text search, then, could theoretically be any value, depending on the content of the records. In practice, however, the nature of language causes the values to range from 0 to 20.

b. Take the probability for each selected feature and multiply it by that feature's slider, which ranges from 1 to 200 and defaults to 100. (This was the smallest range that had an appreciable effect on the ordering of the result set).
c. Sum these values and sort in descending order.
d. Take the top 700.

As example, suppose a user entered the following features and slider weights:

keywords 4
Outdoors 50
People 100

All the returned shots will have a nonzero full-text value for the keywords and at least a .5 probability of being outdoors and containing people. These shots would be ordered by (keywords value * 4) + (Outdoors probability * 50) + (People probability * 100). So if shot A had a full-text score of 9, but only .3 probability of being outdoors and 0 probability of having people, its score would be (9 * 4) + (.3 * 50) + (0 * 100) = 32 + 15 + 0 = 47. If shot B had a small relevance to the text and had a full-text score of 2, but a 0 probability of being outdoors and .9 probability of having people, its score would be (2 * 4) + (0*50) + (.9 * 100) = 8 + 0 + 90 = 98. Thus, in this query, shot B is more relevant that shot A. If the user then moves the Outdoors slider to 200 and the people slider to 50, shot A's score is (9 * 4) + (.3 * 200) + (0 *

100) = 32 + 60 + 0 = 92, while shot B’s score becomes (2 * 4) + (0 * 200) + (.9 * 50) = 8 + 0 + 45 = 53. By placing more weight on the Outdoors feature, the shots are reordered.

The ranges for the sliders were chosen to maximize control over the ordering. Larger ranges tended to have unpredictable results from even small changes in weights, while smaller ranges had no appreciable effect at all. The text slider only ranges from 0 to 7 because the text values are an order of magnitude larger than those of the other features.

IV. Methods

Seventeen subjects ranging in age from 19 to 62 were recruited from the University of North Carolina-Chapel Hill campus area. There were nine males and nine females. Five subjects were enrolled undergraduates, eight were graduate students, and the remaining five were full time employees, including a nurse, a medical school professor, a pastor, and two tech support specialists. All 17 subjects reported using a computer daily and watching videos at least once a month, usually for entertainment. Subjects were paid $15.00 for participation.

After completing a brief questionnaire to provide demographic data (Appendix A), each subject was asked to complete 14 search tasks, seven on the system with the sliders (System S) and seven on the system without the sliders (System N). To eliminate learning effects, some subjects used System S first, which others used System N first. Also, some subjects did the first set of questions first, while others did the second set first, according to the counterbalancing plan in table 2.

Subject	First System	First Questions	Second System	Second Questions
2	S	1	N	2
3	N	1	S	2
4	S	2	N	1
5	N	2	S	1
6	S	1	N	2
7	N	1	S	2
8	S	2	N	1
9	N	2	S	1
10	S	1	N	2
11	N	1	S	2
12	S	2	N	1
13	N	2	S	1
14	S	1	N	2
15	N	1	S	2
16	S	2	N	1
17	N	2	S	1
18	S	1	N	2

Table 2. Counterbalancing plan. Note: Data for subject 1 was discarded.

The tasks were completed on a Pentium 4 PC with a 17 inch LCD display. The prompts for the tasks were displayed on a laptop next to the PC. The time to complete all tasks ranged from 1:15 to just under three hours. The video collection consisted of 176 different digital videos from the Internet Archive and Open Video, ranging in duration from five minutes to half and hour, with 14,522 shots total.

Tasks consisted of a single question followed by a set of image examples and/or video examples. All users were encouraged to play the sample videos because they might be in the search collection. The tasks from the first set of questions were:

> Task 1-1: Find shots of people spending leisure time at the beach, for example: walking, swimming, sunning, playing in the sand. Some part of the beach or the buildings on it should be visible. (Two image examples and two video examples).
>
> Task 1-2: Find shots of one or more musicians: a man or woman playing a musical instrument with instrumental music audible. Musician(s) and instrument(s) must be at least partly visible some time during the shot. (Two image examples and two video examples)
>
> Task 1-3: Find shots of one or more women standing in long dresses. Dress should be one piece and extend below knees. The entire dress from top to end of dress below knees should be visible at some point. (Two image examples and two video examples).
>
> Task 1-4: Find shots with one or more sailboats, sailing ships, clipper ships, or tall ships - with some sail(s) unfurled (Two image examples and one video example).
>
> Task 1-5: Find more shots of one or more groups of people, a crowd, walking in an urban environment (for example with streets, traffic, and/or buildings) (Two image examples and 2 video examples)
>
> Task 1-6: Find this shot: (11-second video example)
>
> Task 1-7: Find the shot that contains this image (Figure 7).

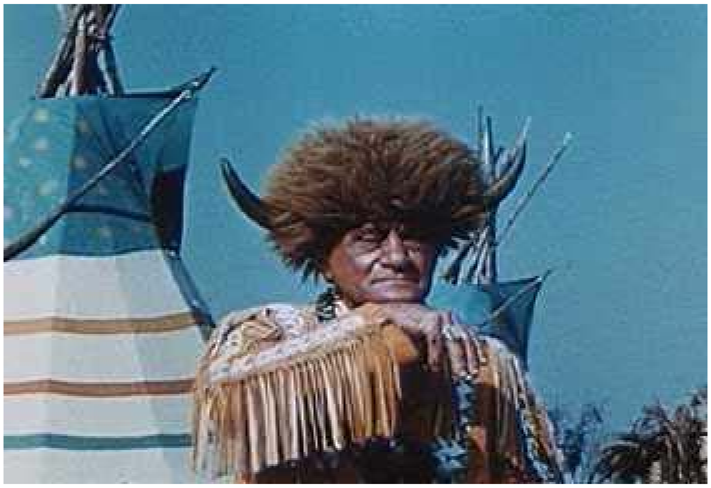


Figure 7. Image example for task 1-7.

The tasks from the second set were:

Task 2-1: Find shots of the Golden Gate Bridge (Two image examples)

Task 2-2: Find overhead views of cities - downtown and suburbs. The viewpoint should be higher than the highest building visible.(Two image examples and two video examples).

Task 2-3: Find more shots with one or more snow-covered mountain peaks or ridges. Some sky must be visible them behind (Two image examples and two video examples).

Task 2-4: Find shots about live beef or dairy cattle, individual cows or bulls, herds of cattle (Two image examples and one video example).

Task 2-5: Find shots of a nuclear explosion with a mushroom cloud (Two image examples and one video example).

Task 2-6: Find this shot: (8-second video example).

Task 2-7: Find the shot that contains this image (Figure 8).

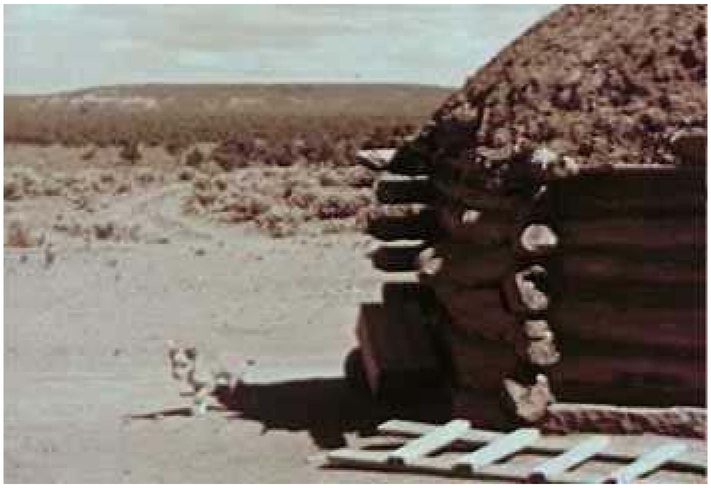


Figure 8. Image example for task 2-7.

Assuming that the number of relevant shots in the collection is a reliable indicator, there was a wide range of difficulty among the tasks, as demonstrated	Relevant Shots in the Collection

in Table 3.Task	
1-1	33
1-2	30
1-3	119
1-4	32
1-5	133
1-6	1
1-7	1
2-1	23
2-2	55
2-3	45
2-4	148
2-5	7
2-6	1
2-7	1

Table 3. Task difficulty as approximated by relevant shots in the collection

Text transaction logs tracked user queries, videos played, and videos selected, along with timestamps for each action (see Appendix D for a sample log).

After completing each search task, users circled answers on a Likert Scale ranging from 1 (Not at all) to 5 (Extremely) to six questions:

1. Are you familiar with this topic?
2. Was it easy for you to get started on this search?
3. Was it easy to do the search for this topic?
4. Was the ability to search by particular features useful?
5. Are you satisfied with your results?
6. Did you have enough time to do an effective search?

When users finished the tasks for each system, they completed a questionnaire designed to gather some feedback on how useful, simple, and enjoyable to use the system was (Appendix B). At the end of the session, after all tasks on both systems had been completed, users were invited to comment more generally on what they liked and did not like about each system.

V. Results

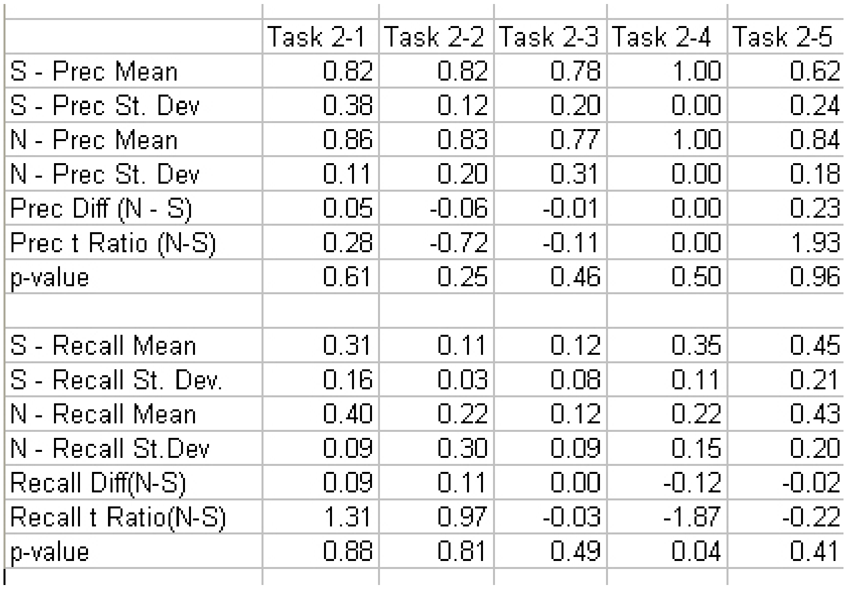
This study sought to answer four main questions about the design of video retrieval software:

1) Will the ability to adjust the relative weights of low-level visual features in a query improve user recall on search tasks?

Hypothesis: The ability to adjust the relative weights of low-level visual features in a query will improve user recall on search tasks.

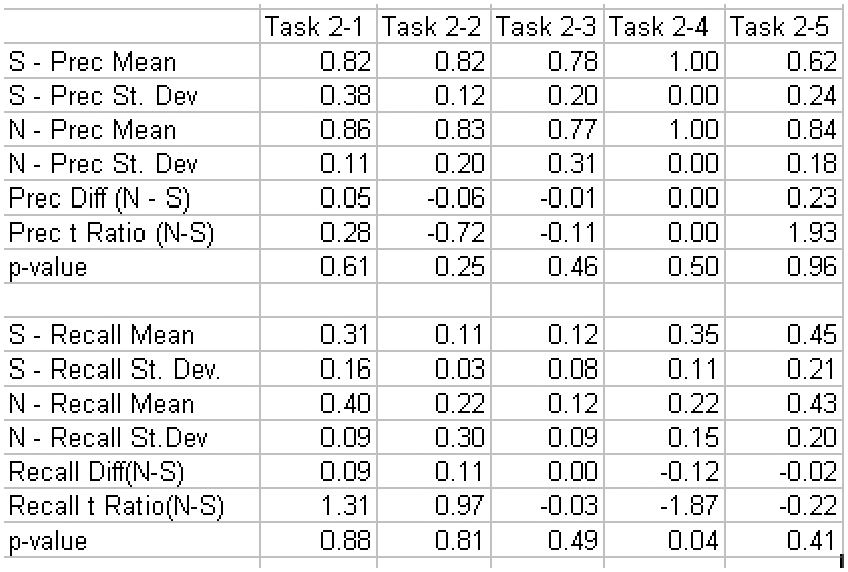
Null hypothesis: The ability to adjust the relative weights of low-level visual features in a query will not improve user recall on search tasks.

A one-tailed independent-sample t-test indicates that the null hypothesis is not rejected ($p < .08$). Subjects using System S performed significantly better on only three tasks (1-1, 1-5, and 2-4). Subjects using System S performed better on 8 of the 10 non-exact-match tasks (tasks 1-1 through 1-5 and 2-1 through 2-5), but not by a significant margin, which suggests that if the same study were conducted with a larger sample size, H_0 might safely be rejected. Precision and recall by task are summarized in Table 4 and Table 5.



	Task 2-1	Task 2-2	Task 2-3	Task 2-4	Task 2-5
S - Prec Mean	0.82	0.82	0.78	1.00	0.62
S - Prec St. Dev	0.38	0.12	0.20	0.00	0.24
N - Prec Mean	0.86	0.83	0.77	1.00	0.84
N - Prec St. Dev	0.11	0.20	0.31	0.00	0.18
Prec Diff (N - S)	0.05	-0.06	-0.01	0.00	0.23
Prec t Ratio (N-S)	0.28	-0.72	-0.11	0.00	1.93
p-value	0.61	0.25	0.46	0.50	0.96
S - Recall Mean	0.31	0.11	0.12	0.35	0.45
S - Recall St. Dev.	0.16	0.03	0.08	0.11	0.21
N - Recall Mean	0.40	0.22	0.12	0.22	0.43
N - Recall St.Dev	0.09	0.30	0.09	0.15	0.20
Recall Diff(N-S)	0.09	0.11	0.00	-0.12	-0.02
Recall t Ratio(N-S)	1.31	0.97	-0.03	-1.87	-0.22
p-value	0.88	0.81	0.49	0.04	0.41

Table 4. Mean Precision and Recall values for tasks 1-1 through 1-5



	Task 2-1	Task 2-2	Task 2-3	Task 2-4	Task 2-5
S - Prec Mean	0.82	0.82	0.78	1.00	0.62
S - Prec St. Dev	0.38	0.12	0.20	0.00	0.24
N - Prec Mean	0.86	0.83	0.77	1.00	0.84
N - Prec St. Dev	0.11	0.20	0.31	0.00	0.18
Prec Diff (N - S)	0.05	-0.06	-0.01	0.00	0.23
Prec t Ratio (N-S)	0.28	-0.72	-0.11	0.00	1.93
p-value	0.61	0.25	0.46	0.50	0.96
S - Recall Mean	0.31	0.11	0.12	0.35	0.45
S - Recall St. Dev.	0.16	0.03	0.08	0.11	0.21
N - Recall Mean	0.40	0.22	0.12	0.22	0.43
N - Recall St.Dev	0.09	0.30	0.09	0.15	0.20
Recall Diff(N-S)	0.09	0.11	0.00	-0.12	-0.02
Recall t Ratio(N-S)	1.31	0.97	-0.03	-1.87	-0.22
p-value	0.88	0.81	0.49	0.04	0.41

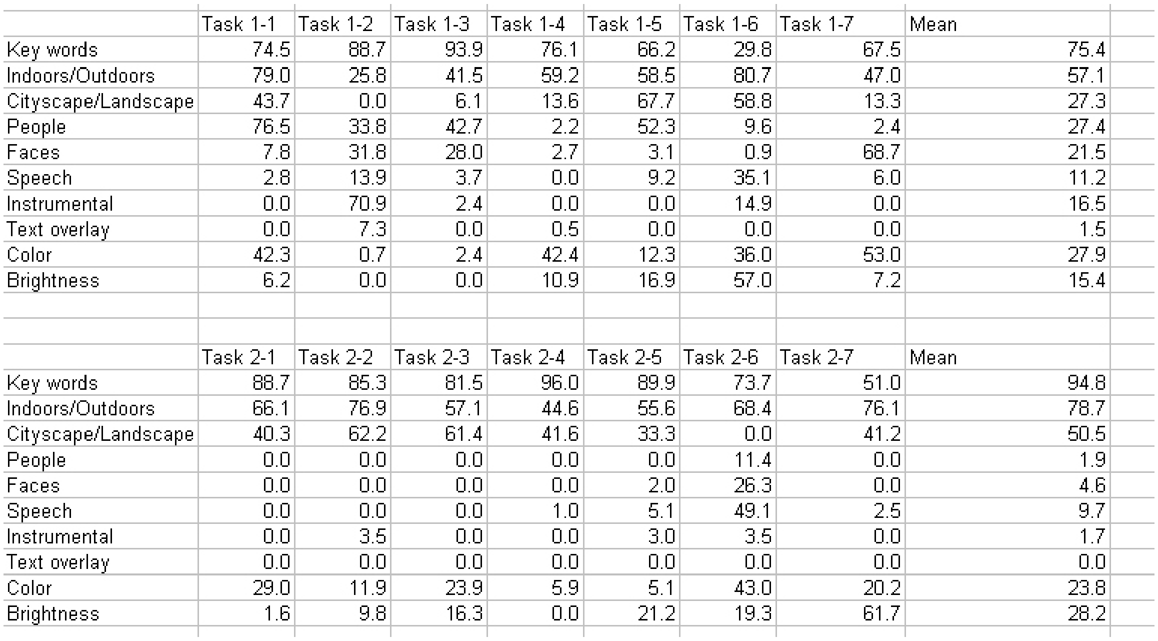
Table 5. Mean Precision and Recall values for tasks 2-1 through 2-5

Appendix E shows the recall on System S and on System N broken down by task. Only recall is considered, since precision scores usually only dropped a result of misunderstanding the task (e.g., the subject might have forgotten in task 1-3 that the women must be standing). These figures demonstrate that users performing the task with System S did consistently better, but not significantly.

2) Which of these features will be most useful in typical search tasks?

indoors/outdoors
cityscape/landscape
people
faces
human speech
instrumental
text overlay
color
brightness

The figures in Table 6 represent the percentage of queries for each task that used a particular feature. Which features were most frequently used for each task was not surprising. For task 1-1 ("Find shots of people spending leisure time at the beach"), the Outdoors feature was used in 79% of the queries and the People feature was used in 76%. For task 1-2, ("Find shots of musicians"), the Instrumental feature was used 70% of the time. For task 1-4 ("Find shots with one or more sailboats**"),** the Outdoor feature was used 59% of the time and the color feature (using blue for the water) was used 42% of the time. For task 1-5 ("Find shots of people walking in an urban environment), the Cityscape feature was used 67% of the time, the Outdoors feature was used 58% of the time, and the People feature was used 52% of the time. Subjects used the greatest variety of tasks while doing the exact match tasks. The most useful feature for task 1-6, which involved finding a particular shot in which the sun was rising over the horizon, was brightness, which was used 57% of the time. The most useful feature for task 1-7, which involved finding a shot that had a Native American against a bright blue sky, was color, which was used 53% of the time. Likewise, a highly useful feature for task 2-6, which involved finding a particular shot of a woman in a red dress against a blue background, was color (43%), and for task 2-7, which involved finding a shot of a log cabin that was bright on the left and dark on the right, was brightness (61%).

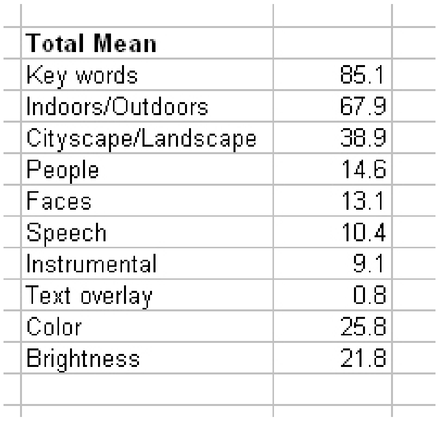


	Task 1-1	Task 1-2	Task 1-3	Task 1-4	Task 1-5	Task 1-6	Task 1-7	Mean
Key words	74.5	88.7	93.9	76.1	66.2	29.8	67.5	75.4
Indoors/Outdoors	79.0	25.8	41.5	59.2	58.5	80.7	47.0	57.1
Cityscape/Landscape	43.7	0.0	6.1	13.6	67.7	58.8	13.3	27.3
People	76.5	33.8	42.7	2.2	52.3	9.6	2.4	27.4
Faces	7.8	31.8	28.0	2.7	3.1	0.9	68.7	21.5
Speech	2.8	13.9	3.7	0.0	9.2	35.1	6.0	11.2
Instrumental	0.0	70.9	2.4	0.0	0.0	14.9	0.0	16.5
Text overlay	0.0	7.3	0.0	0.5	0.0	0.0	0.0	1.5
Color	42.3	0.7	2.4	42.4	12.3	36.0	53.0	27.9
Brightness	6.2	0.0	0.0	10.9	16.9	57.0	7.2	15.4

	Task 2-1	Task 2-2	Task 2-3	Task 2-4	Task 2-5	Task 2-6	Task 2-7	Mean
Key words	88.7	85.3	81.5	96.0	89.9	73.7	51.0	94.8
Indoors/Outdoors	66.1	76.9	57.1	44.6	55.6	68.4	76.1	78.7
Cityscape/Landscape	40.3	62.2	61.4	41.6	33.3	0.0	41.2	50.5
People	0.0	0.0	0.0	0.0	0.0	11.4	0.0	1.9
Faces	0.0	0.0	0.0	0.0	2.0	26.3	0.0	4.6
Speech	0.0	0.0	0.0	1.0	5.1	49.1	2.5	9.7
Instrumental	0.0	3.5	0.0	0.0	3.0	3.5	0.0	1.7
Text overlay	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Color	29.0	11.9	23.9	5.9	5.1	43.0	20.2	23.8
Brightness	1.6	9.8	16.3	0.0	21.2	19.3	61.7	28.2

Table 6. Percentage of queries using features, broken down by task.

The overall percentage of queries that used each feature is summarized in Table 7. In general, the most frequently used features were keywords, used in 85% of all queries, followed by Indoors/Outdoors (67%) and Cityscape/Landscape(38%). One user admitted that he used features left to right, and the left-to-right ordering of the feature components on the interface corresponds exactly to the ordering of the top three features. After these three, the color (25%) and brightness (21%) features were the most frequently used.



Total Mean	
Key words	85.1
Indoors/Outdoors	67.9
Cityscape/Landscape	38.9
People	14.6
Faces	13.1
Speech	10.4
Instrumental	9.1
Text overlay	0.8
Color	25.8
Brightness	21.8

Table 7. Mean use of individual features.

3) Will users find it difficult to formulate queries using low-level features?

The difficulty of each system was measured using the middle section of the Post-System Questionnaire (Appendix B). The possible difficulty score ranged from 6 (easiest) to 30 (hardest). For all questionnaires, the mean difficulty was 14.8. Users were neutral on questions of difficult; on average, they neither agreed nor disagreed that the system was difficult or confusing.

4) Will the addition of the sliders make the system too complicated or frustrating for users?

There was not a significant difference between the mean difficulty scores for each system. The mean difficulty for System S was 14.3, while the mean difficulty for System N was 15. Flow, a measure of interest and involvement, was measured using the bottom section of the Post-System Questionnaire. A score of 0 was assigned for answers on the right (“uninteresting”) and a score of 6 was assigned for answers on the left ("interesting") side, for a total possible score of 48. The system with the sliders averaged 36, while the system without the sliders averaged 35.1875. The difference is not significant.

5) Will the ability to search by keyframe hue or brightness reduce the time required to find specific shots?

A Person's R correlation indicates a consistent negative correlation between time to find the exact-match shots and the subject's tendency to use the brightness and color features. This tendency is approximated using the percentage of the subject's total queries that contained some brightness or color query.

SubjectID	Total Queries	# using Brightness	% using Brightness	# using Color	% using Color	Time Task 1-6	Time Task 1-7	Time Task 2-6	Time Task 2-7
2	98	27	27.6	25	25.5	310	90	50	140
3	71	11	15.5	14	19.7	840	50	180	150
4	163	53	32.5	59	36.2	150	60	120	100
5	129	17	13.2	30	23.3	150	300	180	570
6	106	8	7.5	17	16.0	380	160	120	360
7	216	31	14.4	22	10.2	300	120	240	540
8	77	12	15.6	16	20.8	NA	60	90	210
9	131	10	7.6	27	20.6	NA	NA	195	300
10	104	32	30.8	49	47.1	140	90	N/A	220
11	45	10	22.2	10	22.2	NA	NA	540	600
12	154	24	15.6	30	19.5	180	80	270	90
13	104	21	20.2	35	33.7	300	180	300	300
14	89	19	21.3	10	11.2	NA	NA	280	300
15	164	48	29.3	64	39.0	NA	80	140	100
16	41	9	22.0	27	65.9	360	130	NA	NA
17	101	7	6.9	12	11.9	120	150	300	340
18	189	23	12.2	66	34.9	60	90	120	130

Table 8. Use of color and brightness components by subject

Table 8 summarizes users' tendency to use the color and brightness features and the time required to successfully complete the exact-match tasks. Although there was a consistent negative correlation between the use of these features and the time required to complete the task, the wide variance in time prevented these correlations from being significant.

VI. Conclusions

Much of the literature in video retrieval is concerned with automatically extracting features from video streams. Electrical engineering departments are discovering mathematical ways of describing the angularity that is suggestive of a cityscape, or the ellipticality and color that might be a face, or the fractal textures and ambient light that characterize a landscape. All of this ingenuity seems driven by the supposition that there will be a use for these detection algorithms. This study was an attempt to build a practical video search tool that employs these detection algorithms in an effort to discover empirically which of these low-level features in fact prove useful for normal people doing normal search tasks.

Whether a study like this one can in fact simulate a normal person performing normal search tasks is a difficult question. Video search tasks, for normal people, seldom happen at a computer. Except for one (the only one over 60), all subjects reported watching at least one video a week for entertainment, and their search was usually determined by the arrangement of their preferred video store: genre at Blockbuster, ethnicity and auteur at Visart. Subjects were encouraged to treat the search tasks as naturally as they could, but most appeared anxious and competitive about their performance. They had no background as to why they were looking for these shots, and they had no input as to what shots they could look for. Lacking this context changes the search behavior.

Another limitation of the study is that it lasted, in some cases, almost three hours, and fatigue caused subjects to rush through the last few tasks of whatever set they did second. Because of this, the mean recall scores for some tasks did not necessarily reflect that task's difficulty. Some subjects chose not to spend very long on any of the tasks, and consequently had lower recall scores, even though they were performing well per unit of time. Also, some subjects were distracted by the content of the videos, and sometimes watched them for several seconds. Two subjects in particular, subjects 8 and 16, enjoyed browsing and commenting on the videos.

The results lead to several recommendations for designing a video search interface:

1) *Investment in gathering text data about a video and providing rich text-search features such as thesauri, stemming and latent semantic indexing will be more useful than refining algorithms to detect low-level features.*

Without exception, users tried a text query first for every task, and almost all found the lack of keyword sophistication in the system "frustrating." The keyword field was the most often used, at 85%, even when users were encouraged to use other features more. "I started on the left with the keywords and worked my way to the right," one user said. "I tried keyword and after keyword and if I got no results, I'd do the other things." The idea of searching without keywords was such an alien concept that one user repeatedly forgot that she was not required to have keywords. "How am I supposed to find a beach? I tried beach, sand, ocean, shore, waves…I don't know what else to do." Users generally grew more comfortable with using features the more they used the system.

2) *A simple component that allows users to specify a limited amount of color or brightness data will improve performance when users are searching for a specific shot.*

Systems that allow users to sketch an example image tend to have poor results because it is difficult to judge exactly how to use the sketch. Too close an approximation yields zero results, while too rough an approximation yields results that are not similar at all. VisOR's simple system of allowing users to specify color and brightness values for quadrants allows the user and they system to meet in the middle: the query is not too specific, and there are ample results.

Users enjoyed the novelty of the color search, and this caused them to use these components more often than they really needed to. "This is fun," one user said. Another user described it as "cool" and demanded an explanation of how it worked before he would proceed with the tasks. The most successful searches for two tasks—beaches and boats—resulted from using the color system. Users who put cyan in the top two quadrants and yellow in the bottom two quadrants found themselves looking directly at several beach shots. Likewise, users who entered blue for the bottom two quadrants and selected ("Match any") found several boats floating on the water. One user felt that this had its limitations. "It only works for obvious things like sunsets and horizons."

3) *Of the features available, Indoors/Outdoors and Cityscape/Landscape prove the most useful for regular searches. The least useful is Text Overlay and Human Speech.*

Indoors/Outdoors may have been most useful because of the nature of the tasks, but it is also likely that is it a general enough characteristic to apply to all videos. Text Overlay is very specific, and speech appears in too many shots to be a good discriminator. Users suggested some other features that they would like to use, including shape, man/woman, vertical/horizontal, and shot type (close up/long shot).

4) *Sliders do not make a significant difference in performance, but users generally feel like the sliders provide a powerful benefit in ordering a large result set.*

Although some users reported that the sliders did not make a difference, many felt a greater sense of control with the slider system. "I don't know if it made a difference, but the sliders made me feel like I had more control. Without the sliders, I had to scroll too much through all the images." Another user said, "I used the sliders in the first set of tasks, and there were 2 occasions when I wished I had them in the second."

One common impression was that the sliders could be useful, but it would take some time to learn to use them effectively. One user said, “The system with the sliders seemed more sophisticated, but I don’t think I used it very well. It's something I would have to practice.” Sliders can, however be too abstract, even for people with technical expertise. One user, whose performance was higher than average, said, “I found the sliders confusing. When I pulled the People slider over, did that mean there would be more people?”

5) *Users are capable of sifting through large sets (150 on a computer screen) of thumbnail images, but fatigue sets in quickly.*

Only one user commented on the size of the thumbnails without prompting. When asked what they thought about the number of images that were squeezed into the result frame, most subjects that the number was fine. Two users said that the thumbnails were too small, even for a rough scan, and one user said that the images became harder and harder to look at the longer he used the system. Any system that is designed to be used for repeated searches should allow users to specify the size of the result set thumbnails according to how tired they are. Also, if a larger preview image pops up when a user mouses over a thumbnail, that image should be close to the mouse pointer, not in a designated location to the left. Having to brush their eyes back and forth frequently probably led to accelerated user fatigue.

6) Sliders have no significant effect on users’ general satisfaction of a search interface, nor on how difficult they perceive the system to be.

Neither the difficulty scores nor the flow scores differed significantly between System S and System N, which suggests that the sliders did not add any complexity or discomfort.

As algorithms for automatic analysis of video streams improve, the most important accomplishments, user behavior in this study indicates, will be in object recognition. In performing tasks in this study, users typically followed a process in which they entered an abstract keyword ("music") and ran the query. If the query failed, they began listing objects that might be in the frame ("guitar," "tuba," "flute"). In the task that asked users to find an exact match of a shot of a woman in a red dress, the most frequently-occurring words were "woman," "dress," "lamp," and "table." The objects had nothing to do with the semantic content of the shot, but people naturally tried queries based on physical, observable objects in the frame.

One aim of research in video retrieval is provide something of practical use to the consumers who are rapidly building video collections. Engineers developing algorithms to extract features and researchers conducting studies like this one that test the utility of those features should strive to enable a man with a 200-hour video collection on his hard drive to immediately find a shot that includes a closeup of his son playing the guitar indoors in a blue shirt, and then a shot of his daughter playing the tuba with the sunset in the background.

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Appendix A: Pre-session Questionnaire

Gruss Video Retrieval Study
Pre-Session Questionnaire

Subject ID: _______

1. What is your age? ________

2. What is your sex? ______Female ______Male

3. What is your status?
   - □ Undergraduate student
   - □ Graduate student
   - □ Faculty
   - □ Staff
   - □ Other: ___________________________

4. With what department are you affiliated?
   ____

5. How often do you use a computer?
   - □ Never
   - □ Occasionally
   - □ Monthly
   - □ Weekly
   - □ Daily

8. How often do you watch videos or films?
   - □ Never
   - □ Occasionally
   - □ Monthly
   - □ Weekly
   - □ Daily

8. How often do you search for videos or films?
   - □ Never
   - □ Occasionally
   - □ Monthly
   - □ Weekly
   - □ Daily

8. When you search for films or videos, where do you go?
   - □ Online
   - □ Newspaper or magazine
   - □ Film archives
   - □ Other: ____

9. How do you usually search for videos or films?
   - □ By title
   - □ By author or actor
   - □ By topic
   - □ By trailer
   - □ Other: ____

10. For what purposes do you usually search for videos or films?

____

____

____

Appendix B: Post-System Questionnaire

Subject ID: ____________
System: A B
Date: ____________

Gruss Video Retrieval Study: Post-System Questionnaire

Usefulness: Place an x in the column that most applies.

VIDEO RETRIEVAL SYSTEM

useful :____:____:____:____:____:____:____: useless
advantageous :____:____:____:____:____:____:____: disadvantageous
helpful :____:____:____:____:____:____:____: not helpful
functional :____:____:____:____:____:____:____: not functional
valuable :____:____:____:____:____:____:____: worthless
appropriate :____:____:____:____:____:____:____: inappropriate
beneficial :____:____:____:____:____:____:____: not beneficial
effective :____:____:____:____:____:____:____: ineffective
adequate :____:____:____:____:____:____:____: inadequate
productive :____:____:____:____:____:____:____: unproductive

Ease of use:

	Strongly agree				Strongly disagree
Learning to operate this system was easy for me.	1	2	3	4	5
I found it easy to get this system to do what I wanted it to do.	1	2	3	4	5
My interaction with this system was clear and understandable.	1	2	3	4	5
I found this system to be flexible to interact wth.	1	2	3	4	5
It would be easy for me to become skillful at using this system.	1	2	3	4	5
I found this system easy to use.	1	2	3	4	5

Flow :

USING THE VIDEO RETRIEVAL SYSTEM

interesting :____:____:____:____:____:____:____: uninteresting
enjoyable :____:____:____:____:____:____:____: not enjoyable
exciting :____:____:____:____:____:____:____: dull
fun :____:____:____:____:____:____:____: not fun

WHILE USING THE VIDEO RETRIEVAL SYSTEM

absorbed intensely :____:____:____:____:____:____:____: not absorbed intensely
attention was focused :____:____:____:____:____:____:____: attention was not
focused
concentrated fully :____:____:____:____:____:____:____: did not fully
concentrate
deeply engrossed :____:____:____:____:____:____:____: not deeply engrossed

Appendix C: MySQL database table

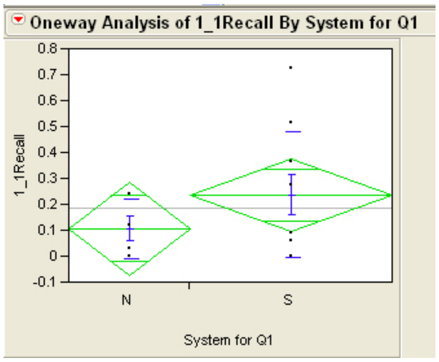
Shot table:

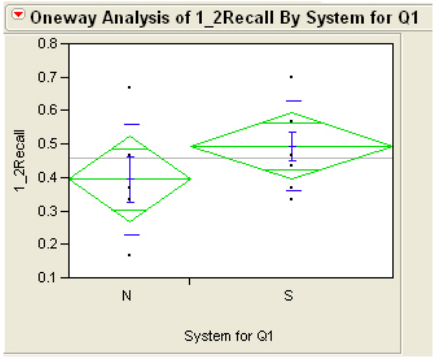
ShotName	varchar(50)
VideoID	smallint(6)
VideoTitle	tinytext
VideoDescription	text
VideoKeywords	tinytext
VideoDuration	varchar(20)
VideoCreationDate	varchar(10)
VideoSound	enum('Yes','No')
ShotNo	mediumint(9)
TimePoint	varchar(50)
Duration	varchar(50)
BeginTime	varchar(20)
BeginSeconds	int(11)
EndTime	time
KeyframeFilename	varchar(250)
KeyframeTimePoint	varchar(50)
KeyframeTime	time
KeyframeUpperLeftDomHue	smallint(6)
KeyframeUpperLeftAvMax	smallint(6)
KeyframeUpperLeftAvMin	smallint(6)
KeyframeUpperLeftAvDifsmallint(6)	
KeyframeUpperLeftAvSum	smallint(6)
KeyframeUpperRightDomHue	smallint(6)
KeyframeUpperRightAvMax	smallint(6)
KeyframeUpperRightAvMin	smallint(6)
KeyframeUpperRightAvDif	smallint(6)
KeyframeUpperRightAvSum	smallint(6)
KeyframeLowerLeftDomHue	smallint(6)
KeyframeLowerLeftAvMax	smallint(6)
KeyframeLowerLeftAvMin	smallint(6)
KeyframeLowerLeftAvDif	smallint(6)
KeyframeLowerLeftAvSum	smallint(6)
KeyframeLowerRightDomHue	smallint(6)
KeyframeLowerRightAvMax	smallint(6)
KeyframeLowerRightAvMin	smallint(6)
KeyframeLowerRightAvDif	smallint(6)
KeyframeLowerRightAvSum	smallint(6)
Transcript	mediumtext
Annotation	tinytext
Faces	int(3) unsigned
People	double
Indoors	double
Outdoors	double
Cityscape	double
Landscape	double
TextOverlay	double
Speech	double
Sound	double

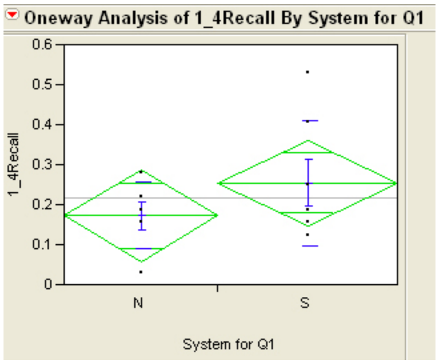
Appendix D: Sample transaction log

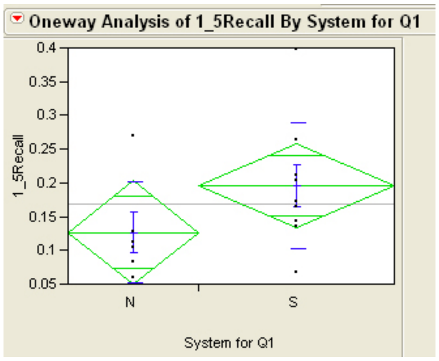
```
BEGAN TASK 1 8:48:55 PM

SLIDER CityLand=156 8:49:35 PM

SLIDER IndoorsOutdoors=200 8:49:36 PM

SLIDER people=152 8:49:41 PM

QUERY: 8:50:12 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND Outdoors > .5 AND
Landscape > .5  AND People > .5  AND ( 1=2  OR
(keyframeupperleftdomhue = 180) OR (keyframeupperrightdomhue = 180)
OR (keyframelowerleftdomhue = 240) OR (keyframelowerrightdomhue =
240) )   ORDER BY 1 +Outdoors*200+Landscape*156+People*152 desc
limit 700

PLAY 11/25/2003 8:50:45 PM  video 102 (00:03:13)

PLAY 11/25/2003 8:50:59 PM  video 102 (00:05:55)

QUERY: 8:51:47 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND match(VideoTitle,
VideoDescription, VideoKeywords) against ('beach') AND Outdoors > .5
AND Landscape > .5  AND People > .5  AND ( 1=2  OR
(keyframeupperleftdomhue = 180) OR (keyframeupperrightdomhue = 180)
OR (keyframelowerleftdomhue = 240) OR (keyframelowerrightdomhue =
240) )   ORDER BY 1  +match(VideoTitle, VideoDescription,
VideoKeywords) against ('beach')
*4+Outdoors*200+Landscape*156+People*200 desc limit 700

QUERY: 8:51:54 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND match(VideoTitle,
VideoDescription, VideoKeywords) against ('beach') AND Outdoors > .5
AND Landscape > .5  AND People > .5   ORDER BY 1  +match(VideoTitle,
VideoDescription, VideoKeywords) against ('beach')
*4+Outdoors*200+Landscape*156+People*200 desc limit 700

QUERY: 8:52:07 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND Outdoors > .5 AND
Landscape > .5  AND People > .5  AND ( 1=2  OR
(keyframeupperleftdomhue = 180) OR (keyframeupperrightdomhue = 180)
OR (keyframelowerleftdomhue = 240) OR (keyframelowerrightdomhue =
240) )   ORDER BY 1 +Outdoors*200+Landscape*156+People*200 desc
limit 700

PLAY 11/25/2003 8:52:16 PM  video 97 (00:02:11)

SLIDER CityLand=200 8:52:28 PM

QUERY: 8:52:35 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND Outdoors > .5 AND
Landscape > .5  AND People > .5  AND ( 1=2  OR
(keyframeupperleftdomhue = 180) OR (keyframeupperrightdomhue = 180)
OR (keyframelowerleftdomhue = 240) OR (keyframelowerrightdomhue =
240) )   ORDER BY 1 +Outdoors*200+Landscape*200+People*200 desc
limit 700

PLAY 11/25/2003 8:53:03 PM  video 50 (00:02:36)

QUERY: 8:54:02 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND match(VideoTitle,
VideoDescription, VideoKeywords) against ('recreation') AND Outdoors
> .5 AND Landscape > .5  AND People > .5  AND ( 1=2  OR
(keyframeupperleftdomhue = 180) OR (keyframeupperrightdomhue = 180)
OR (keyframelowerleftdomhue = 240) OR (keyframelowerrightdomhue =
240) )   ORDER BY 1  +match(VideoTitle, VideoDescription,
VideoKeywords) against ('recreation')
*4+Outdoors*200+Landscape*200+People*200 desc limit 700

QUERY: 8:54:31 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND match(VideoTitle,
VideoDescription, VideoKeywords) against ('san francisco')  ORDER BY
1  +match(VideoTitle, VideoDescription, VideoKeywords) against ('san
francisco') *4 desc limit 700

SLIDER people=186 8:54:39 PM

QUERY: 8:54:42 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND match(VideoTitle,
VideoDescription, VideoKeywords) against ('san francisco') AND
Outdoors > .5 AND Landscape > .5  AND People > .5   ORDER BY 1
+match(VideoTitle, VideoDescription, VideoKeywords) against ('san
francisco') *4+Outdoors*100+Landscape*100+People*186 desc limit 700

PLAY 11/25/2003 8:56:01 PM  video 43 (00:05:12)

QUERY: 8:56:42 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND match(VideoTitle,
VideoDescription, VideoKeywords) against ('leisure') AND Outdoors >
.5 AND Landscape > .5  AND People > .5   ORDER BY 1
+match(VideoTitle, VideoDescription, VideoKeywords) against
('leisure') *4+Outdoors*100+Landscape*100+People*186 desc limit 700

QUERY: 8:56:51 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND match(VideoTitle,
VideoDescription, VideoKeywords) against ('new york') AND Outdoors >
.5 AND Landscape > .5  AND People > .5   ORDER BY 1
+match(VideoTitle, VideoDescription, VideoKeywords) against ('new
york') *4+Outdoors*100+Landscape*100+People*186 desc limit 700

PLAY 11/25/2003 8:57:20 PM  video 22 (00:04:07)

QUERY: 8:59:58 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND match(VideoTitle,
VideoDescription, VideoKeywords) against ('ocean') AND Outdoors > .5
AND Landscape > .5  AND People > .5   ORDER BY 1  +match(VideoTitle,
VideoDescription, VideoKeywords) against ('ocean')
*4+Outdoors*100+Landscape*100+People*186 desc limit 700

SLIDER CityLand=200 9:00:03 PM
SLIDER IndoorsOutdoors=200 9:00:04 PM

QUERY: 9:00:11 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND match(VideoTitle,
VideoDescription, VideoKeywords) against ('sea') AND Outdoors > .5
AND Landscape > .5  AND People > .5   ORDER BY 1  +match(VideoTitle,
VideoDescription, VideoKeywords) against ('sea')
*4+Outdoors*200+Landscape*200+People*186 desc limit 700

QUERY: 9:00:21 PM SELECT videoid, begintime, beginseconds,
keyframefilename from shot   WHERE 1=1  AND match(VideoTitle,
VideoDescription, VideoKeywords) against ('bathing') AND Outdoors >
.5 AND Landscape > .5  AND People > .5   ORDER BY 1
+match(VideoTitle, VideoDescription, VideoKeywords) against
('bathing') *4+Outdoors*200+Landscape*200+People*186 desc limit 700

END TASK 1: 9:01:10
```

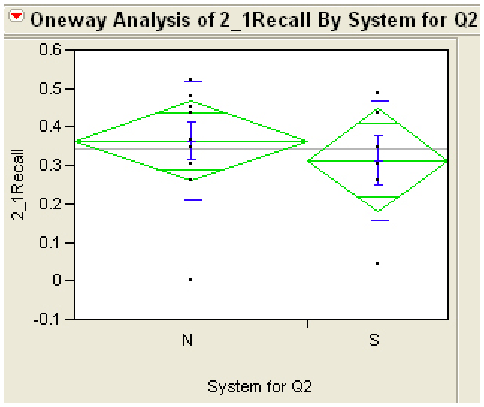
Appendix E: Recall scores on each system, broken down by task.

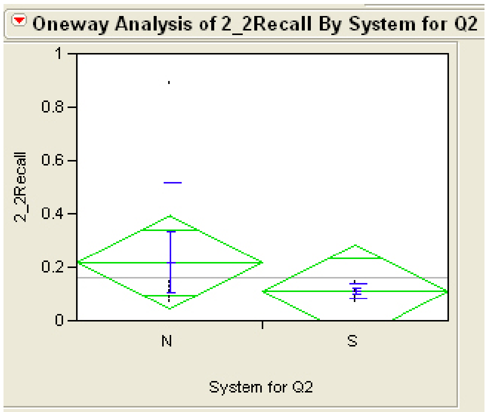


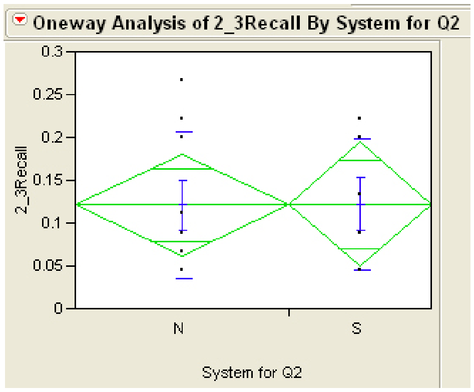


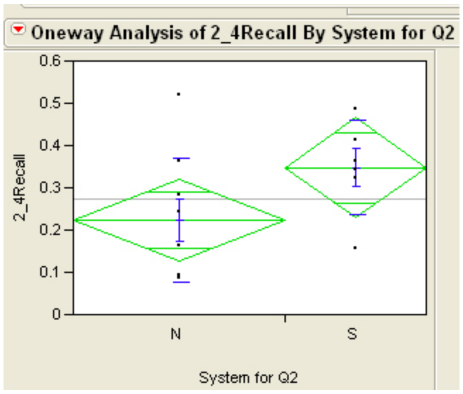


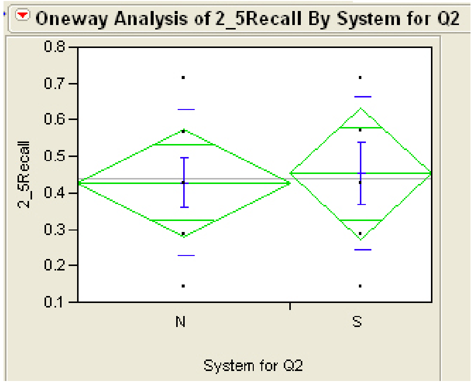



Oneway Analysis of 2_1Recall By System for Q2


Oneway Analysis of 2_2Recall By System for Q2


Oneway Analysis of 2_3Recall By System for Q2


Oneway Analysis of 2_4Recall By System for Q2


Oneway Analysis of 2_5Recall By System for Q2
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
2_5Recall
N
S
System for Q2