TRECVID 2005 Experiments at MediaTeam Oulu

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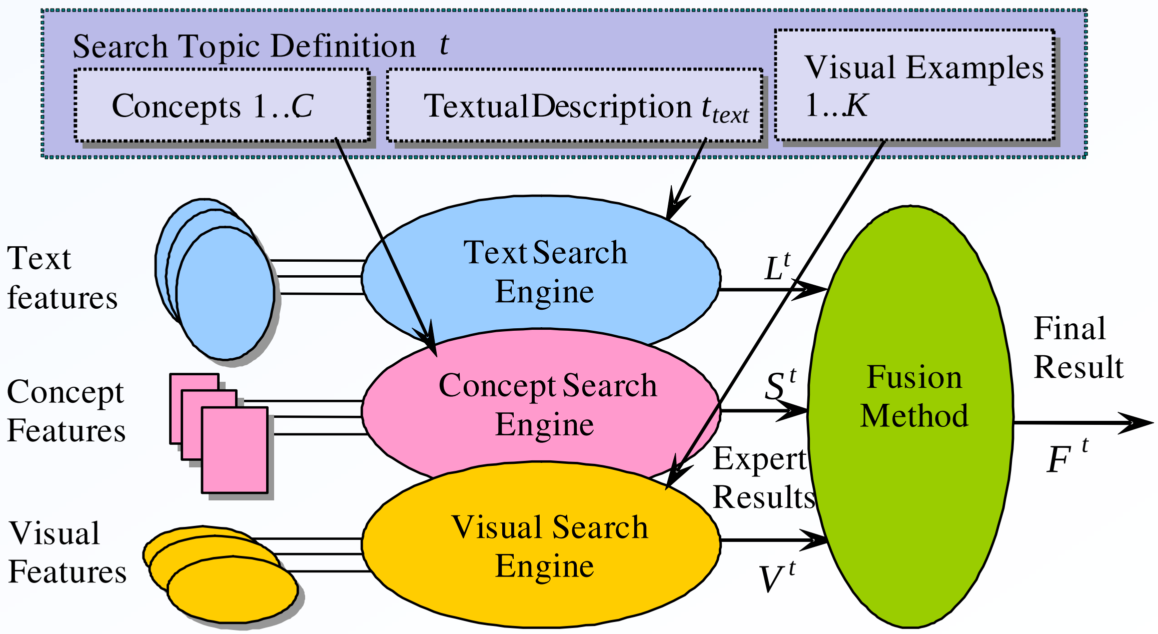
Overview

1. System Overview
2. Experimental Setup
3. 2005 Results
4. Conclusions

The Prototype Search System

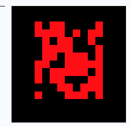
Three search paradigms for retrieval with our video retrieval and browsing system (VIRE):

I Text	Find named people, locations or events. Example: Find shots about the **`inauguration`** of **`Bill Clinton`** in front of the **`White House`**
II Concepts	Find common concept objects, events or scenes. Example: Find shots about **`birds`** flying in the **`sky`**
III Visual Examples	Find other video clips that look similar to this clip. Example: Find all occurrences of this analgesic advertisement in a month's recordings

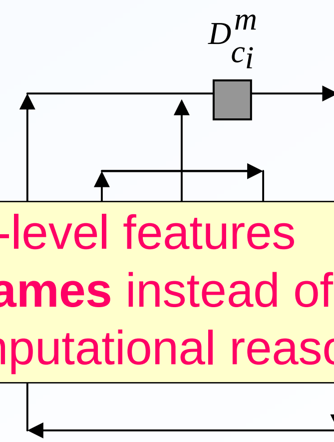


Visual Features

- **Color**
  - Temporal **`Color Correlogram`** (TCC), spatial color occurrences, 432 values



This year, we computed low-level features from **single subshot key frames** instead of temporal domain due to computational reasons



- $$\bar{\gamma}^{(d)}_{c_i,c_j}(S) \equiv \Pr_{p_1 \in D^m_{c_i},\, p_2 \in D^m}\left[p_2 \in D^m_{c_j} \,\middle|\, |p_1 - p_2| = d \right]$$

Visual Feature Fusion

- Dissimilarity by color or structure is defined as a Manhattan distance between the feature vector values

- Fusion of low level similarities for one example query
  - $$r^t(k,n) = sum(\frac{d_1^t(k,n)}{D_{1\max}^t(k)},\ldots,\frac{d_L^t(k,n)}{D_{L\max}^t(k)})$$

Combining features using SUM of ranks works well for features having different dimensionalities [10]

- Combining results from *K* examples
  - $$v^t(n) = min(\frac{r^t(1,n)}{R_{\max}^t(1)},\ldots,\frac{r^t(K,n)}{R_{\max}^t(K)})$$

Using MIN of ranks is more flexible than average when heterogeneous query example sets are provided.

Semantic Concept Features

- Semantic Concept Detectors:

  Three different approaches were used in detectors

  1. SVM:
     - **Entertainment(af+linr.), Outdoor(vf+linr.), Newsroom(vf+linr.), Desert(vf+linr.), Snow(vf+linr.), Natural disaster(vat+2poly)**
  2. Propagated labelling with selected example queries [6]:
     - **Fire-explosion-smoke, Maps-charts, Meeting-footage, Nature-footage, Weather, Sports, Water**
  3. Cascade learning algorithm (Adaboost) [15]: **Faces**
- Concept confidences were based on the shot's relative rank given by the detectors
  - SVM: sigmoid-based probabilistic estimate
  - Labelling: nearest neighbours (ranks)
  - Cascade learning: number of detected faces

Text Search

- Text index from ASR and MT transcripts (NIST & CMU)
  - Indexes created from the transcripts w/pre-processing
    - Re-formatting the source transcripts for our system
    - Stop word removal and Porter stemming
  - Inverted document indexes that are expanded using speaker segmentation boundaries and prioritization
  - ASR texts were patched with closed captions text

- Textual similarity between query text and a video shot
  - Valu n terms
  - Aggregated with a variation of TFIDF measure

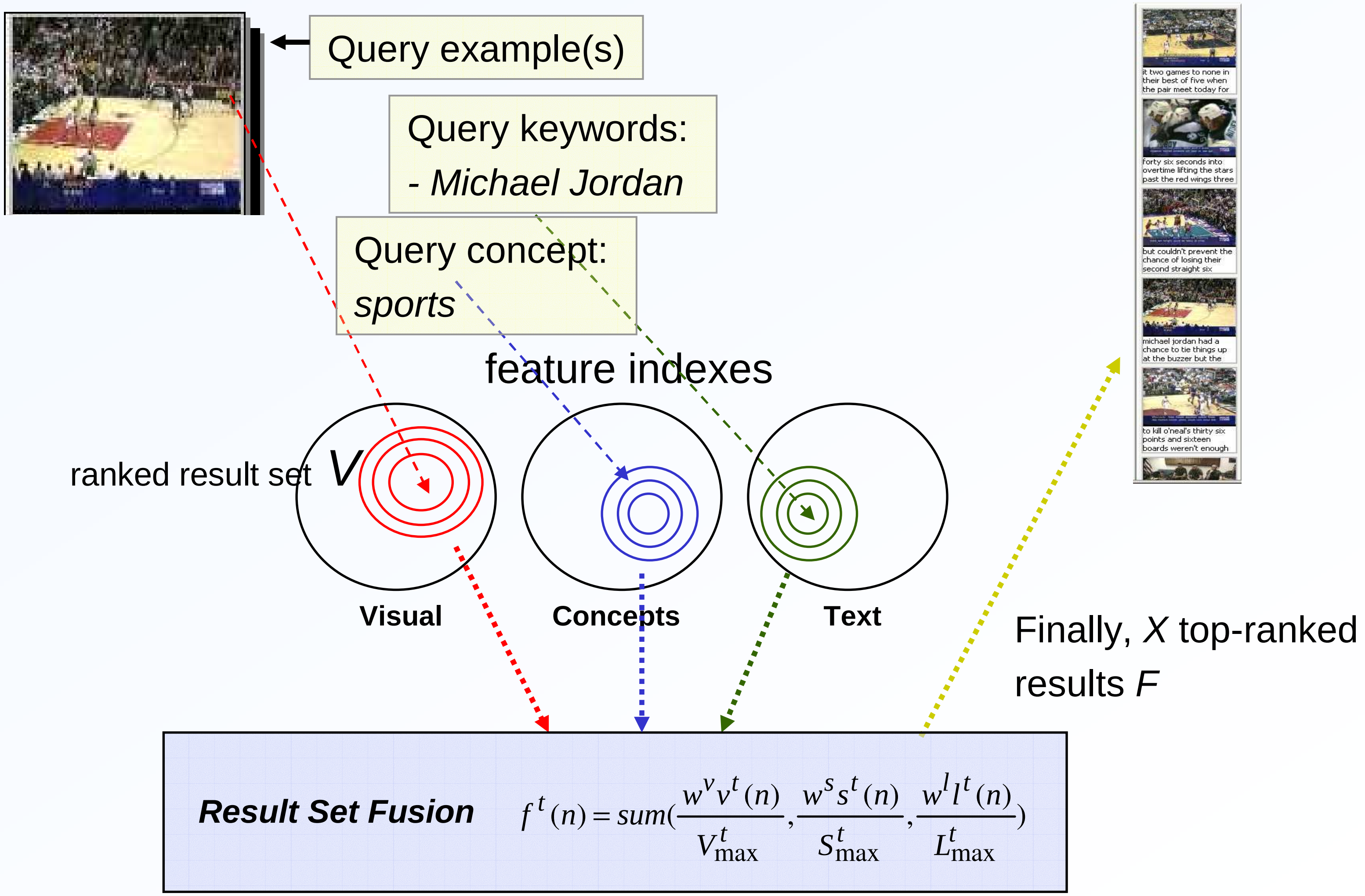
Ratio of matching words in a shot

Inverse freq. of the matching shots

Temporal weighting based on prioritization

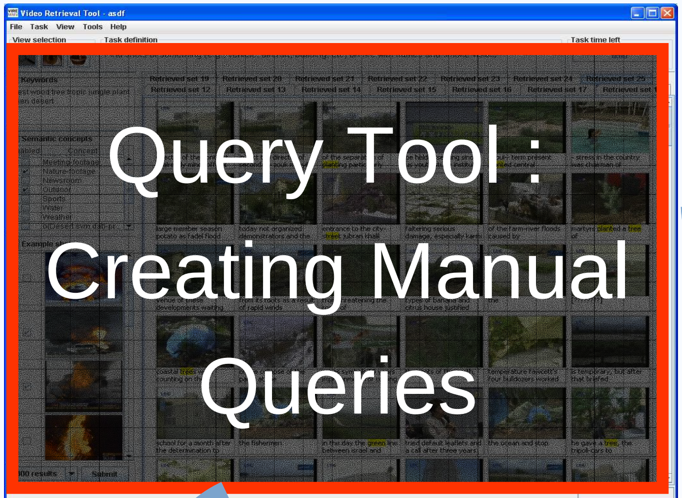
$$L(queryterm, s) = 0.2 \cdot \frac{\log(t+1)}{\log(dl+1)} * \log(\frac{N}{m}) + e^{-B\frac{j}{J}}$$

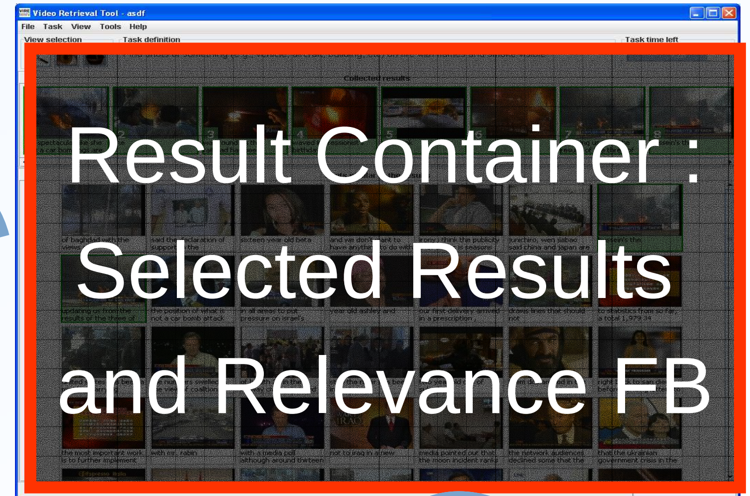
Feature Indexes and Fusion

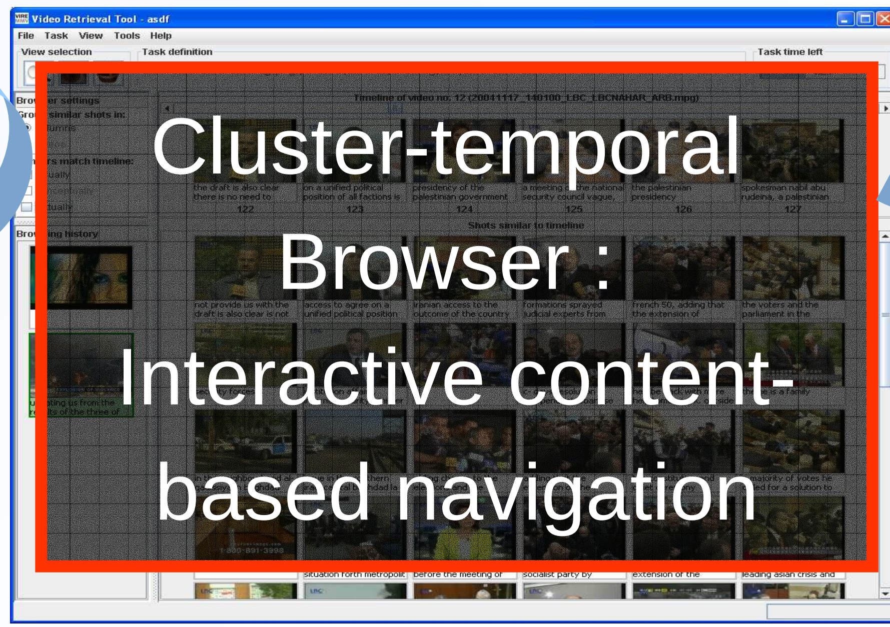


$$f^t(n) = sum\left(\frac{w^v v^t(n)}{V^t_{\max}}, \frac{w^s s^t(n)}{S^t_{\max}}, \frac{w^l l^t(n)}{L^t_{\max}}\right)$$

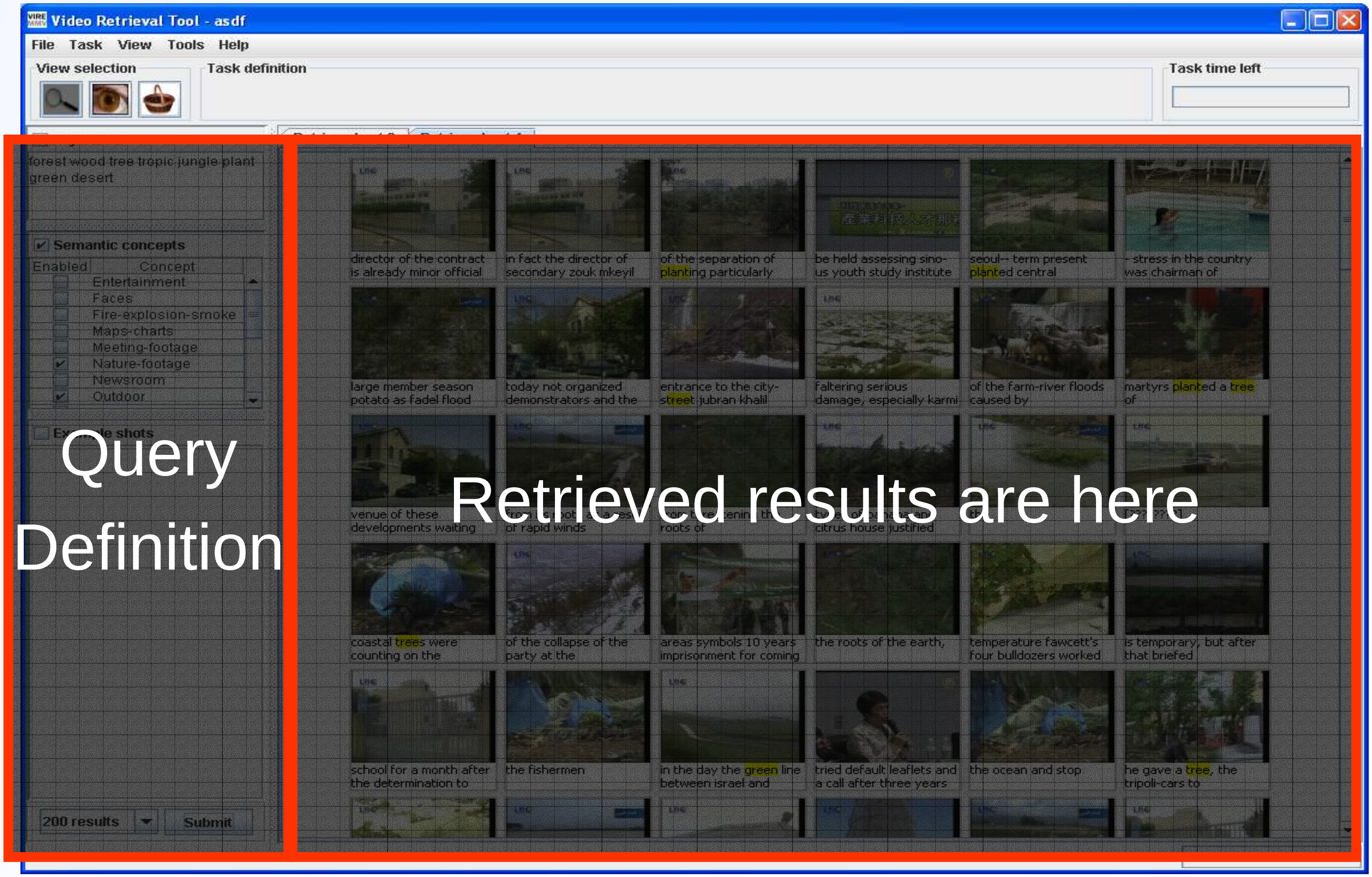
The Search System Interfaces



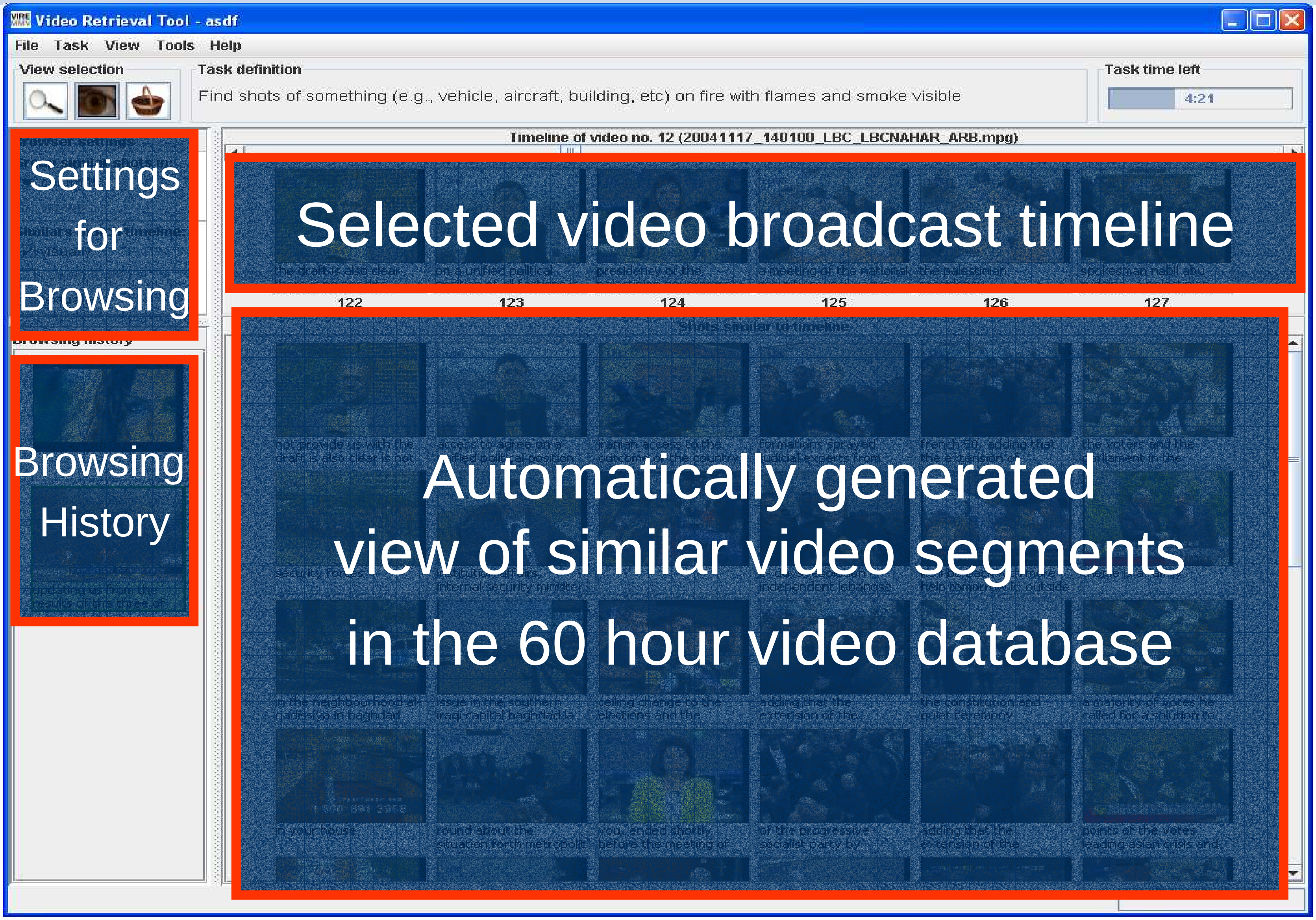




Query Tool


Video Retrieval Tool - asdf
File Task View Tools Help
View selection
Task definition
Task time left
forest wood tree tropic jungle plant green desert
Semantic concepts
Enabled Concept
Entertainment
Faces
Fire-explosion-smoke
Maps-charts
Meeting-footage
Nature-footage
Newsroom
Outdoor
200 results
Submit
Query Definition
Retrieved results are here

Cluster-temporal Browser



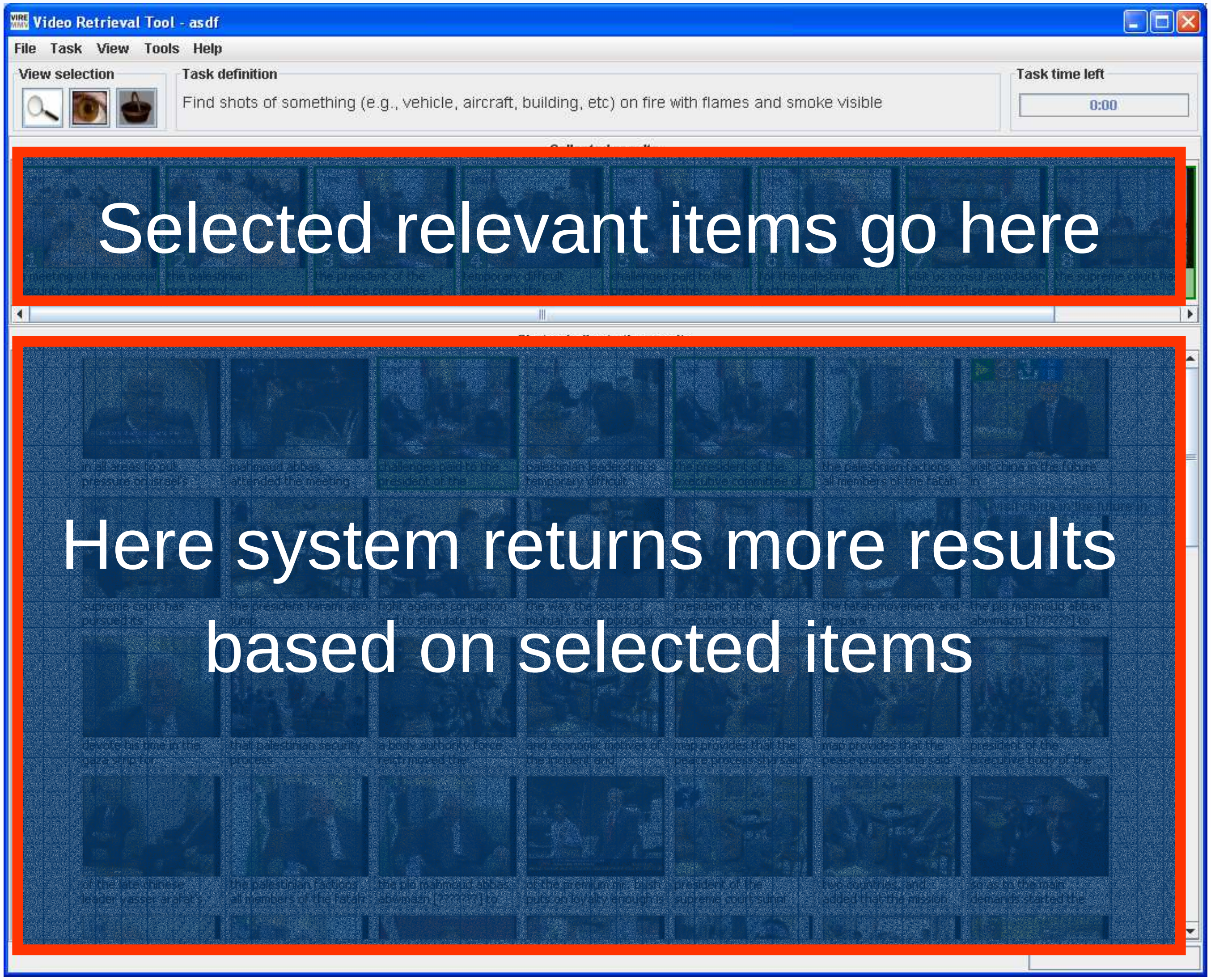
Quick Buttons for Streamlined Interaction

Play Shot

Browse News Video

Select as a result and move to Result Container

Result Container: Relevance Feedback based on selected results



Experiments & Results

- MediaTeam participated in manual and interactive search tasks with following 7 runs:

  - **OUMT_I1Q_1:** interactive with **browsing disabled**, **expert** users
  - **OUMT_I2B_2:** interactive with **browsing enabled**, **expert** users
  - **OUMT_I3Q_3:** interactive with **browsing disabled**, **novice** users
  - **OUMT_I4B_4:** interactive with **browsing enabled**, **novice** users

  - **OUMT_M5T_5:** manual text search with official text transcripts
  - **OUMT_M6TS_6:** manual text search + semantic concepts
  - **OUMT_M7TE_7:** manual text search + visual examples

Interactive Search Experiment Setup

Total of eight test users did

- **12 test topics** using **two** different **system configurations**
- enjoyed break and refreshment after six topics and spent about three hours in total for this experiment

- four users were experts
  - very knowledgeable with the system, but had not seen the given search topics or any content from the test database.
- four users were novices
  - mainly information engineering undergraduate or post-graduate students, having good skills in using computers but little experience in searching video databases.

Search configuration:

I1Q: Variant A: S1[149-154],S3[155-160],S2[161-166],S4[167-172]

I2B: Variant B: S2[149-154],S4[155-160],S1[161-166],S3[167-172]

I3Q: Variant A: S7[149-154],S5[155-160],S6[161-166],S8[167-172]

I4B: Variant B: S8[149-154],S6[155-160],S5[161-166],S7[167-172]

Results

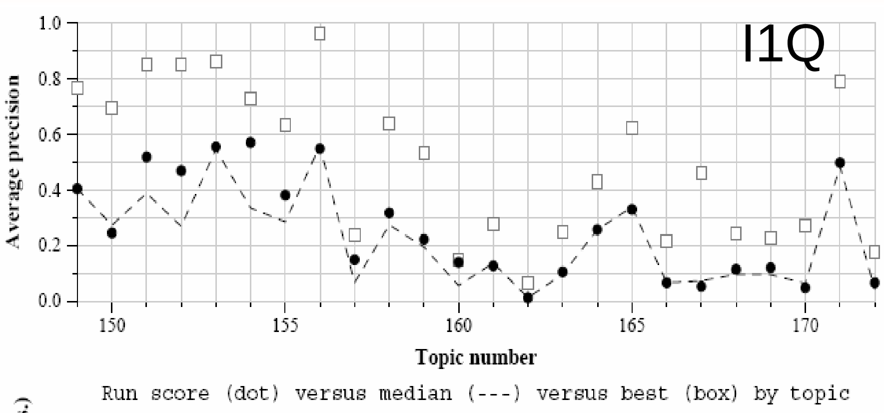
Search Run ID	MAP	Total Relevant Shots Returned
I1Q (interactive, expert users)	0.264	2284
I2B (interactive, expert users)	0.242	1916
I3Q (interactive, novice users)	0.202	1907
I4B (interactive, novice users)	0.226	1998
Mean (interactive)	0.218	1618
Max (interactive)	0.414	3044
M5T (baseline text search)	0.081	1836
M6TS (txt search+semantic)	0.097	2003
M7TE (txt search+examples)	0.102	1972
Mean (manual)	0.067	1510
Max (manual)	0.169	2278

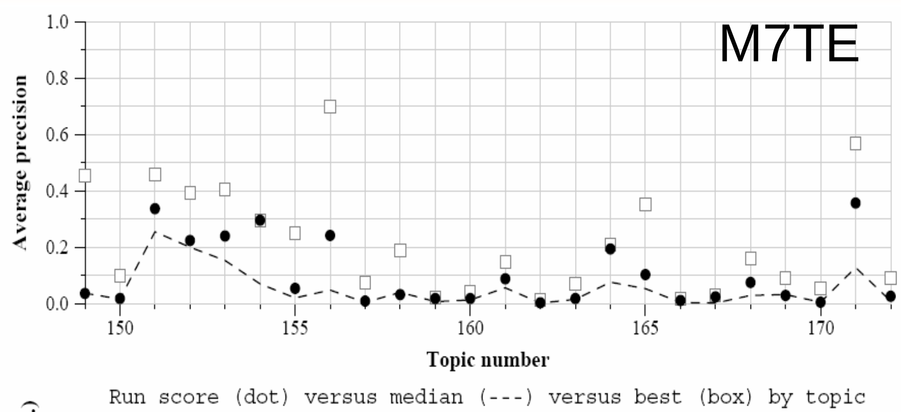
Conclusions

- Interactive runs
  - **12% better** MAP-performance for **novice** users **using cluster-temporal browser than without it**
  - The result is in line with previous reported experiments with novice test users [5].
  - However, expert users had marginally better MAP (0.264 vs 0.242) without the Cluster-temporal Browser, why?
  - Expert knowledge about system capabilities and limitations makes them perform well with every configuration. Also personal skills vary depending on the role in development
  - on average expert users had **18% better search performance over novice users**
  - It shows that the test design has a significant effect to the outcome of the interactive test.

Conclusions

- Manual runs:
  - **text + semantic concept** search gives about **19% better performance than text baseline**
  - **text + example** based search gives approximately **25% performance gain over the baseline.**
  - The results show that specific visual search examples accumulate better overall precision than the queries defined with our detected set of semantic concepts.





Conclusions

- Main conclusions from this study:
  - **Cluster-temporal browsing improves search performance** over traditional query + relevance feedback paradigm for **novice** users
  - content-based example and concept search components **improve search performance** over straightforward text-based search
    - search examples seem to contribute more than concepts in our system
  - The setting for interactive experiment is an important factor in the overall search performance
    - The expert users are able to ’push’ the system limits and obtain good performance in both configurations.

Thank you

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