

Columbia University Automatic Video Search in TRECVID 2006



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Objectives and Unique Features

- + Objective: Enable semantic search over a large video collection. Leverage visual content and text. + Test Concept-Based Search using a large set of pre-trained concept detectors. (374 visual concepts).
- + Supplement concept-based search with other methods through Query-Class-Dependent Models.
- + Analyze impact of fusion of multimodal search methods and query-class-dependency in fully automatic search.

Concept-Based Search

- + Text-based queries against visual content.
- + Concept detectors predict the concept in image.
- + Lexicon of definitions maps keyword to concept.

Search System Overview





Large-Scale Concept Lexicon

- + Leverage LSCOM annotations. (449 concepts).
- + 374 detectable concepts, compared to standard 39.
- + 10x increase in lexicon 30% increase in search

	39 Concepts	374 Concepts	Effect	Combine text and concept sea		
Search Performance ¹	TV2005 - MAP: .035 TV2006 - MAP: .019	TV2005 - MAP: .078 TV2006 - MAP: .025	30-100% increase in retrieval performance	General: for all other queries.		
Query Coverage	11-12 Query Matches 1.1-1.8 Concepts/Query	17 Query Matches 1.3-2.5 Concepts/Query	Smaller than 2x increases in coverage	+ Select classes to suit tools.		
Concept Frequency	Average: 5000 examples	Average: 1200 examples	75% decrease in freq. Min(39) > Median(374)	+ Weights optimize AP (over training queries).		
Detection Quality ²	MAP: 0.39 (over 2005 validation data)	MAP: 0.26 (over 2005 validation data)	33% decrease in concept detection accuracy	+ Classify by query keywords. (automatically at query time)		

Text Search: keywords against story-separated speech recognition text. **Re-ranking:** discover visually recurrent patterns using information bottleneck. Query Expansion: mine names from text contemporary to search set. **Image Search:** query-by image example, using distance and SVMs. **Concept Search:** match text keywords to pre-trained concept detectors.

Query-Class-Dependent Models

Named Person: if named entity detected in query. Rely on text search. **Sports:** if sports keyword detected in query. Rely on visual examples. **Concept:** if keyword maps to concept detector. Rely on concept search.

Named Person + Concept: if both named entity and concept detected. xt and concept search equally.

^r all other queries. Combine text and visual examples equally.

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- sses to suit tools.
- optimize AP ning queries).

Class/Query Coverage

General

Name + Concept

Named Person 3 Sports Concept

12

16

TRECVID 2006

TRECVID 2005

¹ Using Columbia Concept-Based Search Method (Described above). ² Using Columbia Baseline Concept Detection.

Evaluation

	Text	IB	Concept	Visual	Fused	Change
Building	0.04	0.03	0.30	0.10	0.33	+10%
Condi Rice	0.19	0.20	0.00	0.01	0.20	+0%
Soccer	0.34	0.42	0.58	0.42	0.83	+43%
Snow	0.19	0.29	0.33	0.03	0.80	+143%
All (2006)	0.08	0.09	0.10	0.07	0.19	+90%

- + Tested over 160+ hours of multilingual news video: TRECVID 2006.
- + Consistent gains in P@100 (Precision of top) 100) through class-dependent multimodal fusion.
- + Text and Concept-based searches perform well.
- + Most query topics have matching concepts.



+ 30% Change in MAP from concept-based search

LSCOM Lexicon and Annotations http://www.ee.columbia.edu/dvmm/lscom **Digital Video and Multimedia Lab** http://www.ee.columbia.edu/dvmm

CuVid Video Search Engine http://www.ee.columbia.edu/cuvidsearch