



informedia
digital video understanding

SEARCH

summarize

visualize

retrieve

Feature Extraction Techniques CMU at TRECVID 2004

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Outline

- Low level features
- Generic high level feature extractions
 - Uni-modal
 - Multi-modal
 - Multi-concept
- Specialized approach for person finding
- Failure analysis

Low level features overview

- Low level features
 - CMU distributed 16 feature sets available to all TRECVID participants
 - Development set: <http://lastchance.inf.cs.cmu.edu/trec04/devFeat/>
 - Test set: <http://lastchance.inf.cs.cmu.edu/trec04/testFeat/>
 - These features were used for all our submissions
 - We encourage people to compare against these features to eliminate confusion about better features vs better algorithms

Index of /trec04/devFeat

<u>Name</u>	<u>Last modified</u>	<u>Size</u>	<u>Description</u>
 Parent Directory		-	
 abc.zip	06-Aug-2004 14:01	1.6G	
 abc/	09-Jul-2004 12:52	-	
 cnn.zip	06-Aug-2004 17:03	1.5G	
 cnn/	09-Jul-2004 12:52	-	
 cspan.zip	06-Aug-2004 13:00	68M	
 cspan/	09-Jul-2004 12:52	-	
 features.doc	30-Aug-2004 15:20	31K	

Apache/2.0.50 (Win32) Server at lastchance.inf.cs.cmu.edu Port 80

Index of /trec04/testFeat

<u>Name</u>	<u>Last modified</u>	<u>Size</u>	<u>Description</u>
 Parent Directory		-	
 abc.zip	30-Aug-2004 15:13	622M	
 abc/	02-Aug-2004 19:33	-	
 cnn.zip	30-Aug-2004 12:58	651M	
 cnn/	02-Aug-2004 19:33	-	
 features.doc	30-Aug-2004 15:20	31K	
 trec04TESTVOCR.tar	30-Aug-2004 12:49	1.5M	

Apache/2.0.50 (Win32) Server at lastchance.inf.cs.cmu.edu Port 80

Low level features

- Image features
 - Color histogram
 - Texture
 - Edge
- Audio features
 - FFT
 - MFCC
- Motion features
 - Kinetic energy
 - Optical flow
- Detector features
 - Face detection
 - VOQR detection

Image features

- 5 by 5 grids for key-frame per shot
- Color histogram (*.hsv, *.hvc, *.rgb)
 - 5 by 5, 125 bins color histogram
 - HSV, HVC, and RGB color space
 - 3125 dimensions ($5*5*125$)
 - row-wise grids
 - 19980202_CNN.hsv

```
- 0.000000,0.036541,0.009744,0.010962,0.001218,0.000000,0.000000,0.000000,0.000000,0.000000,0.000000,0.000000,0.000000
,0.000000,.....
0.000000,0.091776,0.055418,0.025415,0.008825,0.000000,0.007413,0.000353,0.000000,0.000000,0.000000,0.000000,0.000000
,0.000000,.....
```

- Texture (*.texture_5x5_bhs)
 - Six orientated Gabor filters
- Edge (*.cannyedge)
 - Canny edge detector, 8 orientations



Audio features & Motion features

- Every 20 msec (512 windows at 44100 HZ sampling rate)
 - FFT (*.FFT) – Short Time Fourier Transform
 - MFCC (*.MFCC) – Mel-Frequency cepstral coefficients
 - SFFT (*.SFFT) – simplified FFT
- Kinetic energy (*.kemotion)
 - Capture the pixel difference between frames
- Mpeg motion (*.mpgmotion)
 - Mpeg motion vector extracted from p-frame
- Optical flow (*.opmotion)
 - Capture optical flow in each grid

Detector features

- Face detector (*.faceinfo)
 - Detecting faces in the images



- VOCR detector (*.vocinfo and *.mpg.txt)
 - Detecting and recognizing VOCR



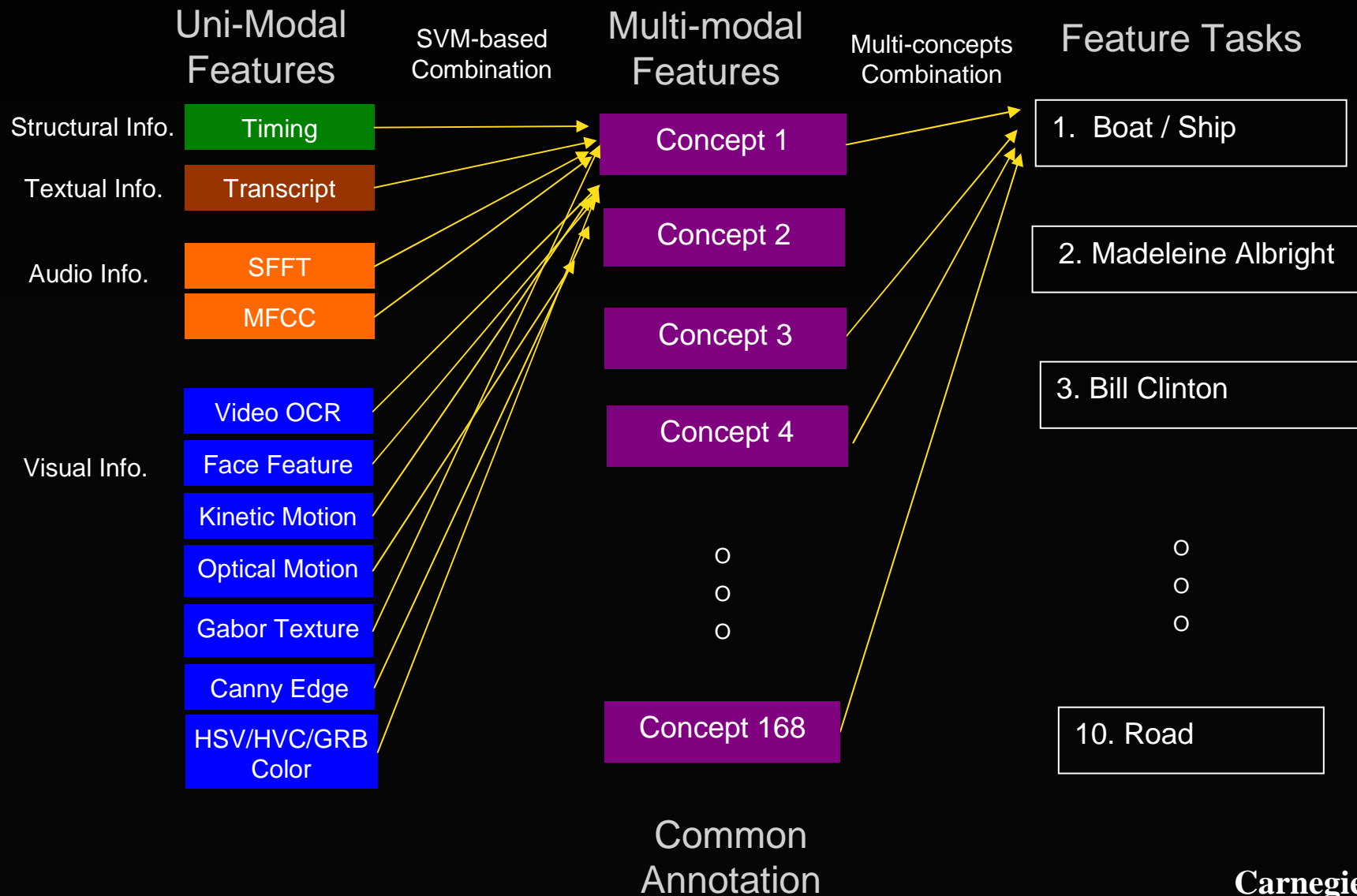
Closed caption alignment and Shot mapping

- Closed caption alignment (*.wordtime)
 - Each word in the closed caption file is assigned an approximate time in millisecond
- Shot Break (*.shots)
 - Provides the mapping table of the shot
- We encourage people to utilize these features
 - Eliminate confusion of better features or better algorithms
 - Encourage more participants who can emphasize their efforts on algorithms

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Generic high level feature extraction



Multi-concepts

- Learning Bayesian Networks from 168 common annotation concepts
- Pick top 4 most related concepts to combine with the target concept

Boat/Ship	Boat, Water_Body, Sky, Cloud
Train	Car_Crash, Man_Made_scene, Smoke, Road
Beach	Sky, Water_Body, Nature_Non-Vegetation, Cloud
Basket Scored	Crowd, People, Running, Non-Studio_Setting
Airplane Takeoff	Airplane, Sky, Smoke, Space_Vehicle_Launch
People Walking/running	Walking, Running, People, Person
Physical violence	Gun_Shot, Building, Gun, Explosion
Road	Car, Road_Traffic, Truck, Vehicle_Noise

Top result for TRECVID tasks

- Uni-modal gets 2 best over CMU results
- Multi-modal gets 3 best, but includes Boat/Ship which is the best overall all
- Multi-concept gets 6 best

	Boat*	Train	Beach	Basket	Airplane	Walking	Violence	Road
Uni-modal	0.097	0.001	0.013	0.503	0.021	0.015	0.005	0.036
Multi-modal	0.137	0.001	0.023	0.517	0.014	0.008	0.002	0.045
Multi-concept	0.110	0.001	0.039	0.517	0.035	0.099	0.003	0.062

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A Text Retrieval Approach

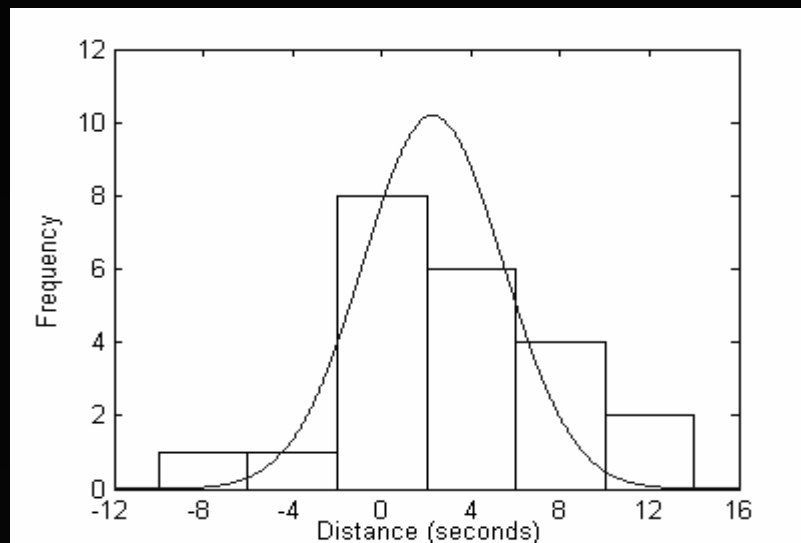
- Search for shots with names appearing in transcript
 - Vector-based IR model with TF*IDF weighting



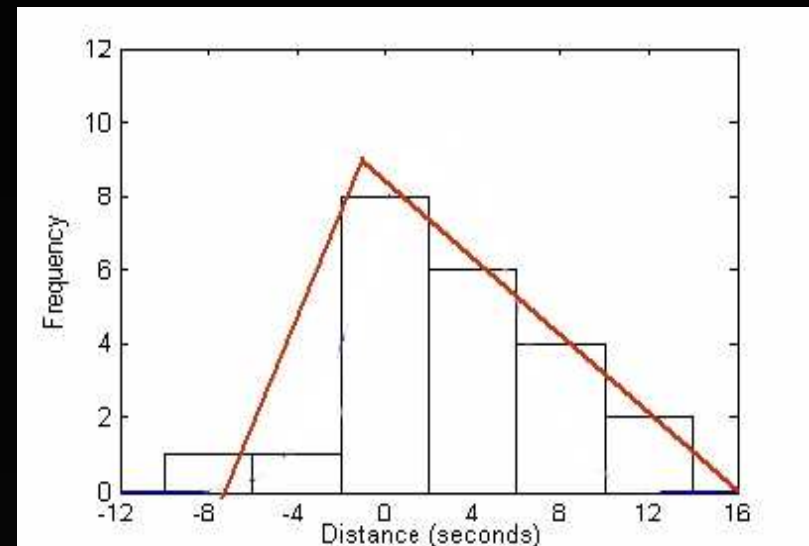
- Temporal Mismatch Drawback
 - Faces do not always temporally co-occur with names
 - Cause false alarms and misses

Expand the Text Retrieval Results

- Propagate the text score to neighbor shots based on the distribution
- $\text{Timing score} = F(\text{Distance}(\text{shot}, \text{name}))$



← before the name ↑ name position → after the name



- Model 1: Gaussian model (trained using Maximum Likelihood)
- Model 2: Linear model (different gradients set on two sides)

Context Information

- Sometimes, a news story has the name but not the face
 - E.g., “.... a big pressure on Clinton administration ...”
 - Cause many false alarms
 - Related to the context “Clinton administration”
- Given the context, how likely a story has the face?
 - Collect bigrams of type “___ Clinton” or “Clinton ___”
 - Compute P_i (*Clinton appears in the story | bigram_i*)

Bigram	P (face bigram)
Clinton says	0.627474
Clinton made	0.625652
.....
Clinton administration	0.242973

Multimodal Features

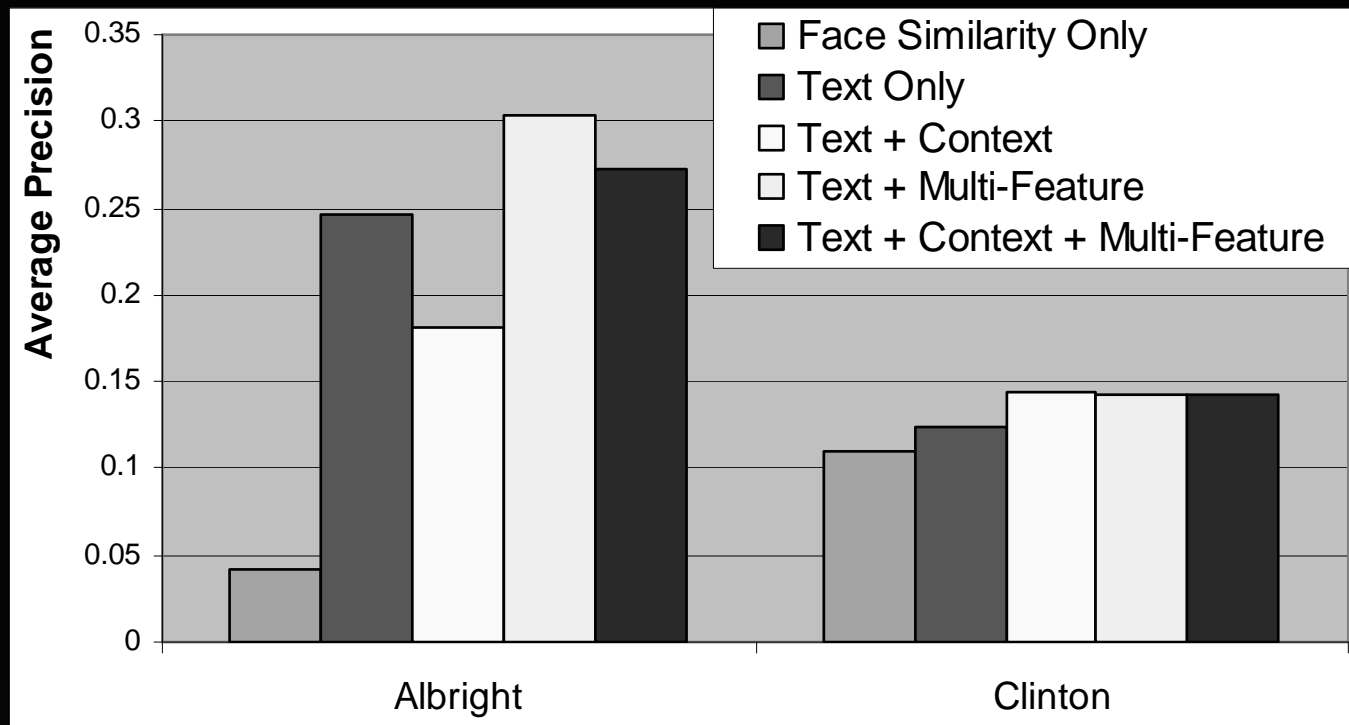
- Multimodal features provide weak clues for person search
 - Face detection – shots w/o detected faces are less likely to be the results
 - Facial recognition – matching detected faces with facial model based on Eigenface representation
 - Anchor classifier – anchor shots rarely have intended faces
 - Video OCR – Fuzzy match by edit distance between video OCR and the target name

Combining Multimodal Info. with Text Search

- Updated Text Score: $R' = R * \text{Timing Score} * \text{Avg}(P_{\text{bigram}_i})$
- Linear combination of all the features with text score
 - Features normalized into (pseudo-) probabilities [0,1]
 - Feature selection based on chi-square statistics
 - Combinational weights trained by logistic regression

Features	weight
Updated text score	6.14
Face similarity	3.94
Face detection	0.50
Anchor detection	-5.65

Performance Comparison



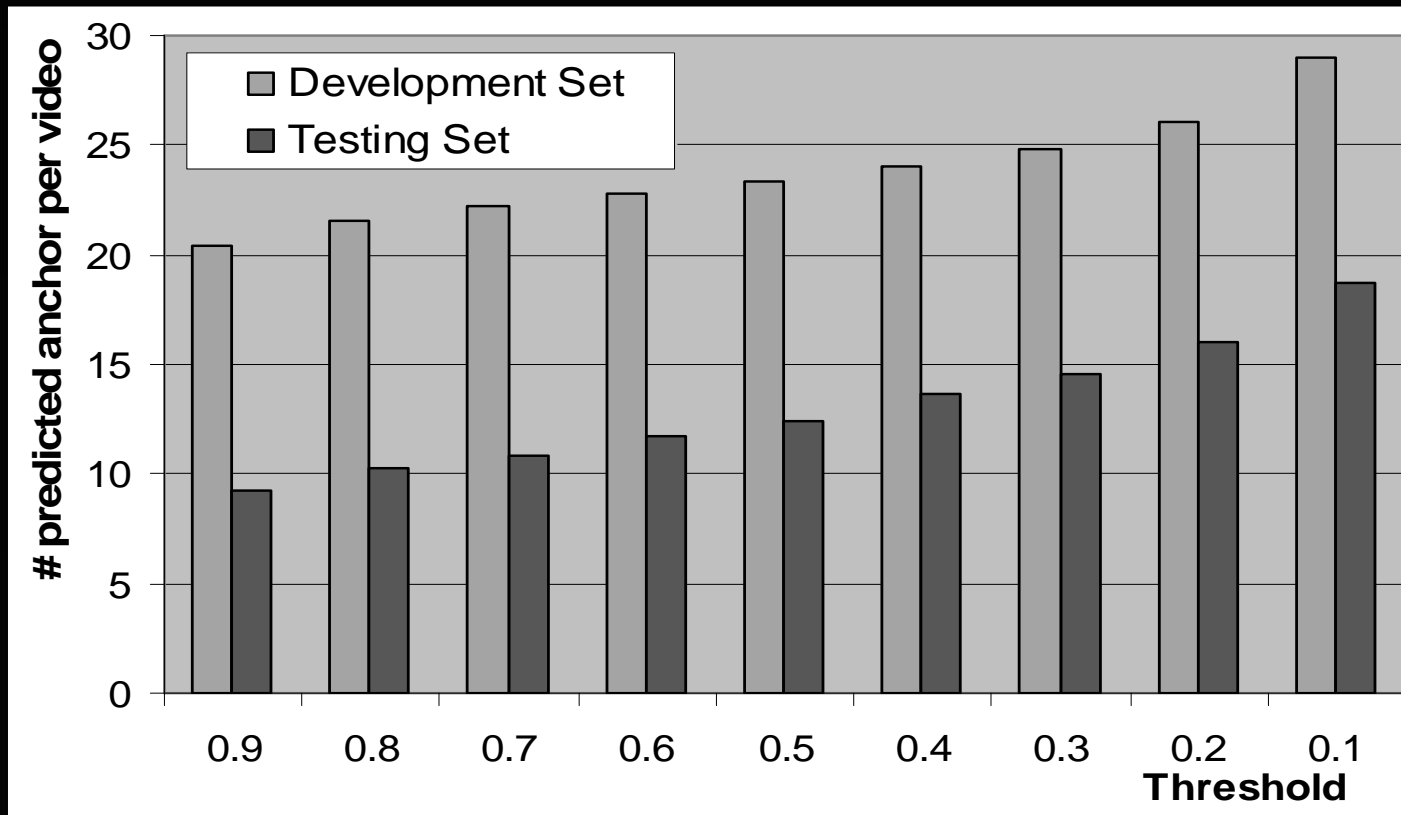
- One of our “Albright” runs is the best among all submissions
- Combining multimodal features helps both tasks
- Context helps “Clinton” but hurts “Albright”
 - Probably due to sparse training data for “Albright”

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Performance Drop on Anchor Classifier

- 95% cross-validation accuracy on development set



- 10 videos in testing set has 0 or 1 detected anchor
 - Average # of anchor shots per video is 20-30

Different Data Distribution

- Different images: change on background, anchor, clothes

Common types
(development set)



Outliers
(testing set)



- Similar images, but probably different MPEG encoding
 - “Peter Jennings” has similar clothes and background in both sets
 - In videos with “Peter Jennings” as the anchor
 - 19 detected per video in development set
 - 13 detected per video in testing set

Other Semantic Features

- Similar performance drop observed on Commercial, Sport News, etc
 - Compromises both high-level feature extraction and search
- Possible solutions
 - Get consistent data next year
 - Rely less on sensitive image features (color, etc)
 - Rely more on robust features -- “Video grammar”
 - Timing, e.g., sports news are in the same temporal session
 - Story structure, e.g., the first shot of a story is usually an anchor shot
 - Speech, e.g., anchor’s speaker ID is easy to identify
 - Constraints, e.g, weather forecast appear only once
 - Re-encoding MPEG video

Q & A

Thank you!