

Joint Audio-Visual Signatures for Web Video Analysis

Dan Ellis, Shih-Fu Chang Yu-Gang Jiang, Xiaohong Zeng, Guangnan Ye, Courtenay Cotton

Department of EE, Columbia University, NY

What are Consumer (Web) Videos?

- Original unedited videos made from consumers
 - Interesting and very diverse contents
 - Very weakly indexed: 3 tags per consumer video vs. 9 tags avg
 - Original audio tracks good for audio-visual joint analysis









• • •

- Challenge: Content-based retrieval
 - Find items similar to example(s)





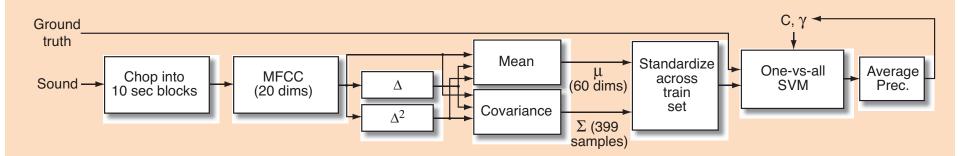


Highlights 2010-2011

- Novel audio features for events (transients) and environments (textures)
- Release of Columbia Consumer Video dataset annotated via Amazon Mechanical Turk
- Best result in TRECVID 2010
 Multimedia Event Detection evaluation

Event + Environment Soundtrack Features

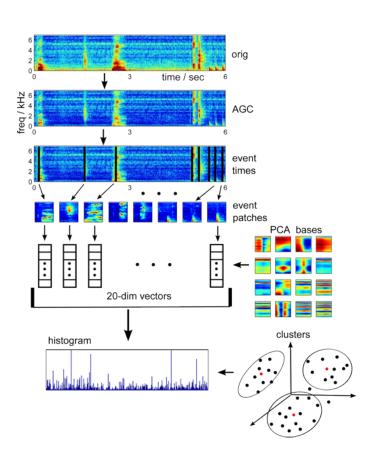
Conventional Bag-of-MFCC features:

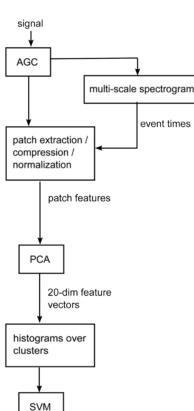


everything mixed in together

 Can we differentiate foreground and background?

Foreground: Transient Features

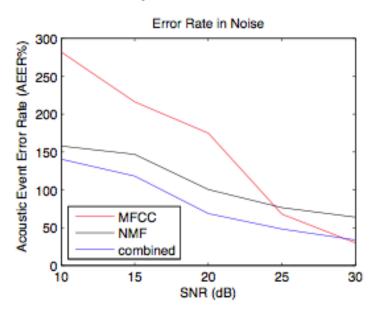


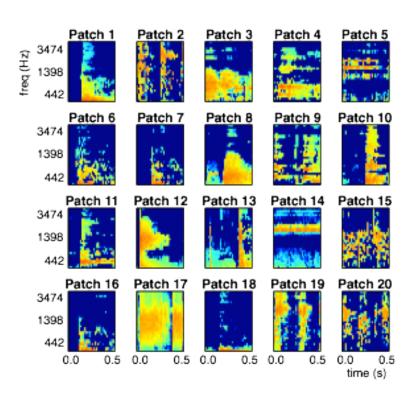


- Transients = foreground events?
- Onset detector finds energy bursts
 - best SNR
- Represent with PCA basis
 - 300 ms x aud freq
- "bag of transients"

NMF Transient Features

- Learn 20 patches by Nonnegative Matrix
 Factorization
- Compare to MFCC-HMM

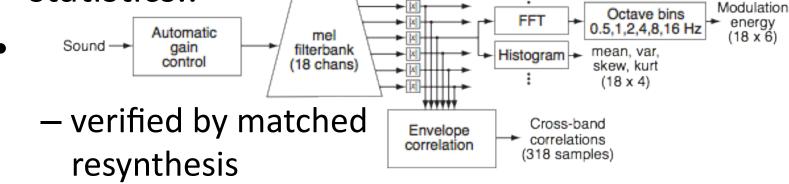




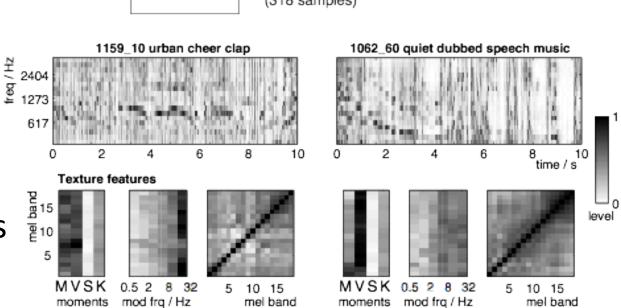
- NMF more noiserobust
 - combines well

Background: Texture features

• Characterize sounds by perceptually-sufficient statistics..

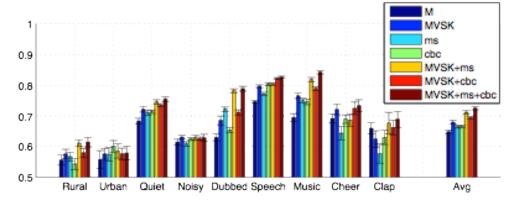


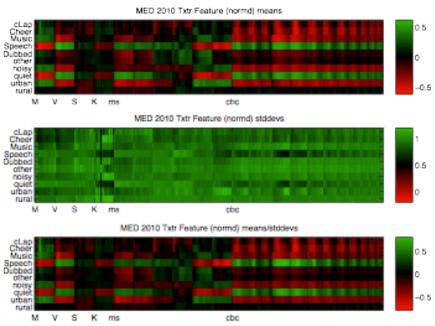
- Subband distributions& env x-corrs
 - Mahalanobis distance ...



Texture Feature Results

- Test on MED 2010 development data
 - 10 labels



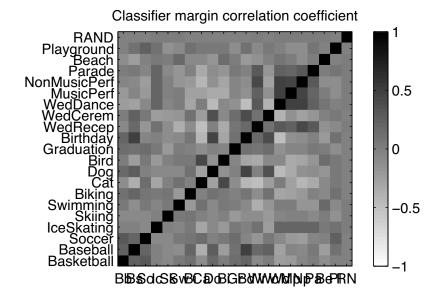


- Contrasts in feature sets
 - correlation of labels
 - Perform ~ same as MFCCs
 - combine well

Audio Classifier Evaluation

- Investigating beyond mAP...
 - Accuracy, Mutual Information Proportion, Correlation

$$MIP = \frac{I(\text{classifier}; \text{label})}{H(\text{label})}$$

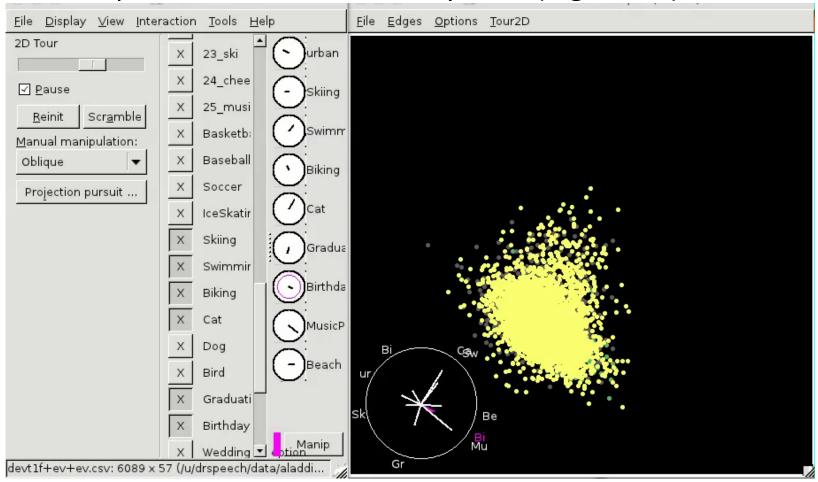


Average Precision (mean=0.397) 0.5 rugno D S M C L RN Balance set acc (mean=0.515) Classifiers (CCV) ruano D S M C L RN Mutual Info Prop (mean=0.090) 0.2 0.15 0.1 0.05 r u q n o D S M C L R N Labels (MED)

Cross-corpus evaluations

Audio Classifier Results Browsing

- Customized version of GGobi links to Movie Player
 - Rapid investigation of high-dimensional data sets
 - Each point is a video, colored by label (e.g. Event)

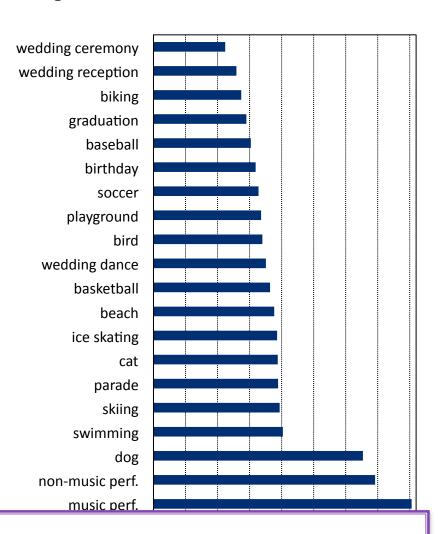


Columbia Consumer Video (CCV) Database



CCV Snapshot

- # videos: 9,317
 - (210 hrs in total)
- video genre
 - unedited consumer videos
- video source
 - YouTube.com
- average length
 - 80 seconds
- # defined categories
 - -20
- annotation method
 - Amazon Mechanical Turk



The trick of digging out consumer videos from YouTube:

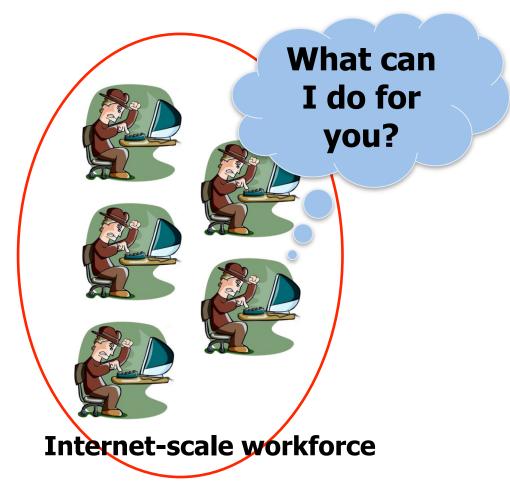
Use default filename prefix of many digital cameras: "MVI and parade".

Existing Database?

	CCV Database	
 Human Action Recognition 		
KTH & Weizmann(constrained environment) 2004-05	Unconstrained YouTube videos	
 Hollywood Database (12 categories, movies) 2008 UCF Database (50 categories, YouTube Videos) 2010 	Higher-level complex events	
 Kodak Consumer Video (25 classes, 1300+ videos) 2007 	More videos & better defined categories	
 LabelMe Video (many classes, 1300+ videos) 2009 	More videos & larger content variations	
• TRECVID MED 2010 • (3 classes, 3400+ videos) 2010	More videos & categories	

Crowdsourcing: Amazon Mechanical Turk

 A web services API that allows developers to easily integrate human intelligence directly into their processing





\$?.??

MTurk: Annotation Interface

Mark all the categories that appear in any part of the video.

Instructions:

- Watch the entire video as more categories may appear over time.
- Mark all the categories that appear in any part of the video.
- Make sure audio is on.
- . If no matching category is found, mark the box in front of "None of the categories matches".
- For categories that appears to be relevant but you're not completely sure, please still mark it.

Submit

Please mouse-over or click on the category names to read detailed definitions.



Sports Animal Celebration Others ■ Basketball ■ Cat Graduation Music Performance ■ Non-music Performance ■ Baseball Birthday ■ Dog ■ Wedding Reception ■ Parade ■ Soccer Bird ■ Wedding Ceremony
■ Beach Ice Skating Skiina ■ Wedding Dance Playground Swimming None of the categories matches. Biking I don't see any video playing. Current Time: 10 sec.

Replay Continue Playing

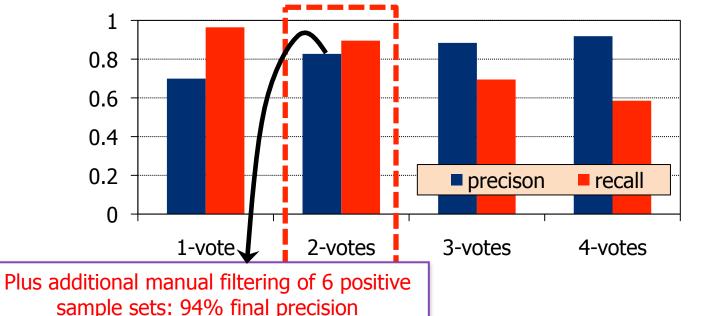
Original URL: http://www.youtube.com/watch?v=-0n50a7seNI

Reliability of Labels: each video was assigned to four MTurk workers



Human Recognition Performance

- How to measure human (MTurk workers) recognition accuracy?
 - We manually and carefully labeled 896 videos
 - Golden ground truth!
- Consolidation of the 4 sets of labels



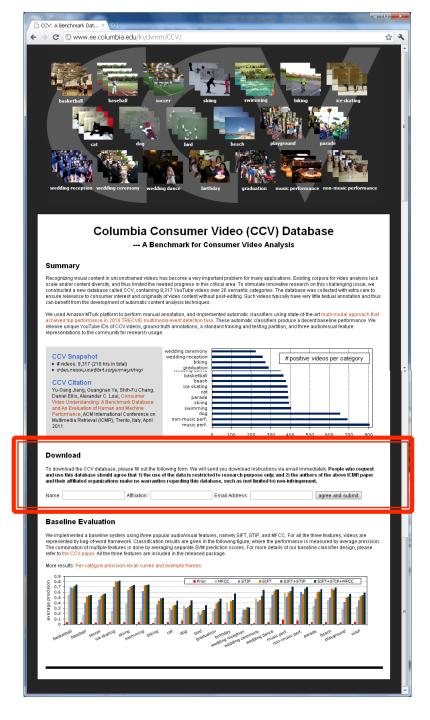
Download

- Unique YouTube Video IDs,
- Labels,
- Training/Test Partition,
- Three Audio/Visual Features

http://www.ee.columbia.edu/dvmm/CCV/

Fill out this ...





TRECVID MED 2010

- Find "multimedia events" among 1700 videos
- 3 target event categories:

Making a cake

Assembling a shelter

Batting a run in





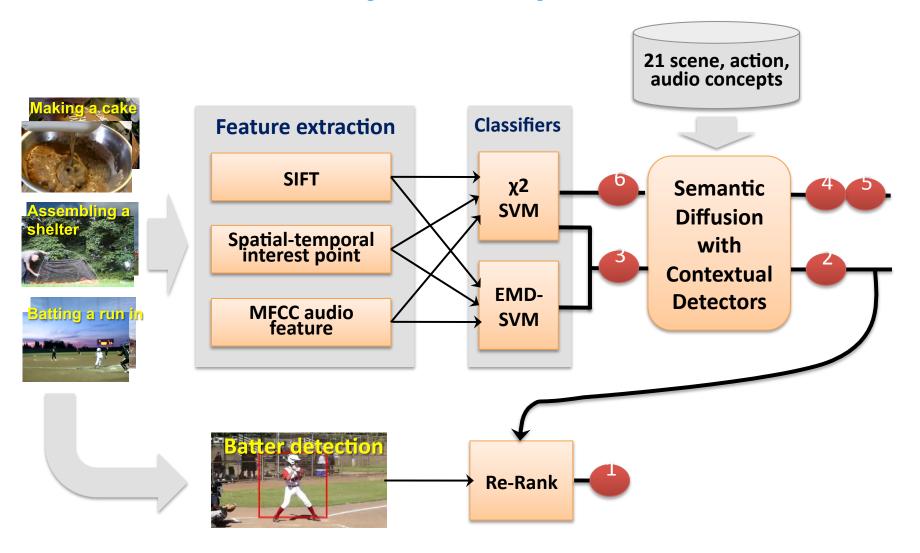




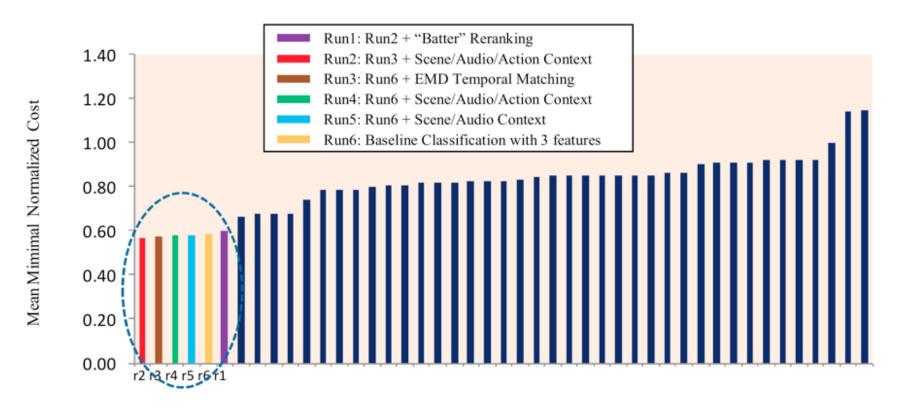




Overview: 4 major components & 6 runs

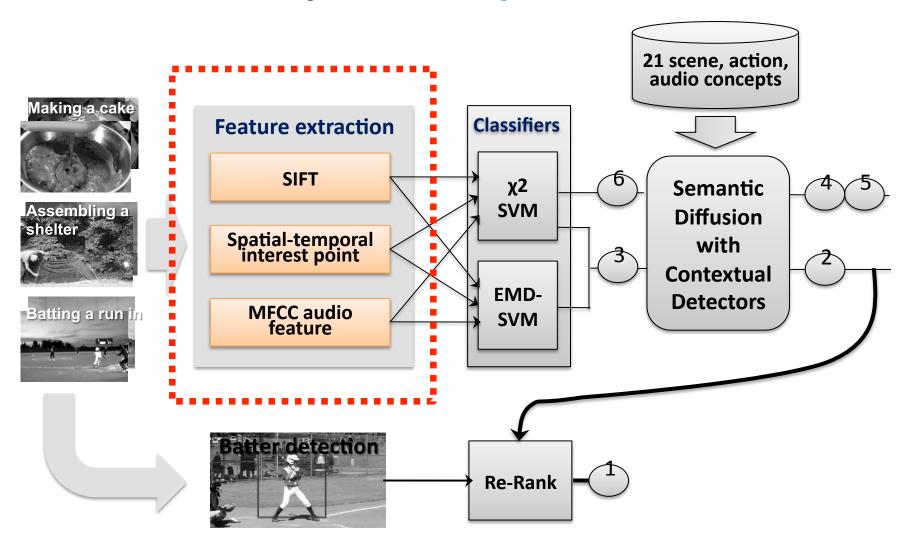


Overview: overall performance



- 45 systems by 8 teams from around the world
- Novel "normalized cost" metric
- Six Columbia systems scored best

Roadmap > multiple modalities

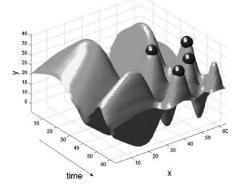


Three Feature Modalities...

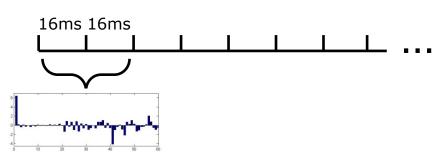
- SIFT (visual)
 - − D. Lowe, IJCV 04.



- STIP (visual)
 - *I. Laptev, IJCV 05.*

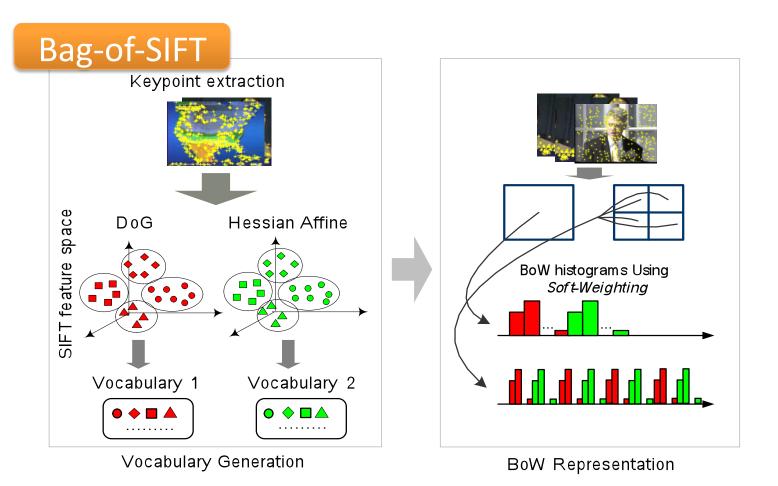


MFCC (audio)



Bag-of-X Representation

- X = SIFT or STIP or MFCC
- Soft weighting (Jiang, Ngo and Yang, ACM CIVR 2007)



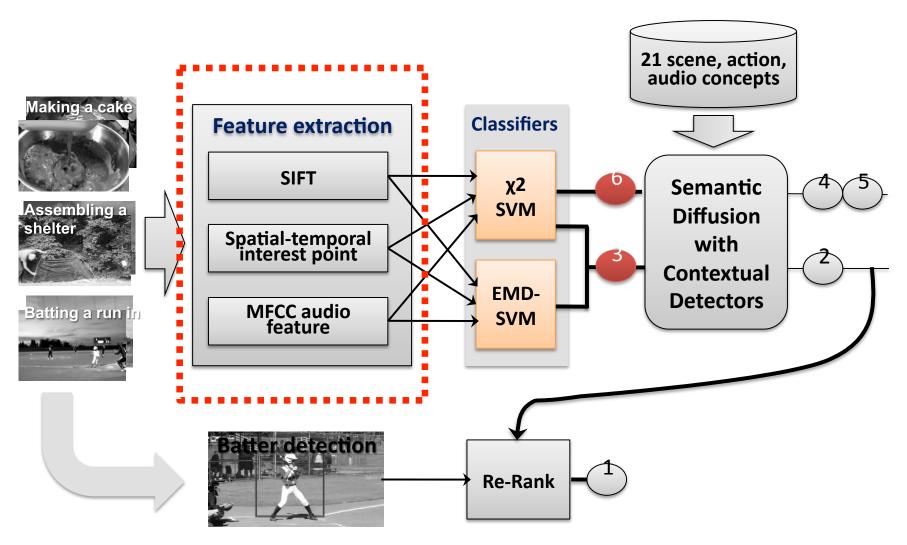
Results on Dry-run Validation Set

Measured by Average Precision (AP)

	Assembling a shelter	Batting a run in	Making a cake	Mean AP
Visual STIP	0.468	0.719	0.476	0.554
Visual SIFT	0.353	0.787	0.396	0.512
Audio MFCC	0.249	0.692	0.270	0.404
STIP+SIFT	0.508	0.796	0.476	0.593
STIP+SIFT+MFCC	<u>0.533</u>	<u>0.873</u>	0.493	<u>0.633</u>

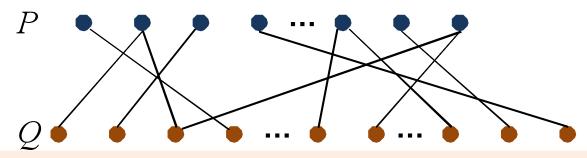
- STIP works best for event detection
- The 3 features are highly complementary!
 - Should be jointly used for multimedia event detection

Roadmap > temporal matching



Temporal Matching With EMD Kernel

Earth Mover's Distance (EMD)



Given two frame sets $P = \{(p_1, w_{p1}), \dots, (p_m, w_{pm})\}$ and $Q = \{(q_1, w_{q1}), \dots, (q_n, w_{qn})\}$, the EMD is computed as $\text{EMD}(P, Q) = \sum_i \sum_j f_{ij} d_{ij} / \sum_i \sum_j f_{ij}$

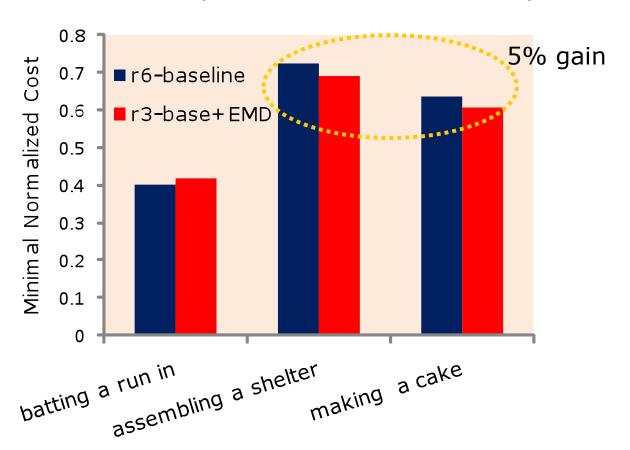
 d_{ij} is the χ^2 visual feature distance of frames p_i and q_j . f_{ij} (weight transferred from p_i and q_j) is optimized by minimizing the overall transportation workload $\Sigma_i \Sigma_i f_{ij} d_{ij}$

• EMD Kernel: $K(P,Q) = \exp^{-\rho EMD(P,Q)}$

Y. Rubner, C. Tomasi, L. J. Guibas, "A metric for distributions with applications to image databases", ICCV, 1998. D. Xu, S.-F. Chang, "Video event recognition using kernel methods with multi-level temporal alignment", PAMI, 2008.

Temporal Matching Results

- EMD is helpful for two events
 - results measured by minimal normalized cost (lower is better)



Conclusions

- Novel audio features focus on foreground and background
 - Successful combinations
- Large-scale annotation for public data set
 - Columbia Consumer Video
- Multimedia Event Detection is feasible
 - Columbia system came top in TREC evaluation