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Multimedia Event Detection: Strong by Integration

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²TNO and Radboud University

November 24, 2015









Overview

- Observations
- Modalities
- System
- Fusion: Joint Probability
- Fusion: Adding Zero-Shot
- Reranking: OCR/ASR
- Experiments: MED14_Test/MED15_Eval
- Conclusion

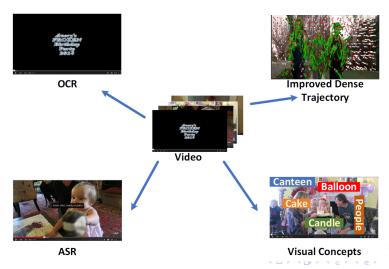








As is well known, multimedia event consists of multi-modalities: Audio, Motion, Visual, Texts ...



Multi-modalities: Audio, Motion, Visual, Texts ...







Multi-modalities: Audio, Motion, Visual, Texts ...

More efforts: single-modality.







Multi-modalities: Audio, Motion, Visual, Texts ...

More efforts: single-modality. e.g:

- Motion features: Dense Trajectories, Improved Dense Trajectories.
- Visual features: HOG, SIFT, Deep Features ...







Multi-modalities: Audio, Motion, Visual, Texts ...

More efforts: single-modality. e.g:

- Motion features: Dense Trajectories, Improved Dense Trajectories.
- Visual features: HOG, SIFT, Deep Features ...

Less efforts: integrate across modalities.







Problem:

Intergrating across modalities







Problem:

Intergrating across modalities

Difficulties:

- Modalities have different meanings.
- Modalities have different precisions.



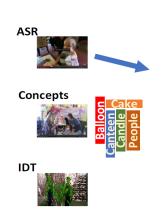








- 1. Semantics
- 2. High Precision (wanted)
- 3. Relevant/Irrelevant
- 4. Low Recall (rare)

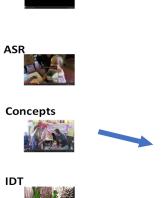




OCR



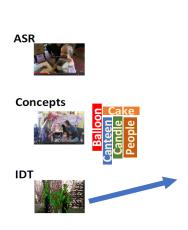
- 2. Low Precision
- 4. Relevant/Irrelevant
- 5.High Recall (many)

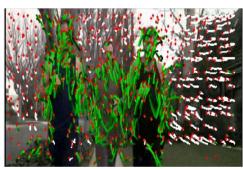






- 1. Non-Semantics
- 2. Low precision
- 3. Relevant/Irrelevant
- 4. High Recall (many)







ASR



Concepts





IDT



- 1. Semantics
- 2. High Precision
- 3. Relevant
- 4. Low Recall
- 1. Semantics
- 2. High Precision
- 3. Relevant/Irrelevant
- 4. Low Recall
- 1. Semantics
- 2. Low Precision
- 3. Relevant/Irrelevant
- 4. High Recall
- 1. Non-Semantics
- 2. Low Precision
- 3. Relevant/irrelevant
- 4. High Recall

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For Event Detection with 100Ex/10Ex:

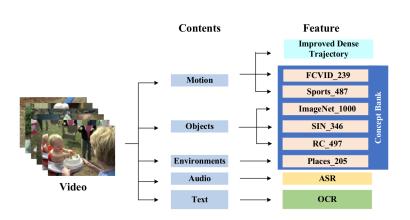
An intergration system with multi-modalities. We present 100Ex/10Ex as:

- Multi-modalities
- Different methods for different modalities
- Integration of modalities















Concept Modalities

Concept Bank

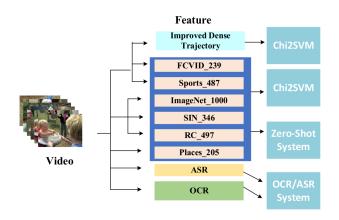
Feature	Dim	Structure	Dataset
Sports_487	487	3D-CNN	Sports-1M
ImageNet_1000	1000	DCNN	ImageNet
SIN_346	346	DCNN	TRECVID SIN
RC_487	487	DCNN	TRECVID Research Set
Places_205	205	DCNN	MIT Places
FCVID_239	239	SVM	Fudan-Columbia Dataset

Table : Concept Bank









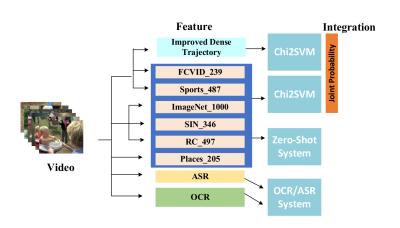
We propose three stages of fusion strategy, which can improve event detection step-by-step.









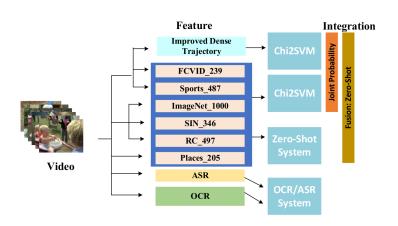










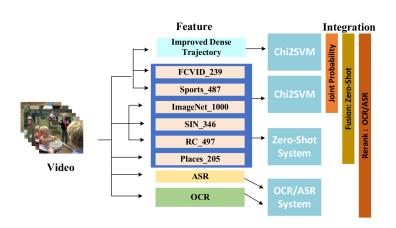










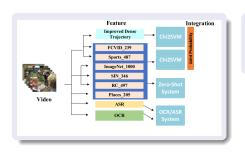












Classification:

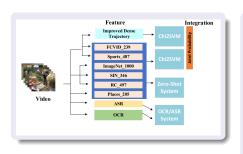
Two classifiers make predicts independently.











Average:

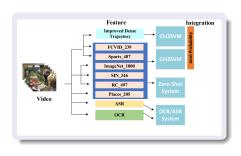
A low score of one type of classifier downgrades a possibly relevant video.











Average:

A low score of one type of classifier downgrades a possibly relevant video.

Joint Probability:

Only videos that receive a low score from both classifiers will be put at the bottom of the ranking list.

$$JP = 1 - (1 - P_{CB}) \times (1 - P_{IDT})$$

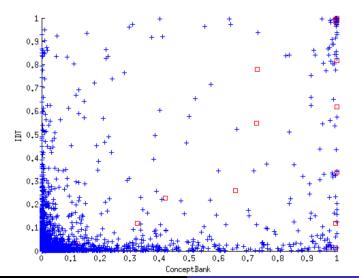






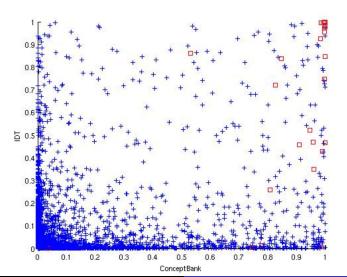


E021-SVM Prediction Scores with Concept feature and Improved Dense Trajectory



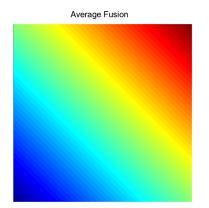


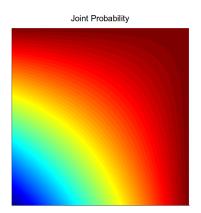
E039-SVM Prediction Scores with Concept feature and Improved Dense Trajectory





Contour Map











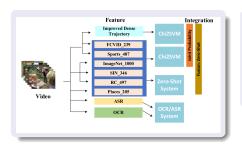
- Joint Probability is our first try to fuse two kinds of prediction scores by distributions of predicted scores.
- Based on the distributions of predicted scores, there might be more powerful unsupervised distribution-based fusion strategy.







Fusion: Adding Zero-Shot



Adding Zero-Shot:

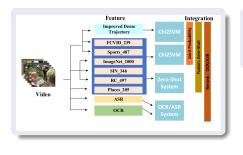
We averaged scores predicted by the Zero-Shot system (the other PPT) with scores predicted by the event detectors (SVM).











"Re-ranking":

Design high precision ASR and OCR systems for reranking.





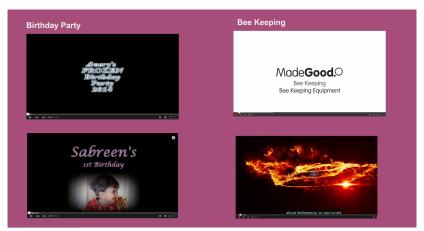




Recall OCR



OCR Observations:



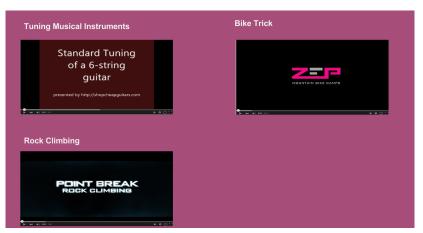








OCR Observations:









OCR Observations and Strategy:

• Parts of relevant videos were post-producted (include titles).







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- Pick out these video by matching OCR and Query.







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OCR Observations and Strategy:

- Parts of relevant videos were post-producted (include titles).
- Pick out these video by matching OCR and Query.
- Rerank these videos with extra-bonus score, boosting their ranks.

Same strategy is used for ASR,







Drawbacks of ASR:

OCR



- 1. Semantics
- 2. High Precision (wanted)
- 3. Relevant/Irrelevant
- 4. Low Recall (rare)

























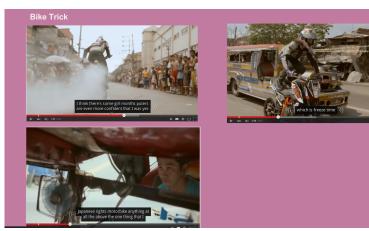




















ASR Observations:

• The portion of relevant ASR results is small.







- The portion of relevant ASR results is small.
- The portion of irrelevant ASR resuts is large.







- The portion of relevant ASR results is small.
- The portion of irrelevant ASR resuts is large.
- Mining event relevance with ASR is still an open topic.







The indexing and search tool Lucene is used for the OCR and ASR data. High precision is retrieved by:

- OCR: manually defining a Boolean Query using the event description and Wikipedia and some information on known common mistakes from the Tesseract tool (e.g. zero (0) and O).
- ASR: manually defining a Boolean Query and adding a PhraseQuery so the words in the query do not occur more than five words from each other. Only the words specific for the event are added.







Based on internal test, we have the following settings for MED 2015 Submission:

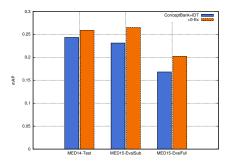
- 10 Exemplars: Adding Zero-Shot, Reranking by OCR/ASR
- 100 Exemplars: Joint Probability, Reranking by OCR/ASR







MED PS_10-Ex: Mean AP of fusion strategies on MED14-Test/EvalSub/Full



For 10 exemplars, adding the results of Zero-Shot case does really improve performance (more than 3%)

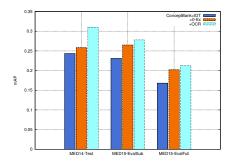








MED PS_10-Ex: Mean AP of fusion strategies on MED14-Test/EvalSub/Full



OCR gives an improvement of 1.2%.

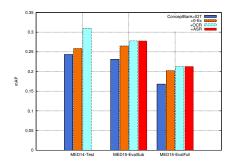








MED PS_10-Ex: Mean AP of fusion strategies on MED14-Test/EvalSub/Full



ASR slightly decreases performance in the Evaluation Set. This is probably because the precision of our ASR system is not as high as our OCR system.

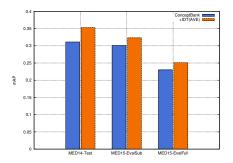








MED PS_100-Ex: Mean AP of fusion strategies on MED14-Test/EvalSub/Full



IDT increases overall performance (2%-4%)

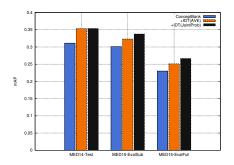








MED PS_100-Ex: Mean AP of fusion strategies on MED14-Test/EvalSub/Full



Joint Probability is better than average fusion, providing for an additional improvement of 1%.

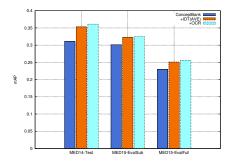








MED PS_100-Ex: Mean AP of fusion strategies on MED14-Test/EvalSub/Full



Adding OCR gives a small improvement.

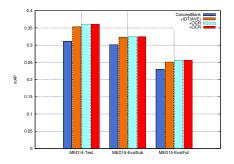








MED PS_100-Ex: Mean AP of fusion strategies on MED14-Test/EvalSub/Full



ASR slightly decreases performance as with the 10Ex Experiments.









Conclusion

- For the 10 Ex case, fusion of the system trained on 10 examples and the zero-shot case improves a lot.
- Fusion with OCR slightly improves performance in all runs.
 Because the precision of ASR system is not as high as OCR system, performance drops a bit by adding ASR.
- Improved Dense Trajectory improves performance, especially with more training data (100 Ex VS 10 Ex).
- Using Joint Probability of concept features and IDT improves performance on 100 Ex task.





