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Shot Descriptors for Video
Temporal Decomposition

CERTH-ITI

Video Segments

● Shot

- Video segment taken without interruption by a single camera

● Scene

- Logical Story Unit (LSU): a series of temporally contiguous shots characterized by overlapping links that connect shots with similar content
- A division of an act presenting continuous action in one place

● Story

- Only in news broadcasts

Video Temporal Decomposition (1)

- Partition of video sequence V into convex sub-sets

$$\bigcup V_i = V$$

$$V_i \cap V_j = \emptyset, \forall i \neq j$$

$\forall V_i$ if $x_1, x_2 \in V_i$ then all $x, x_1 \leq x \leq x_2$ belong also to V_i

Segment 1	Segment 2	Segment 3
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Segment 1	Segment 2	Segment 1
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Video Temporal Decomposition (2)

- Shot segmentation
 - State-of-the-art F-score level of 95% [1]
 - Eliminated from TRECVID in 2008
- Scene (story) segmentation
 - Still open issue

[1] Z. Liu, E. Zavesky, D. Gibbon, B. Shahraray, and P. Haffner, "AT&T research at TRECVID 2007," 2007.

Basic Assumption

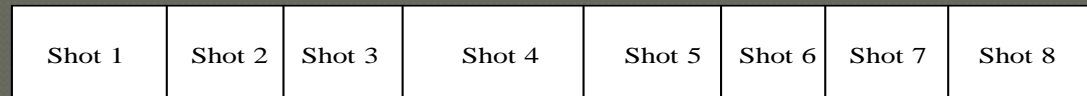
- **Each shot belongs to exactly one scene**
 - Scene boundaries are a subset of shot boundaries
 - Not valid in story segmentation
 - 9% of story boundaries not shot boundaries [1]
 - **Shot grouping = Scene segmentation**

[1] Winston Hsu et al. “Discovery and Fusion of Salient Multi-modal Features towards News Story Segmentation”, Proc. of Storage and retrieval methods and applications for multimedia, vol. 5307, 2004, pp. 244–258.

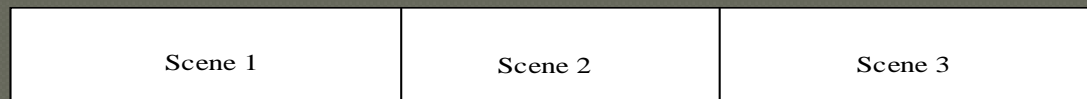
Video Stream - Frame Level



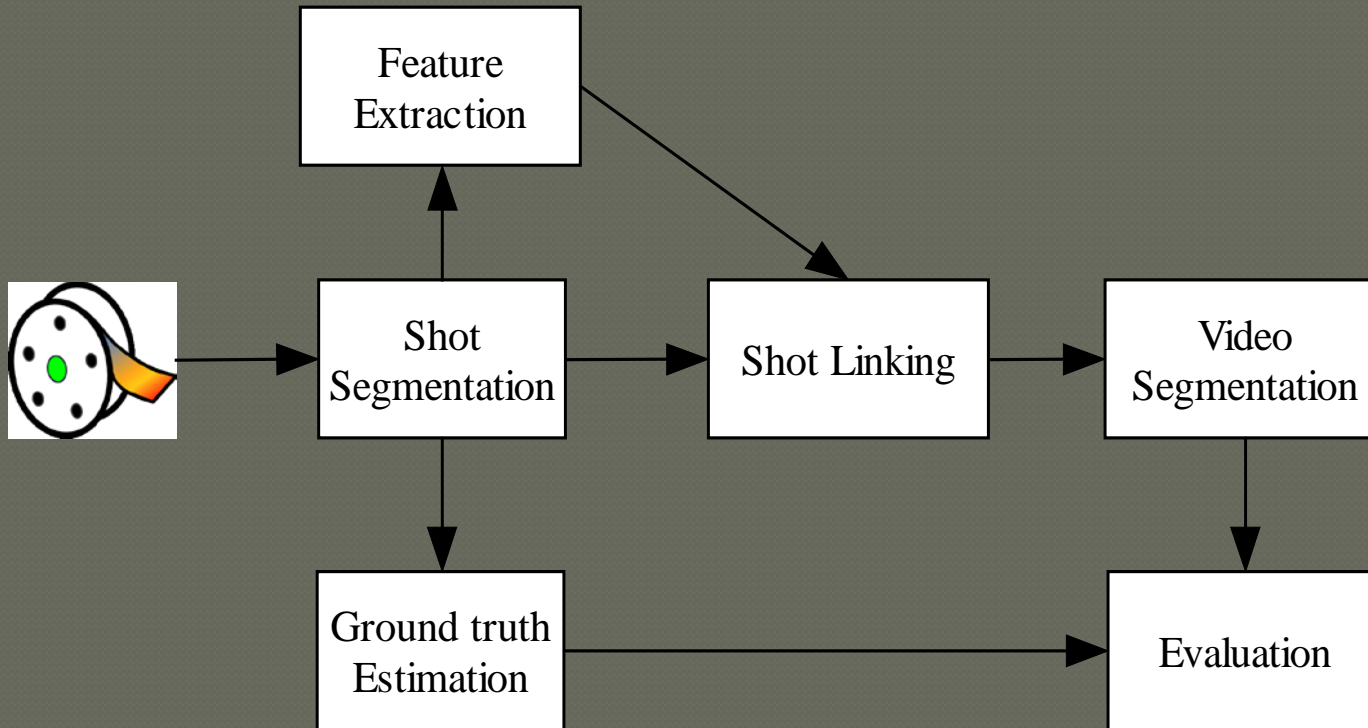
Video Stream - Shot Level



Video Stream - Scene Level



Scene Segmentation Overview



Scene Segmentation Points

- ◉ Shot Descriptor Extraction
- ◉ Descriptor use/fusion
- ◉ Scene Disambiguation
- ◉ Development of evaluation measures

Scene Segmentation Points

- ① **Shot Descriptor Extraction**
- ② Descriptor use/fusion
- ③ Scene Disambiguation
- ④ Development of evaluation measures

Temporal Position

- ⊙ Shot index or frame index of a representative frame
- ⊙ Temporal similarity is a function of their temporal distance
 - Binary
 - Prune the set of candidate shot links
 - Continuous
 - Filter shot content similarity (exponential).

Low-level Visual Descriptors

- Representative key-frame extraction
- Low-level descriptors
 - Hint in relevant literature that descriptor selection does not play critical role
 - HSV or L^*u^*v histogram

Visual Concepts

- High-level visual descriptors
 - Visual concept detectors representing key-frame semantic visual content
 - Confidence value (estimated probability the visual concept present)
 - Confidence-value feature vector
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- [1] V. Mezaris, P. Sidiropoulos, A. Dimou, I. Kompatsiaris, “On the use of visual soft semantics for video temporal decomposition into scenes,” IEEE Fourth International Conference on Semantic Computing (ICSC), 2010, pp. 141-148

Motion Descriptors

- ⊙ Based on video spatio - temporal nature
- ⊙ Pair-wise comparison of frames and extraction of global motion properties
- ⊙ Spatio – temporal slices (one axis in time, one axis in space)
 - Tensor Histograms for shot motion descriptor.
- ⊙ Require computations in frame level
 - Computational expensive

Low-level Audio Descriptors

- Volume
 - Energy
 - Zero-crossing Rate
 - Mel-frequency cepstral coefficients
 - Etc...
-
- Comparisons between adjacent shots
 - Discontinuity recognition

Speaker Histogram

- The distribution of speakers across two shots can measure audio similarity.
- Speaker diarization.
 - Identifying in an audio stream segments homogeneous according to the speaker identity.
 - Assign a speaker ID in each speaker segment.
- The histogram of the speakers present in each shot is estimated
- [1] P. Sidiropoulos, V. Mezaris, I. Kompatsiaris, H. Meinedo, I. Trancoso, “Multi-modal scene segmentation using scene transition graphs”, ACM International Conference on Multimedia (ACM MM), 2009, pp. 665-668.

Audio Events

- High-level audio descriptors
- Audio-corresponding to visual concepts
- Confidence-value feature vectors
- Audio events and speaker histogram experimentally tested during Vidi-Video project.
 - Enhance low-level visual results

[1] P. Sidiropoulos, V. Mezaris, I. Kompatsiaris, H. Meinedo, I. Trancoso, “On the use of audio events for improving scene segmentation”, 11th International Workshop on Image Analysis for Multimedia Interactive Services (WIAMIS), 2010.

- ◉ ASR Results
- ◉ Light source estimation
- ◉ Low-level visual descriptors from key-frame areas corresponding to background
- ◉ Face recognition or at least face detection

Scene Segmentation Points

- Shot Descriptor Extraction
- **Descriptor use/fusion**
- Scene Disambiguation
- Development of evaluation measures

Uni-descriptor Approaches

- Common approach: Graphs, estimate cuts.
- Scene Transition Graph (STG) [1]
 - Use visual similarity and temporal proximity
 - Two thresholds: one visual, one temporal.
 - Scene Convexity
 - Generalization to all kind of descriptors and modalities
- [1] Minerva Yeung, Boon-Lock Yeo, and Bede Liu, Segmentation of video by clustering and graph analysis, *Computer Vision and Image Understanding* 71 (1998), no. 1, 94–109.

Multi-descriptor Approaches/ Descriptor Fusion

● Early Fusion

- Append descriptors to a “bigger” one
- Employ a uni-descriptor approach

● Late Fusion

- For each descriptor extract results exclusively based on it
- Combine results

STG-based Late Fusion Probabilistic Framework (1)

● Included types of STGs

- Low-level visual (HSV)
- High-level visual (visual concepts)
- Speaker Histogram
- High-level audio (audio events)

STG-based Late Fusion Probabilistic Framework (2)

- For each type of STG
 - Generalization of multiple STGs for different, randomly selected values of content similarity and temporal proximity parameters
 - Approximation of the probability value for each shot boundaries to be also a scene boundary, based on the descriptor of the STG type
 - Random walk to parameter space
- Probability values linear combination
 - Thresholding
- Four Parameters to tune
 - 3 Weights, 1 Global Threshold

Experimental Results

Documentary Base

- 15 Documentaries
- 513 minutes
- 3459 shots
- 525 scenes

Film Base

- 6 movies
- 643 minutes
- 6665 shots
- 357 scenes

Method
GSTG ($y \in \{V, VC, A, AE\}$)
Method of [12]
Method of [21]
Method of [24]

Coverage(%)	Overflow(%)	F-Score(%)
86.30	10.91	87.67 (87.40)
70.90	24.13	73.30
77.59	17.31	80.06
78.22	16.73	80.67

Coverage(%)	Overflow(%)	F-Score(%)
87.91	17.89	84.91 (84.64)
76.43	16.15	79.97
75.12	24.29	75.41
79.50	21.17	79.16

Framework Limitations

- **Linear Combination: Limited Scalability**
 - Curse of dimensionality
 - Space dimension = Number of descriptors
 - As the number of descriptors increase tuning with dense uniform sampling leads to a prohibitively high number of sample points
- **In General**
 - Probability late fusion is a function (linear or not) in the descriptor space.
 - Metric space for fully exploiting dimensionality reduction field.
 - Measure: estimates distance of experimental segmentation from the ground truth segmentation.

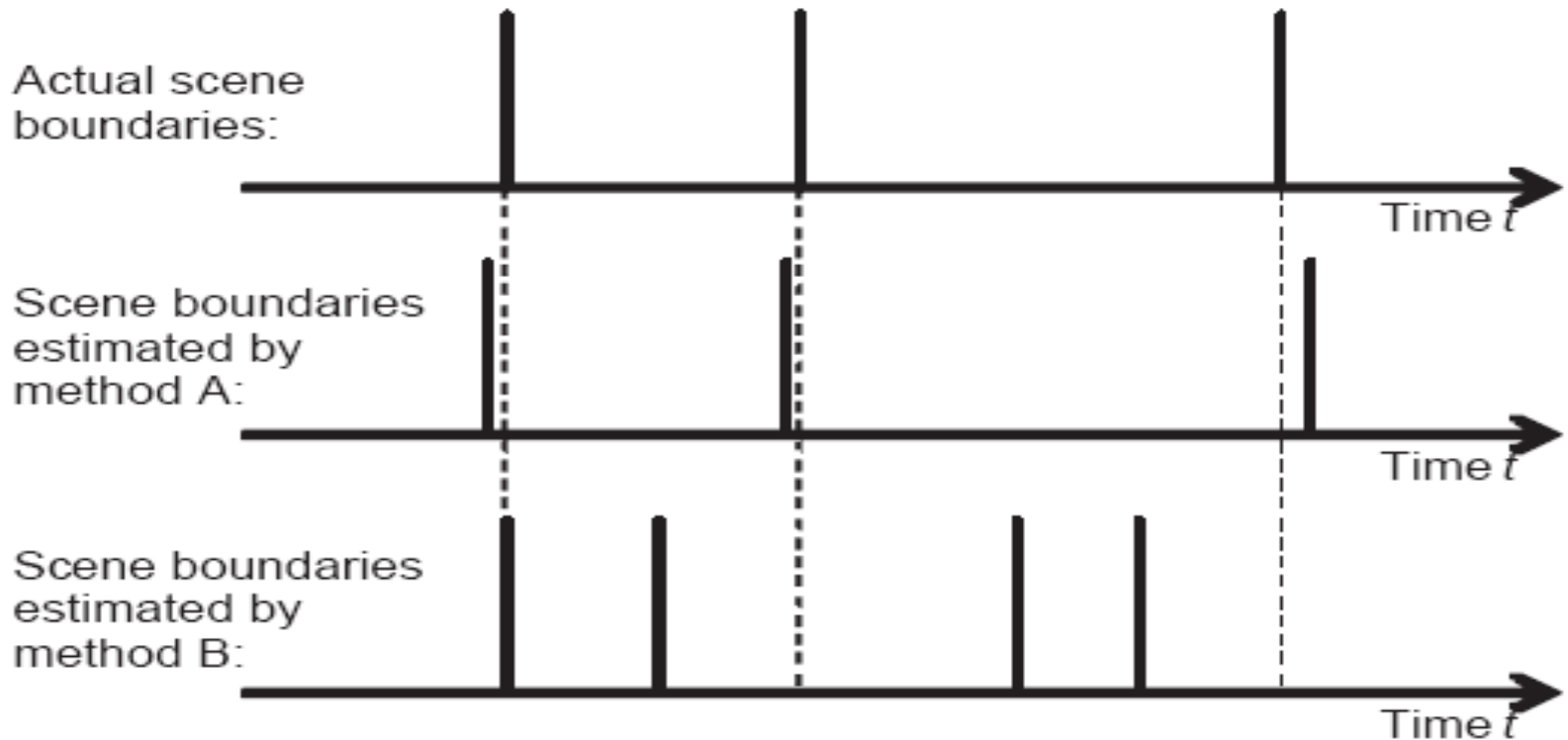
Scene Segmentation Points

- ① Shot Descriptor Extraction
- ① Descriptor use/fusion
- ① Scene Disambiguation
- ① **Development of evaluation measures**

Temporal Decomposition Measures

- Not common ground for comparison
- Evaluation left to the reader
- Recall-Precision
 - Counting false negatives and false positives.
 - Feasible for shot segmentation since start and end are well defined.
 - Not adequate for scene segmentation (or story segmentation)
 - Do not communicate error magnitude

Recall-Precision Inadequacy



- Method A: Recall 0% Precision 0%
- Method B: Recall 33% Precision 25%

Coverage - Overflow

- Two assumptions
 1. The content of a scene is dissimilar from the content of a succeeding scene.
 2. Within a scene shots with similar content are repeated.
- Overflow measures to what extent assumption 1 is met (optimal value 0%)
- Coverage measures to what extent assumption 2 is met (optimal value 100%)
- Good modelling of segmentation flaws
 - Over-segmentation (Overflow)
 - Under-segmentation (Coverage)

[1] Jeroen Vendrig and Marcel Worring, Systematic evaluation of logical story unit segmentation, IEEE Transactions on Multimedia 4 (2002), no. 4, 492–499.

Coverage-Overflow Inadequacy

- No obvious way to combine Coverage-Overflow
 - Two algorithms, one performing better in terms of coverage and the other in terms of overflow, which is overall better?
- Coverage-Overflow or their geometrical mean (F-Score) do not define a metric space.
- DED:
 - Single Measure
 - Metric Space

Differential Edit Distance (DED)

- Idea:

- Best system is the one that minimizes the work that is left for human

- Formally:

- The minimum quantity of set elements that need to change sub-set to transform the initial partition into the final.

- Scene Segmentation:

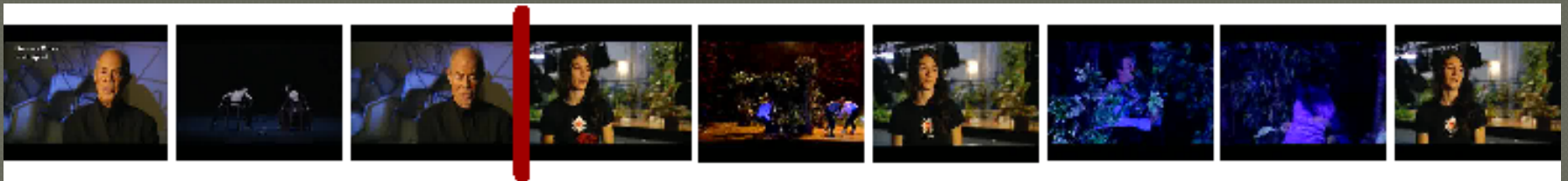
- The minimum number of shots that need to change scene to transform the experimentally estimated partition into the ground truth partition

- Analogous to Earth Mover's Distance

- Resembles Edit Distance

Scene Segmentation as shot labeling

- Labels are arbitrate
- Same scene \Leftrightarrow Same label
- Different scene \Leftrightarrow Different label



1	1	1	2	2	2	2	2	2	2
2	2	2	1	1	1	1	1	1	1
*	*	*	+	+	+	+	+	+	+

Differential Edit Distance (DED)

- Differentially equivalent label strings
 - If two corresponding elements have the same label in the first sequence they will also have the same in the second sequence
 - If two corresponding elements have different labels in the first sequence they will also have different in the second sequence
 - Strings 'AABBCC', '112233', '221133', 'BB11AA', '+ + - **' are differentially equivalent
- Differential edit distance (DED) of label strings
 - the minimum number of label modifications that are required to transform the first string into a string that is differentially equivalent to the second.

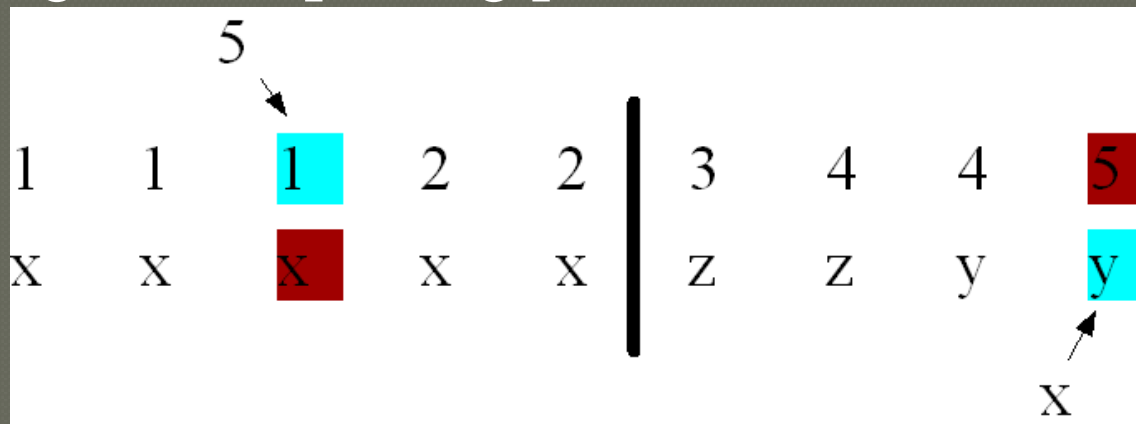
DED Estimation

- Set of labels of first and second string
- Occurrence matrix
 - 2-d histogram of shots: position (x,y) is the number of shots with label x in the first string and y in the second
- In the minimum distance(=DED) solution
 - If m and n the number of elements in label strings then $\min(m,n)$ labels of the first set are assigned to a label to the second
 - The total number of shots related to the assignment labels is maximized
- Job Assignment Problem: Hungarian Algorithm [1]

[1] H. W. Kuhn, "The Hungarian Method for the assignment problem", Naval Research Logistics Quarterly, vol. 2, 1955, pp. 83-97.

DED Efficiency Optimization

- Job Assignment Computational Complexity
 - $O(N^3)$, N is the number of scenes.
- Computational Optimization Property:
 - Two adjacent shots with different labels in both label strings identify a “splitting” point.
 - Video can be divided into two sub-videos, one ending to the splitting point and one starting from it.



DED Estimation Algorithm

- Find common “label” boundaries
- Split video into sub-videos
- For each sub-video
 - Estimate Occurrence Matrix
 - Find sub-videos DED
- Sum all DEDs

DED Metric Properties

- $d(x,y) = 0$ iff $x = y$
- $d(x,y) = d(y,x)$
- $d(x,z) \leq d(x,y) + d(y,z)$ (transitivity)
 - Suppose $d(x,z) > d(x,y) + d(y,z)$
 - There are more shot labels that need change between x and z than between x and y and y and z .
 - There are shot labels that change between x and z but do not change between both x and y and y and z .
 - This can not stand since we can transform string x to z either by first “passing” from y or not, and the results need to be identical.

DED Advantages

- Metric
- Uni-dimensional
- Polynomial Complexity
- Easily implemented

Thanks

Questions?