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# Motion-based Approach for BBC Rushes Structuring and Characterization

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#### **BBC** Rushes

#### n Rushes

- Unedited videos
- Similar to home videos, but with better capturing skills and visual quality

#### n Always....

- pan to have another view of scene
- Zoom-and-hold to freeze the impression
- Search for something
- z Long take without camera motion
- Pan to have panoramic view

#### **BBC** Rushes

#### n Intentional

- Another view of scene
- **Impression**
- Something
- Long take, panoramic view

#### n Intermediate

- □ *Pan* to have....
- □ Zoom-and-hold to freeze ....
- □ Search for .....
- A series of search, pan, zoom
- n Shaking













#### Our Intuition...

- n Detecting <u>intentions</u> are useful for search, browsing and summarization
- n <u>Intermediate</u> motions are not really meaningful for most tasks
- n Shaking clips can be either useful or not useful



## Objective

- n To structure-and-characterize (or characterized-andstructure) video content, we propose
  - □ Finite State Machine (FSM)
  - □ Support Vector Machine (SVM)
  - □ Hidden Markov Model (HMM)

		FSM	SVM	HMM
I	Intentional	√	<b>√</b>	√
II	Intermediate	√	<b>√</b>	√
III	Shaking	√	<b>√</b>	√

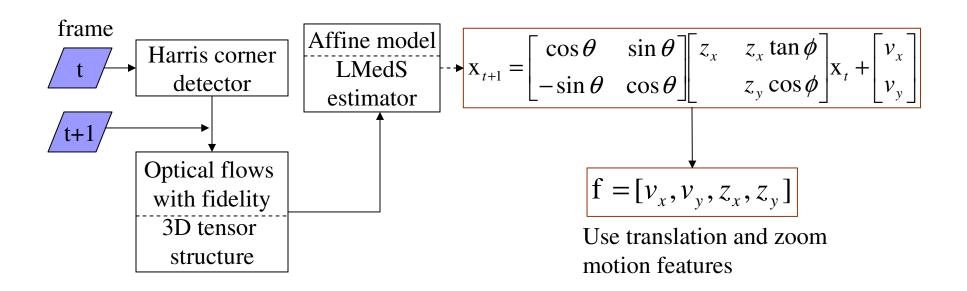




## M

#### Global Motion Estimation

The motion-driven FSM, SVM and HMM are all based on the inter-frame global motion estimation. Considering the generalization and complexity, we choose to use the *affine motion model*.

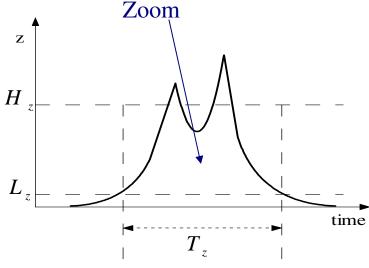


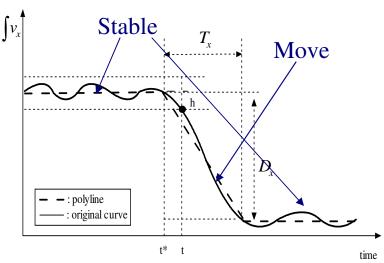


#### FSM—Partition

**Zoom partition**: The techniques of hysteresis thresholding are used for the zoom motion feature. Two thresholds are used: higher one for locating the position; lower one for the zoom partition **Z**.

**Static and move partition**: A polyline is fitted to the camera trajectory using Kalman filter. Based on the properties of the lines, camera trajectory are partitioned into long stable *Ls*, short stable *Ss*, long move *Lm* and short move *Sm*.

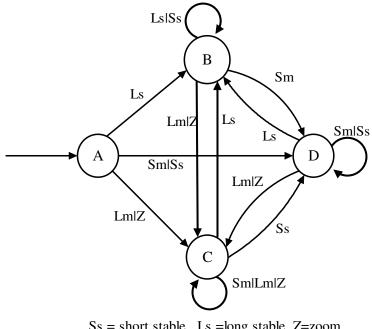






#### FSM—Classification

- n A 4-state FSM is employed to refine the partition and characterize video.
  - A: initial state.
  - B: intentional motion.
  - C: intermediate and shaky motions.
    They are further separated by the rate of camera direction changes.
  - D: temporarily undetermined short segments.

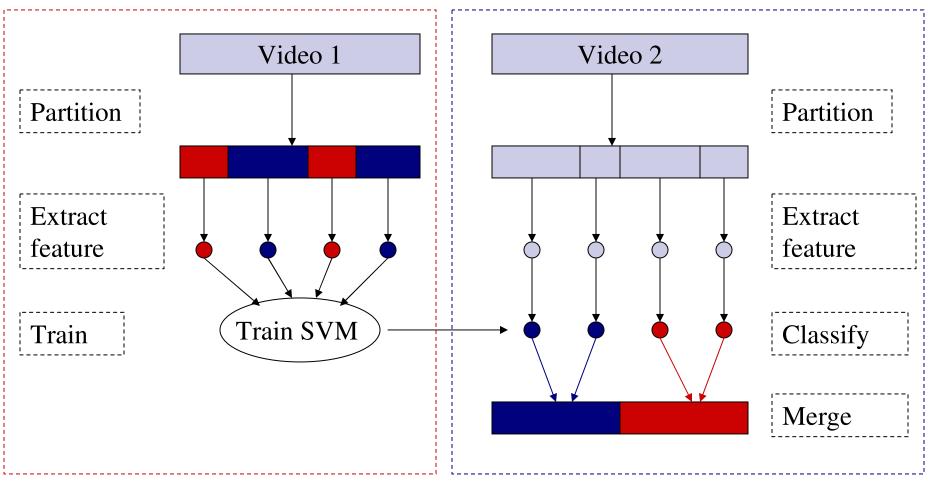


Ss = short stable Ls =long stable Z=zoom Sm= short move Lm=long move

Z. Pan and C.-W. Ngo, "Structuring home video by snippet detection and pattern parsing," in *ACM SIGMM Int'l Workshop on MIR*, 2004.



#### Flowchart of SVM



Train Classify

## M

## **SVM** Implementation

- n Partition: video is divided into segments of equal fixed duration.
- n Feature extraction: 9 features from motion are extracted for each video segment. They are:

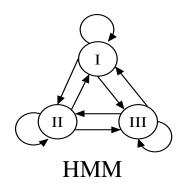
Speed: 
$$M_{x} = \max_{i=1}^{N} (|v_{i}^{x}|), \quad M_{y} = \max_{i=1}^{N} (|v_{i}^{y}|)$$
 Zoom: 
$$Z_{x} = \max_{i=1}^{N} (|z_{i}^{x}|), \quad Z_{y} = \max_{i=1}^{N} (|z_{i}^{y}|)$$
 Acceleration: 
$$D_{x} = \max_{i=1}^{N-1} (|v_{i+1}^{x} - v_{i}^{x}|), \quad D_{y} = \max_{i=1}^{N-1} (|v_{i+1}^{y} - v_{i}^{y}|)$$
 Acceleration variance: 
$$V_{x} = \max_{i=1}^{N-1} (|v_{i+1}^{x} - v_{i}^{x}|), \quad V_{y} = \max_{i=1}^{N-1} (|v_{i+1}^{y} - v_{i}^{y}|)$$
 Motion change: 
$$S = \max_{i=1}^{N-1} (|\mathbf{v}_{i+1}| ||\mathbf{v}_{i}| - \mathbf{v}_{i+1} \cdot \mathbf{v}_{i})$$

**Motion change** feature actually is  $|\mathbf{v}_{i+1}| |\mathbf{v}_i| (1 - \cos \theta)$ , which considers both the angle change and motion magnitude.



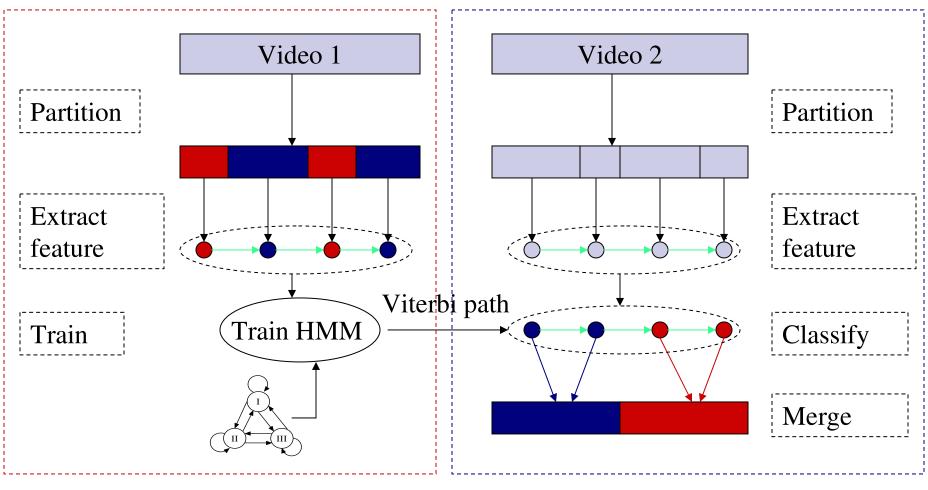
#### HMM-based Approach

- Motivation: *First order decision* (look at one sample and make decision at a time) may not be sufficient, *Second order decision* (look at multiple samples to make decision) should be better in principle.
- n **Hidden Markov Model (HMM)** is then used as second order decision for video structuring and characterization.
  - HMM State transition à video structuring
  - HMM State prediction à video characterizing
- 3-state hidden Markov model is used to represent respectively the intentional, intermediate and shaky motions.





#### Flowchart of HMM



Train Classify



#### MHMM & SHMM

- We investigate two kinds of HMM, called *MHMM* and *SHMM*. The difference is,
  - □ MHMM (*m*otion-based):

Partition: Video is divided into segments of equal fixed duration.

Feature: Extract <u>9 features</u> from motion.

□ SHMM (*s*hot-based):

Partition: Video is divided into shots by cut detector.

Feature: Extract shot duration

□ *Note*: We use SHMM as baseline

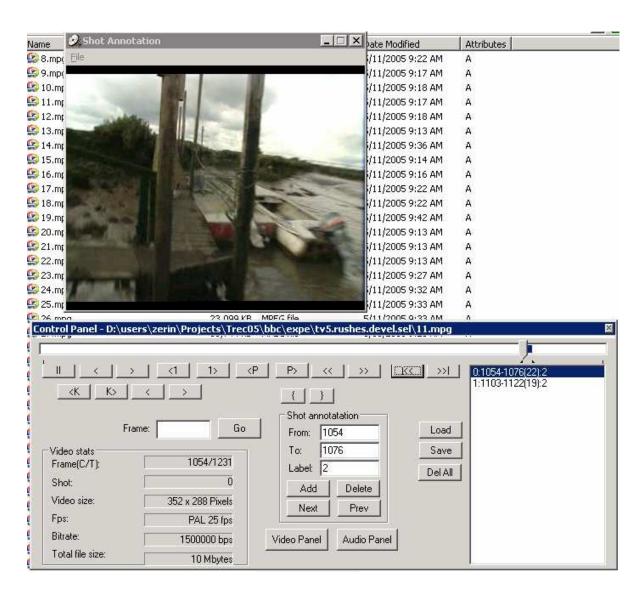
n Intuition: Short shots correspond to shaking/intermediate motion



#### Experiments – Data Set and Training

- n 60 videos (337K frames) from the development set
- n Manually annotate sub-shots and their characteristics
- n 768 shots and 1135 sub-shots
- n 30 videos for training and 30 videos for testing.

#### **Annotation Tool**





## Approaches

	Segment Unit	Feature Number	Feature Types	Training	Decision
FSM	Sub-shot	4	Motion	No	1st
SVM	Equal duration	9	Motion	Yes	1st
MHMM	Equal duration	9	Motion	Yes	2nd
SHMM	Cut	1	Time	Yes	2nd

1st: look at one sample and make decision at a time

2nd: look at multiple samples to make decision



## Experiment – Structuring

- n Sub-shot boundary detection
- n A sub-shot boundary is counted as correct as long as we can find a matched ground-truth boundary within 1 second.

	Training		Testing		
	Recall Prec.		Recall	Prec.	
FSM	0.614	0.282	0.593	0.279	
SVM	0.769	0.281	0.763	0.289	
MHMM	0.461	0.419	0.395	0.379	
SHMM	0.060	0.355	0.056	0.322	

Results of structuring BBC rushes



## Experiment – Characterization

- n Sub-shot classification
- n Use frame as basic unit for evaluation

	Intentional		Intermediate		Shaky	
	Recall	Prec.	Recall	Prec.	Recall	Prec.
FSM	0.815	0.981	0.802	0.118	0.011	0.050
SVM	0.827	0.990	0.701	0.162	0.715	0.239
MHMM	0.927	0.970	0.329	0.137	0.311	0.339

Results of characterizing BBC rushes (training videos)



#### Experiment – Characterization Cont'

#### n 30 testing videos

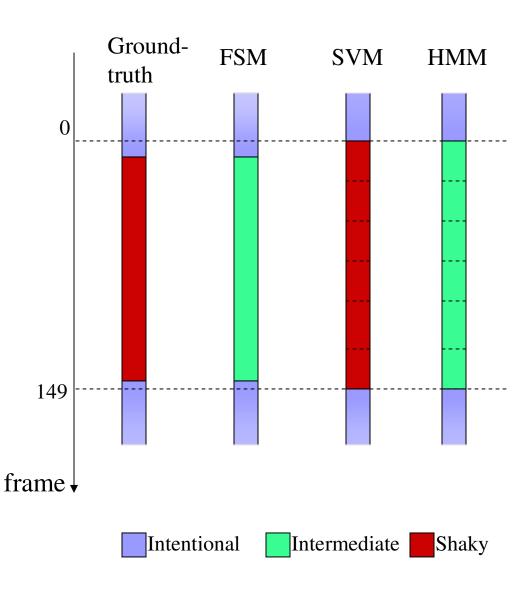
	Intentional		Intermediate		Shaky	
	Recall	Prec.	Recall	Prec.	Recall	Prec.
FSM	0.756	0.968	0.844	0.128	0.000	0.000
SVM	0.778	0.975	0.456	0.120	0.362	0.182
MHMM	0.909	0.929	0.375	0.196	0.043	0.067

Results of characterizing BBC rushes (testing videos)



## Example







## Summary

- n For <u>structuring</u>, SVM gives the best recall (above 75%), followed by FSM (about 60%); the performances of MHMM and SHMM are poor.
- n For <u>characterization</u>:
  - MMM performs best for extracting intentional motion
  - **The FSM performs best for intermediate motion detection**
  - □ On average, SVM is best for three characteristics.
- n Several problems remain difficult and challenging



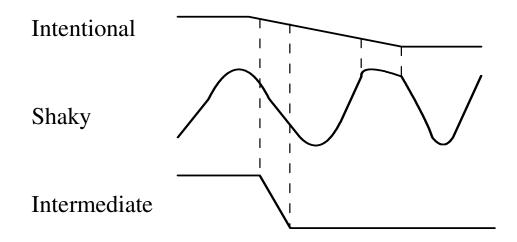
#### FSM—Limitation

- n For FSM, the following issues should be considered.
  - The threshold is difficult to set empirically to distinguish between intentional and intermediate. For example, "panorama view" or "pan to search"?
  - The use of rate of directional changes as features for separating shaky and intermediate motions is poor.



#### SVM—Limitation

- n For SVM, the following sorts of segments are ambiguous by just looking at small time frame:
  - □ A panoramic or "pan to search"?
  - "Pan to search" or one part of a shaky?
  - A relative stable part of a shaky or intentional?





#### MHMM—Limitation

- n More works can be done in HMM:
  - Only one state is not enough to represent the intentional, intermediate or shaky characteristic, e.g.
    - n "Intermediate" may have two sub-state: "pan to search" and "zoom-and-hold"
    - "Shaky" may have sub-states such as "shake left", "shake right", "shake up", "shake down".
  - State "intentional: is over trained since sequences has more intentional than intermediate/shaky segments. Over-trained "intentional" state compresses the detection of other two types, especially shaky.



## More on Characteristic of BBC Rushes...

- I. Intentional
- **II.** Intermediate Motion
- **III.Shaky Motion**



#### **IV.Blur**

- n motion blur, defocusing blur
- v. Illumination Change





## Challenge in Motion Estimation

n Camera motion estimation is difficult for cases like blur, illumination and large foreground objects



Blur



Illumination



Foreground object



#### Future Work

- Detecting segments with blur and sharp/inconsistentillumination changes
  - □ facilitate browse/search/summarization
  - Motion estimation can be an easier task
- n Consider variants of SVM and HMM models for more accurate structuring and characterization.