

# A Temporal Bayesian Model for Classifying, Detecting and Localizing Activities in Video Sequences

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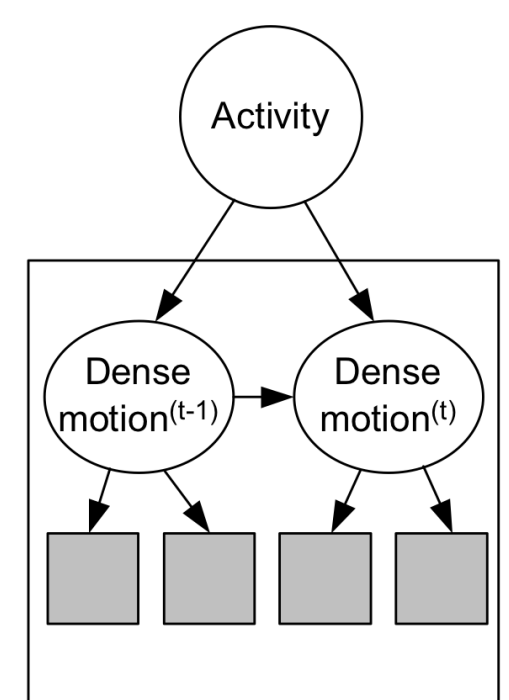
## Problem Statement

- To detect activities in videos
  - Mostly unconstrained videos (HMDB)
- Perform one shot learning
  - Learn gesture model from one sample
  - Locate and recognize gestures in a video sequence

## Related Work

- Spatio temporal interest points were earlier introduced by Laptev and Linde [4] and since then other interest-points descriptors have been proposed
- Wang et al. [6] performed an evaluation of spatio temporal features for activity recognition and showed that dense features points perform better
- Wang et al. in [5] proposed an approach to describe videos by dense trajectories. They sample dense points from each frame and track them based on displacement information from optical flow field.
- Gaur et al. [2] proposed a model based on string representation of the video.
- Brendel et al. [1] proposed a model to represent videos by spatiotemporal graphs, where the nodes correspond to multiscale video segments and edges capture hierarchical, temporal and spatial relationships

## Model description



- Standard HMM with minor variations
- Multiple observations per state
- Multiple channels

• Initial state distribution

$$\hat{\pi} = \sum_{r=1}^R \gamma_r^r(i);$$

• State transition probability

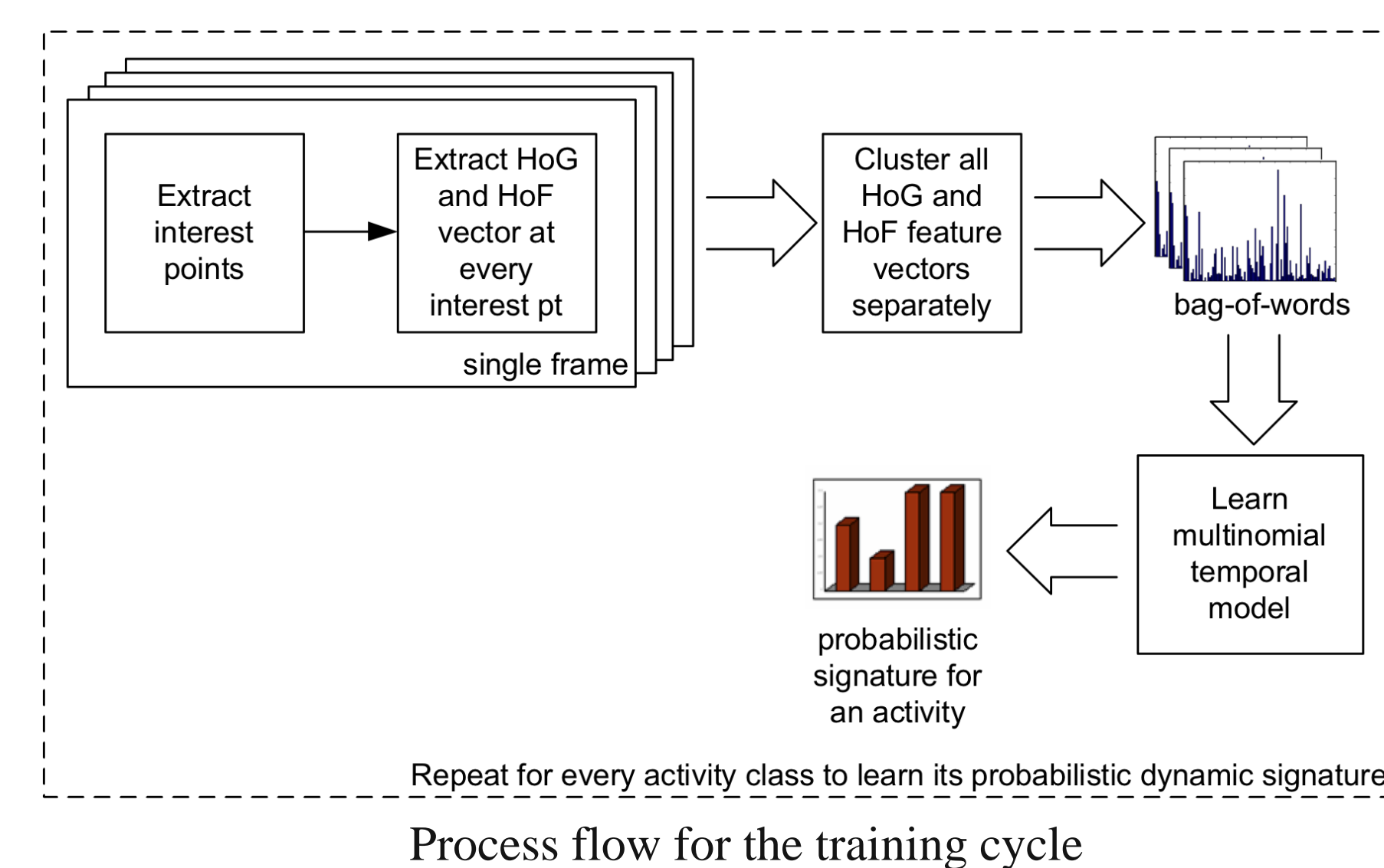
$$\hat{a}_{ij} = \frac{\sum_{r=1}^R \sum_{t=1}^T \eta_t^r(i, j)}{\sum_{r=1}^R \sum_{t=1}^T \gamma_t^r(i)}$$

• Observation densities

$$\hat{b}_j^d(k) = \frac{\sum_{r=1}^R \sum_{t=1}^T \gamma_t^r(j) \cdot \frac{n_{t,r}^{d,k}}{n_{t,r}^{d,*}}}{\sum_{r=1}^R \sum_{t=1}^T \gamma_t^r(j)}$$

## Proposed Approach

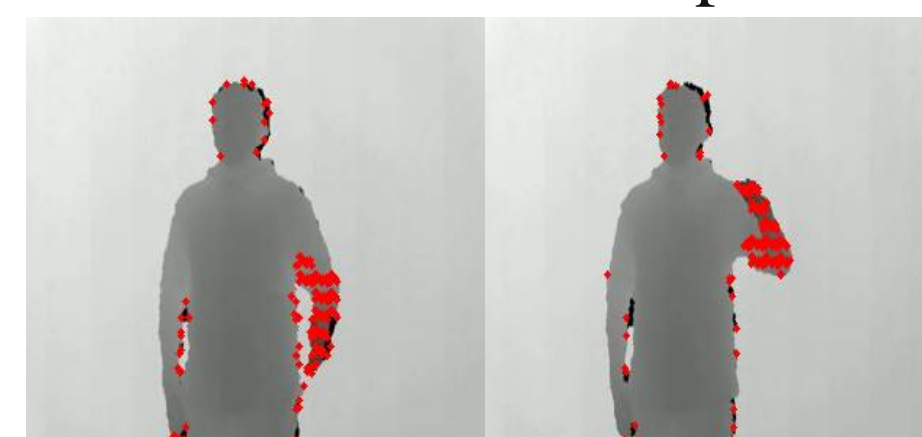
- Interest points
  - Dense sampling
  - Optical Flow points
- Descriptors
  - HOG, HOF



- Clustering
  - Kmeans
  - Hierarchical
- Classifier
  - HMM with multiple observations

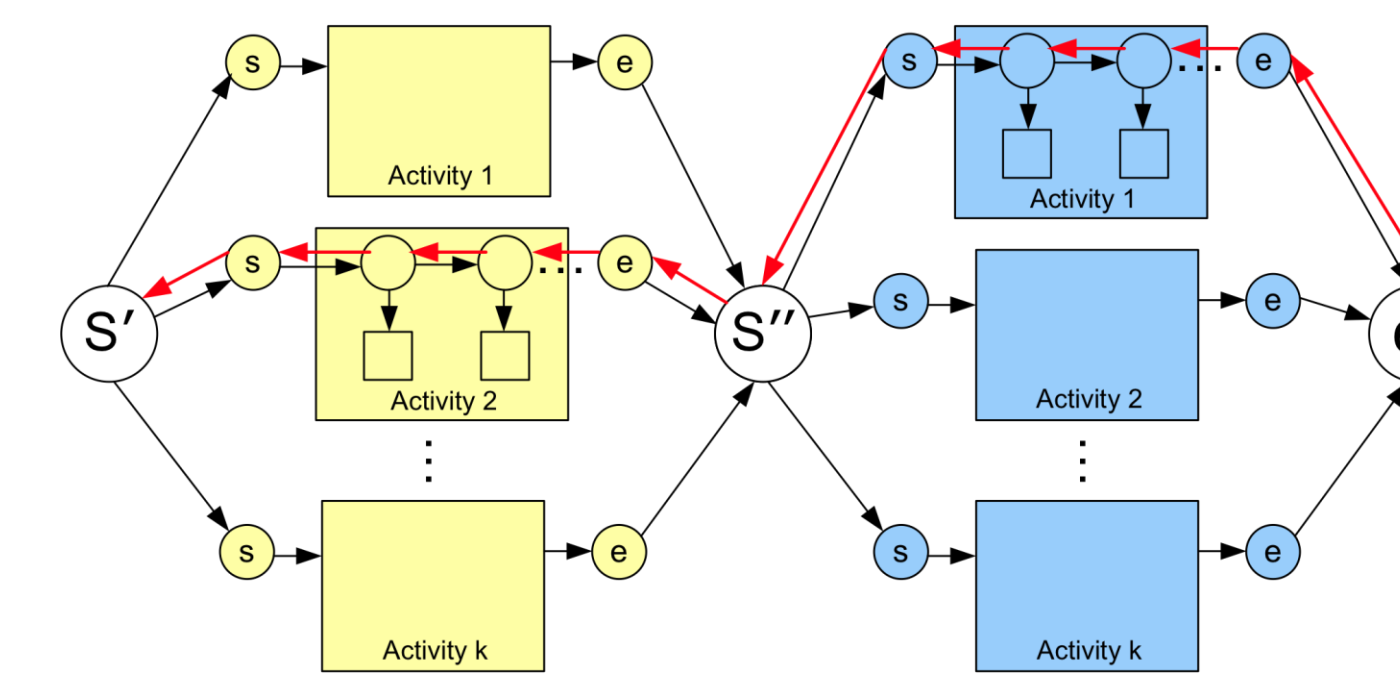
## Interest points and features

- HMDB Dataset
  - Extract dense points from each frame
  - Track each point for L frames
  - Extract HOG and HOF descriptors for each trajectory
- Chalearn Dataset
  - Extract motion points by frame differencing
  - Extract HOG and HOF descriptors for each point



- Visual words in chalearn data
  - cluster all the descriptors from training data using kmeans to form visual words
  - Use Latent Dirichlet allocation to form more meaningful visual words
- Visual words in HMDB/KTH data
  - Number of points are in the order of 30,000,000
  - Construct visual words for each activity class separately
  - Use these words as samples for constructing final visual words

## Gesture spotting



Gesture spotting by computing likelihoods via Viterbi decoding

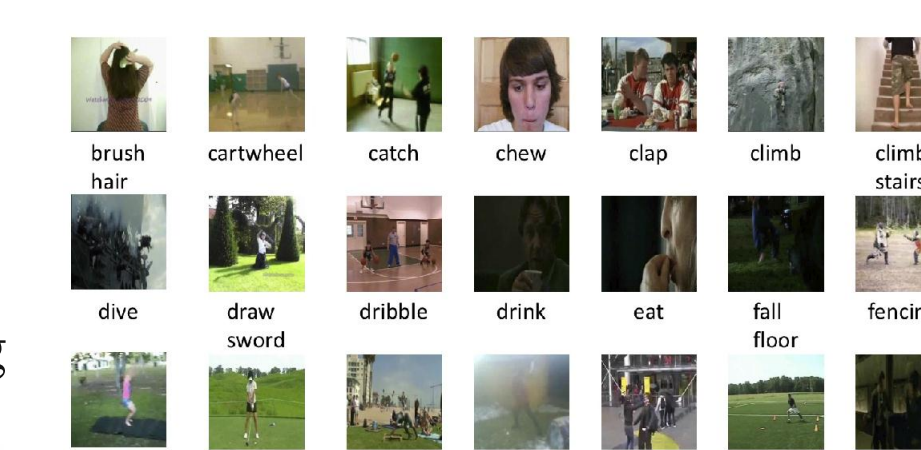
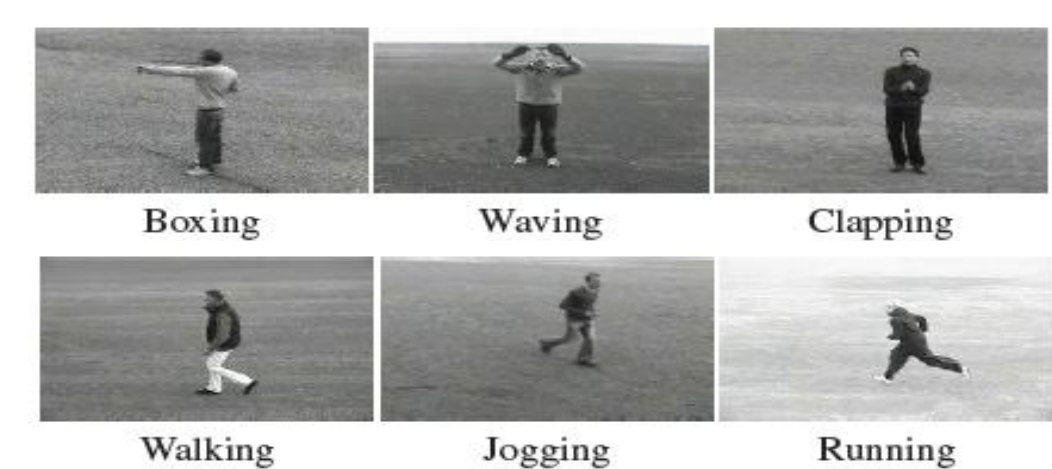
- Learn individual gesture models
- Construct a network of models with at most 5 gestures
- Transition between gestures has equal probabilities
- Find most likely gestures from Viterbi decoding

## Experiments and Results



- Chalearn Dataset
  - Dataset is divided into 20 batches
  - 47 videos per batch
  - First M videos are used for training
  - 3-5 gestures in each test video

- HMDB Dataset
  - 51 class
  - ~ 100 videos per class
  - 70-30 split for training and testing



- KTH Dataset
  - 4 actions
  - 25 subjects, 4 scenarios
  - 16 subjects for training

Method	Accuracy
Laptev et al. [8]	91.8%
Yuan et al. [9]	93.3%
Wang et al. [5]	94.2%
Gilbert et al. [10]	94.5%
Kovashka and Gruman et al. [11]	94.53%
Ours	<b>94.67%</b>

Method	Accuracy
Kuehne et al. on 51 activities [3]	23.18%
Kuehne et al. on 10 activities [3]	54.3%
Ours results on 51 activities	<b>25.64%</b>
Ours results on 10 activities (stabilized)	<b>66.67%</b>

Results for KTH (left) and HMDB (right) dataset

Method	Dataset	Edit Distance
Ours	Development	0.26336
Ours + LDA	Development	0.2409
Ours	Validation	0.26036
Ours + LDA	Validation	<b>0.23328</b>
Baseline	Validation	0.59978
Top Ranking	Validation	0.1426

Results for Chalearn dataset

## Implementation details

- We obtained best results on KTH dataset with 2000 visual words and 25 states
- 1000 visual words and 25 states for HMDB dataset
- Visual words for Chalearn data depends on number of classes (10\*Nclasses)
- LDA is used to reduce the number of visual words to a factor of eight (8\*Nclasses)
- 10 states were found to be optimal for Chalearn data

## Conclusion and Future Work

- Presented a model for activity classification and spotting that competes well with state-of-the-art systems
- Verified the model by testing it on two extreme datasets (KTH and HMDB)
- Participated in Chalearn gesture challenge and finished in top-5

## References

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