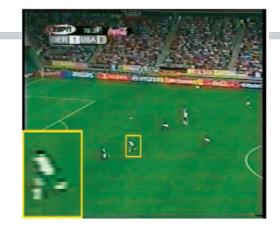
Human Action Recognition Using Semi-Latent Topic Models

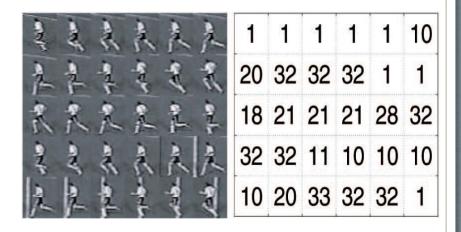
Yang Wang and Greg Mori, 2009

SE367 Paper PresentationDeepak Pathak10222

Introduction

- Human Action Recognition (What ?)
- Still Images (eg: Poselets) v/s Video Sequences
- Motivation: Bag of words representation of image – good results in Object Recognition





Bag of Words

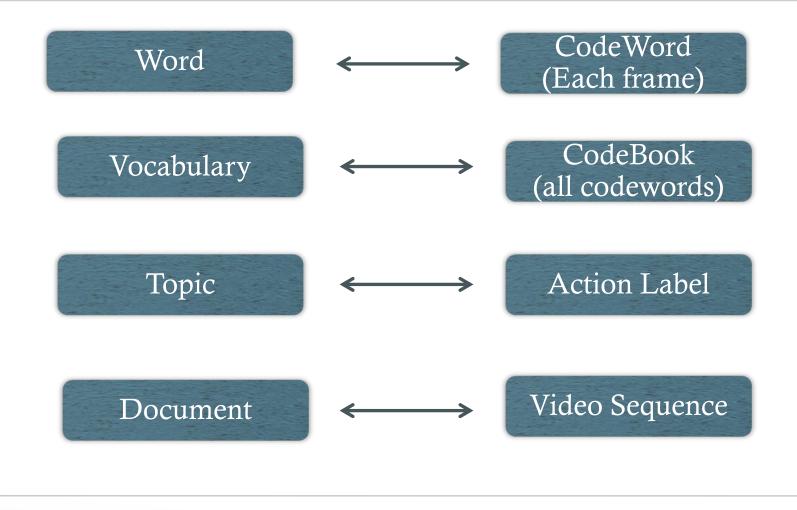
[Wang,Mori,2009]

Earlier Work (Action Recognition)

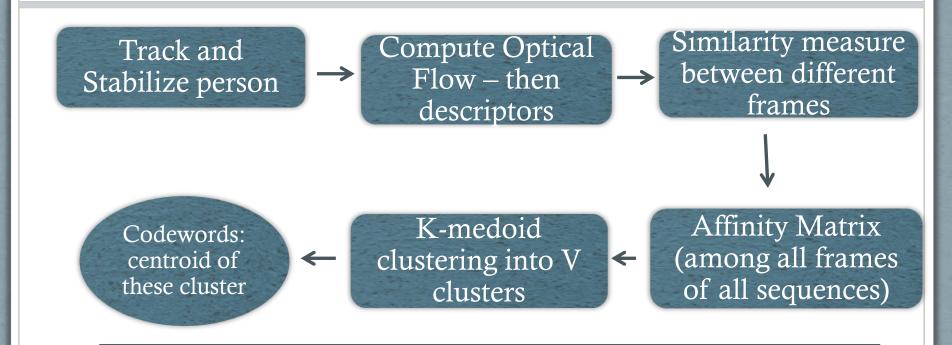
- Motion Based: Learning features which based on visual cues (motion + shape), optical flows
- Temporal Dynamic Models: Generative (e.g. HMM) and Discriminative (e.g. CRF) to model and learn features

- Interest Point Methods:
 Capture local features e.g.
 train SVM over the
 features obtained by STIP
- Topic Models:
 "Bag of Words"
 Paradigm.
 (analogous to NLP)

Bag of Words (analogue: NLP to VISION)



Construction of CodeBook



* Here codeword capture large scale features (containing overall temporal information of all videos in training set)
* Each video is a sequence of frames where each frame is represented by any codeword obtained above, thus video is a bag of words, removing temporal information.

Topic Models

 LDA : Genereative model to learn the distribution of topics(actions) given a document(video) and distribution of topics (action) over words (codewords).
 Dirichlet Distribution

Proposed Modification Semilatent LDA: Introduces supervision in LDA by making use of action labels present in training dataset.

- Thus, better estimate the parameters of probability distribution

Semilatent CTM-Supervised CTM

> Note: Don't have to choose topics as they are just equal to class labels (unlike unsupervised)

 CTM : Similar but Logistic Distribution to properly correlation of different topics in a document.

Classification

- Classify each frame in the sequence: For each frame, given frame calculate its distribution over action labels i.e. p(z_i | W). Here, we chose W instead of just the corresponding frame so as to ensure that action label not just depend on the frame itself but video sequence as a whole
- **SLDA** : Models/approximates this probability distribution using other distribution by minimizing KL divergence between the two.
- **SCTM** : It approximates by using coordinate ascent techniques (Variational EM-expected maximization)
- Firstly **we can classify each frame** using distribution over action labels(take maximum) and then if video contains single action then perform majority voting.

Results

(per video classification)

- KTH Dataset: SLDA - 91.2% SCTM - 90.33%
- Weizmann Dataset: SLDA - 100% SCTM - 100%
- Hockey Dataset: SLDA - 87.5% SCTM - 76.04%

- Soccer Dataset: SCTM - 78.64%
 SLDA - 77.81%
- Ballet Dataset: SCTM - 91.36% SLDA - 88.66%

CTM captures correlations better than LDA, thus performs better on multiple action video datasets (i.e. soccer & ballet).



Sample frames from our datasets

[Wang,Mori,2009]

Conclusion

• **Proposals**:

- 1. A novel "Bag of words" approach for representing video sequences where each frame corresponds to a word, thus capturing large scale features.
- 2. Two new models : SLDA & SCTM which are basically supervised form of LDA &CTM, thus training is easy with better performance.
- **Benefit**: This paper focuses mainly on per-frame classification, thus works significantly well on datasets of video containing multiple actions.

References

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Thank You

