同济大学计算机科学与技术系

多媒体与智能计算实验室

Encoding Scale into Fisher Vector for Human Action Recognition

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Content

Outline

Action Recognition Task

Testing Video

Classification

Results

- Brush hair
- Cartwheel
- Catch
- Chew
- Clap
- Climb
- Climb stairs
- Dive
- Draw sword
- Dribble

- Camera motions
- Different viewpoints/backgrounds/…
- Variety of movements

Outline

Related Work

- **Trajectory based Feature Extraction and Description**
  - KLT trajectory [Lucas et al 1981]
  - SIFT trajectory [Sun et al 2009]
  - Dense Trajectory (DT) [Wang et al 2013]
  - Improved Dense Trajectory (iDT) [Wang et al 2013]
  - ……
- **Feature Encoding Method**
  - Bag-of-Visual-Words (BoVW) [Sivic et al 2003]
  - Fisher Vector (FV) [Perronin et al 2010]
  - Spatial Fisher Vector (SFV) [Krapac et al 2011]
  - Spatial Temporal Fisher Vector (STFV) [Oneata et al 2013]
  - ……

Outline

Temporal Scale in Video

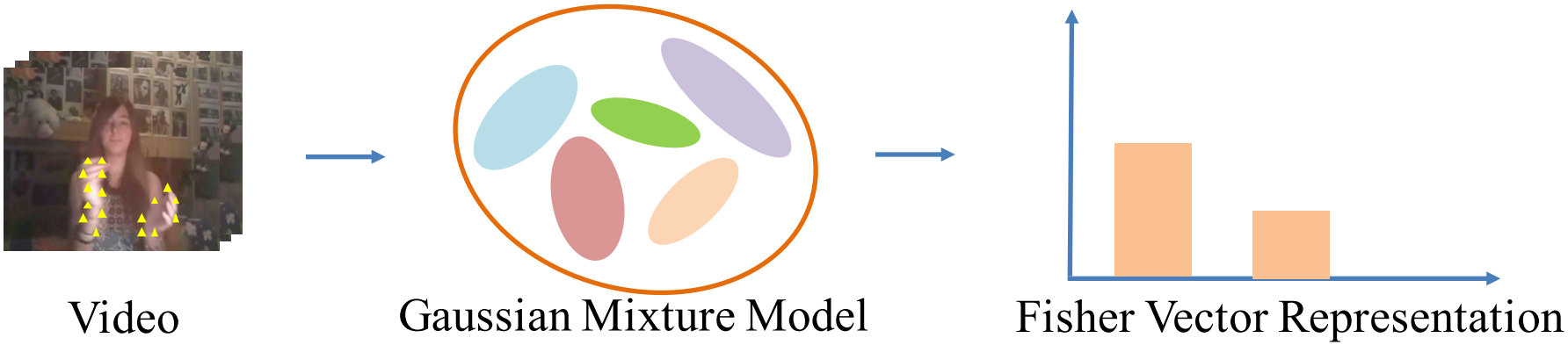
Motivation

- Scale information plays a great role in image area.

  Low level features like SIFT and SURF use spatial scale information to determine salient points. Recent work like Domain-size Pooling [Dong et al 2015] utilizes scale information to improve matching performance.

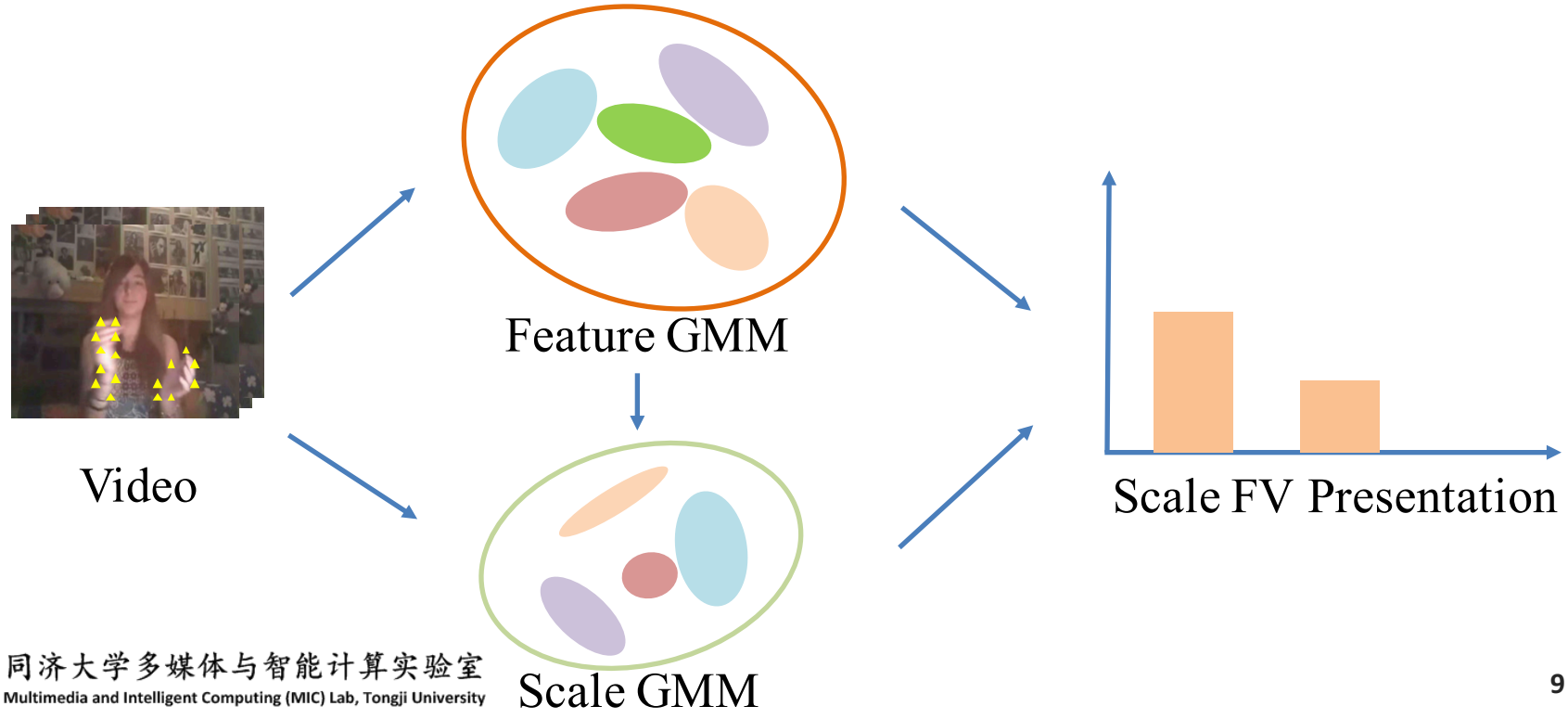
- Different actions should have divergent movement patterns.

  Movement pattern contains discriminative information.



Temporal Scale in Video

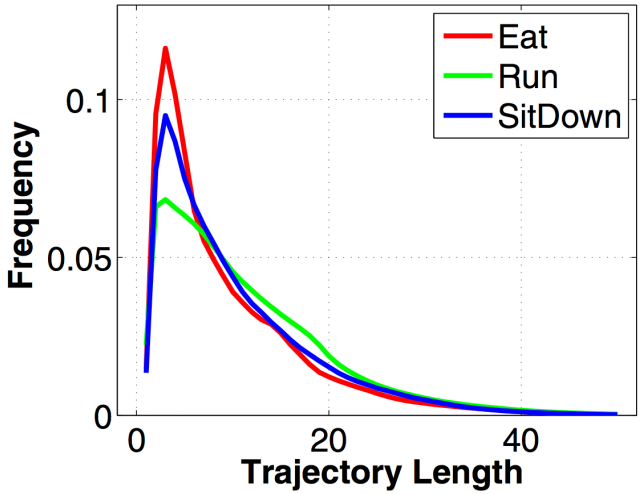
- **We want to …**
  - Give a definition to temporal scale information in video.
  - Encode scale information into Fisher Vector.
  - Combine scale and position information with low level features to strengthen the performance.



Temporal Scale in Video

Definition

- We define the temporal scale in videos as the length of an event trajectory within a specific time period.



Frequency of trajectory length about three action classes ('Eat', 'Run' and 'SitDown') in Hollywood-2

Outline

Fisher Vector Revisited

- **Gaussian Mixture Model**

GMM: $p(y_t) = \sum_{i=1}^{K} \pi_i N(y_t; \mu_i, \Sigma_i)$

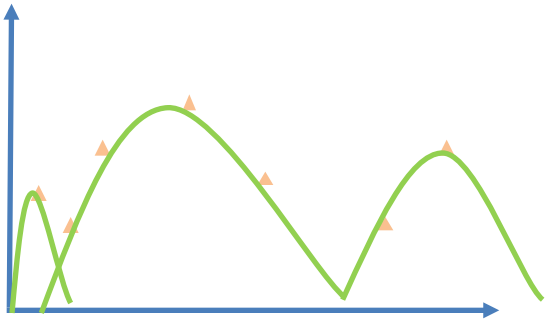
Features: y_t

Prior possibility: $\pi_i = \frac{e^{\alpha_i}}{\sum_j e^{\alpha_j}}$

Mean: μ_i

Covariance Matrix: Σ_i

Total number of GMM: K



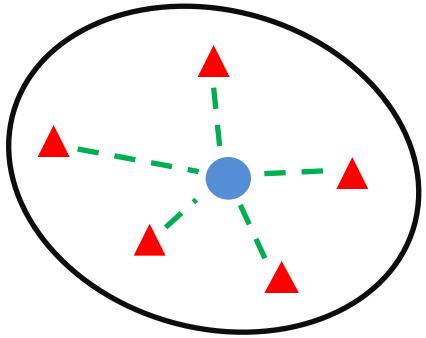
Fisher Vector Revisited

- **Fisher Vector**

$$\frac{\partial \ln p(y_t)}{\partial \alpha_i} = q_i(t) - \pi_i,$$
$$\frac{\partial \ln p(y_t)}{\partial \mu_i} = q_i(t)\Sigma_i^{-1}(y_t - \mu_i),$$
$$\frac{\partial \ln p(y_t)}{\partial \Sigma_i^{-1}} = q_i(t)\frac{\Sigma_i - diag\left((y_t - \mu_i)^2\right)}{2}.$$

Posterior possibility: $q_i(t) = \frac{\pi_i N(y_t; \mu_i, \Sigma_i)}{\sum_{j=1}^{K} \pi_j N(y_t; \mu_j, \Sigma_j)}$

Dimensions: $(2D + 1)K$



Outline

Scale Fisher Vector

- **Scale Gaussian Mixture Model**

Scale GMM: $p(y_t, s_t) = \sum_{i=1}^{K} \pi_i N(y_t; \mu_i, \Sigma_i) \sum_{j=1}^{J} \lambda_{ji} N(s_t; \delta_{ji}, \mathrm{Z}_{ji})$

Scale information: $s_t = \{\delta_t, \tau_t\}$

Prior possibility for scale: $\lambda_{ji} = \frac{e^{\alpha_{ji}}}{\sum_m e^{\alpha_{mi}}}$

Mean for scale information: δ_{ji}

Covariance Matrix for scale information: Z_{ji}

Total number of GMM for scale information: J

Scale Fisher Vector

- **Scale Fisher Vector**

$$\frac{\partial \ln p(y_t)}{\partial \alpha_i} = q_i(t) - \pi_i,$$
$$\frac{\partial \ln p(y_t)}{\partial \mu_i} = q_i(t)\Sigma_i^{-1}(y_t - \mu_i),$$
$$\frac{\partial \ln p(y_t)}{\partial \Sigma_i^{-1}} = q_i(t)\frac{\Sigma_i - diag\left((y_t - \mu_i)^2\right)}{2},$$
$$\frac{\partial \ln p(y_t, s_t)}{\partial \alpha_{ji}} = q_i(t)\left(r_{ji}(t) - \lambda_{ji}\right),$$
$$\frac{\partial \ln p(y_t, s_t)}{\partial \delta_{ji}} = q_i(t) r_{ji}(t) \mathrm{Z}_{ji}^{-1}(s_t - \delta_{ji}),$$
$$\frac{\partial \ln p(y_t, s_t)}{\partial \mathrm{Z}_{ji}^{-1}} = q_i(t) r_{ji}(t)\frac{\mathrm{Z}_{ji} - diag\left((s_t - \delta_{ji})^2\right)}{2}.$$

Posterior possibility: $$q_i(t) = \frac{\pi_i N(y_t; \mu_i, \Sigma_i)\sum_{j=1}^{J}\lambda_{ji}N(s_t; \delta_{ji}, \mathrm{Z}_{ji})}{\sum_{l=1}^{K}\pi_j N(y_t; \mu_l, \Sigma_l)\sum_{j=1}^{J}\lambda_{jl}N(s_t; \delta_{jl}, \mathrm{Z}_{jl})}$$

Dimensions: $$((2D + 1) + 1 + J(2d + 1))K$$

Scale Fisher Vector

- **Combined Fisher Vector**

Combined GMM: $p(y_t, s_t) = \sum_{i=1}^{K} \pi_i N(y_t; \mu_i, \Sigma_i) \sum_{j=1}^{J} \lambda_{ji} N(u_t; \delta_{ji}, \mathrm{Z}_{ji})$

CombFV:

$$\frac{\partial \ln p(y_t)}{\partial \alpha_i} = q_i(t) - \pi_i,$$

$$\frac{\partial \ln p(y_t)}{\partial \mu_i} = q_i(t)\Sigma_i^{-1}(y_t - \mu_i),$$

$$\frac{\partial \ln p(y_t)}{\partial \Sigma_i^{-1}} = q_i(t)\frac{\Sigma_i - diag\left((y_t - \mu_i)^2\right)}{2},$$

$$\frac{\partial \ln p(y_t, s_t)}{\partial \alpha_{ji}} = q_i(t)(r_{ji}(t) - \lambda_{ji}),$$

$$\frac{\partial \ln p(y_t, s_t)}{\partial \delta_{ji}} = q_i(t) r_{ji}(t) \mathrm{Z}_{ji}^{-1}(u_t - \delta_{ji}),$$

$$\frac{\partial \ln p(y_t, s_t)}{\partial \mathrm{Z}_{ji}^{-1}} = q_i(t) r_{ji}(t)\frac{\mathrm{Z}_{ji} - diag\left((u_t - \delta_{ji})^2\right)}{2}.$$

$u_t = \{x_t, y_t, \gamma_t, \delta_t, \tau_t\}$

Position

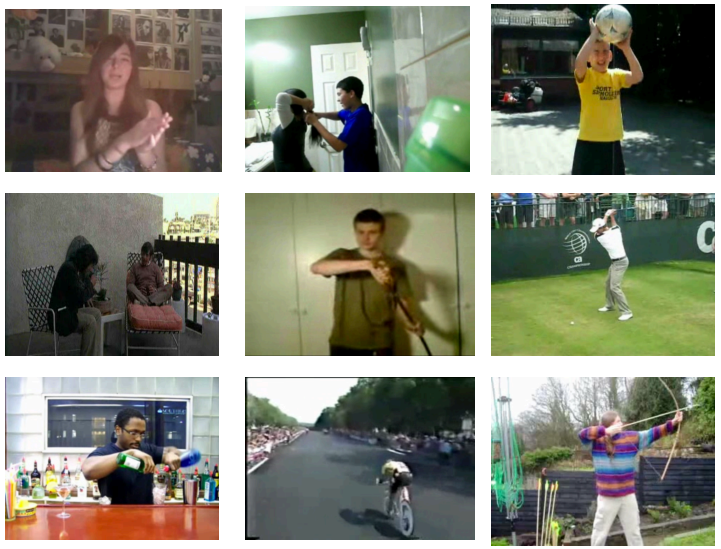
Scale information

Outline

Results on Standard Datasets

Datasets

- Hollywood-2 score: mAP
- HMDB51 score: accuracy



Experiment Setup

- Use improve Dense Trajectory (iDT) as feature extraction and description method.
- K of GMM is set as 256 for fair comparison with state-of-the-art results.
- Linear Support Vector Machine is employed

Results on Standard Datasets

- **Parameter *J* for Scale FV, STFV and CombFV**

Methods	*J*	Hollywood-2	HMDB51
STFV [14]	1	65.92%	60.39%
	2	65.92%	60.35%
	3	66.52%	61.07%
	4	65.69%	60.61%
	5	65.80%	60.96%
ScaleFV	1	64.69%	58.36%
	2	64.84%	58.65%
	3	64.79%	58.61%
	4	64.61%	58.41%
	5	64.65%	57.87%
CombFV	1	66.28%	60.41%
	2	66.29%	60.50%
	3	66.48%	60.41%
	4	66.53%	60.28%
	5	66.50%	60.56%
STFV+CombFV	-	66.72%	**61.50%**
STFV+CombFV+ScaleFV	-	**66.96%**	61.07%

Impact of parameter J on Hollywood-2 and HMDB51 for different methods

Results on Standard Datasets

- **Comparison with state-of-the-art results**

	Hollywood-2	HMDB51
Jain *et al.* [18]	62.5%	52.1%
Oneata *et al.* [14]	63.3%	54.8%
Wang *et al.* [12]	64.3%	57.2%
Wu *et al.* [19]	64.5%	-
Simonyan *et al.* [20]	-	59.4%
STFV+CombFV	66.72%	**61.50%**
STFV+CombFV+ScaleFV	**66.96%**	61.07%

Comparison with state-of-the-art performance on Hollywood-2 and HMDB51

Thank you!

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http://zbwglory.github.io