Poster Spotlights

Session: Object Recognition IV, Wed 16 June 2010, 3:40 - 5:20 pm

Dominant Orientation Templates for Real-Time Detection of Texture-Less Objects

S.Hinterstoisser, V.Lepetit, S.Ilic, P.Fua, N. Navab
Dominant Orientation Templates for Real-Time Detection of Texture-Less Objects

**PROBLEM**
How can we efficiently learn and estimate the 3D pose of a texture-less 3D object in real-time?

**PROPOSED SOLUTION**
- Use gradient orientation templates for robustness
- Scan the whole image instead of using feature points
  - Introduce fast to evaluate template score (using bit operations with SSE instructions)
  - That allows invariance to small deformations/translations and clustering for fast template evaluation

**RESULTS**
- Very fast and efficient template matching approach (e.g. 80fps for 250 templates)
- Very robust and reliable recognition
- Online learning capable

VISIT OUR DEMO!
Poster Spotlights

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The Multiscale Competitive Code via Sparse Representation for Palmprint Verification

Wangmeng Zuo (Harbin Institute of Technology), Zhouchen Lin (Microsoft Research Asia), Zhenhua Guo, David Zhang (The Hong Kong Polytechnic Univ)
The Multiscale Competitive Code via Sparse Representation for Palmprint Verification

- Palmprint Verification
  - One relatively novel and promising biometric technology
  - Multiscale discriminative feature: principal lines, wrinkles

- Multiscale Competitive Code via Sparse Representation
  - Robust estimation of orientation via sparse coding
  - Compact representation of multiscale feature

- High Verification Performance
  - Lower error rate
  - Small template size
  - Fast matching speed
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Learning a Probabilistic Model Mixing 3D and 2D Primitives for View Invariant Object Recognition

Wenze Hu and Song-Chun Zhu
Learning a Probabilistic Model Mixing 3D and 2D Primitives for View Invariant Object Recognition
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Dense Interest Points
Tinne Tuytelaars
Dense Interest Points

- Repeatability
- Invariance

Dense Sampling
- Good coverage
- Constant nb of features
Two Perceptually Motivated Strategies for Shape Classification

Andrew Temlyakov, Brent C. Munsell, Jarrell W. Waggoner, Song Wang
Two Perceptually Motivated Strategies for Shape Classification

<table>
<thead>
<tr>
<th></th>
<th>IDSC</th>
<th>Shape-Tree</th>
<th>Our Method + IDSC</th>
<th>Contour Flexibility</th>
<th>IDSC + LCDP</th>
<th>IDSC + LCDP + Unsuperv. GP</th>
<th>Our Method + IDSC + LCDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiments</td>
<td>85.40%</td>
<td>87.70%</td>
<td>88.39%</td>
<td>89.31%</td>
<td>92.36%</td>
<td>93.32%</td>
<td>95.60%</td>
</tr>
</tbody>
</table>

MPEG-7 Dataset
Large-scale image categorization with explicit data embedding
F. Perronnin, J. Sanchez and Y. Liu
The state-of-the-art in image categorization: BOV + SVM

Classification accuracy vs computational cost:
- linear SVMs: efficient to train and evaluate but perform poorly on the BOV
- non-linear SVMs: yield a higher accuracy but are slow to train and evaluate

How to get the advantages of linear and non-linear?
- perform explicit (approximate) embedding
- learn linear classifiers in the new space

Contribution: explore different strategies for explicit embedding of BOV
- sqrt(BOV) already leads to very significant improvement
- embedding additive kernels brings additional improvement at affordable cost
- we can go beyond additive kernels but at a much higher cost
Probabilistic Models for Supervised Dictionary Learning

Xiao-Chen Lian¹, Zhiwei Li²,³, Changhu Wang³, Bao-Liang Lu¹,², Lei Zhang³

¹Department of Computer Science and Engineering, Shanghai Jiao Tong University, China
²MOE-MS Key Lab for Intelligent Computing and Intelligent Systems, Shanghai Jiao Tong University, China
³Microsoft Research Asia
1. Dictionary for Classification
- Compactness
- Reconstruction
- Discrimination
- Spatial information

2. Probabilistic Model

3. Experimental Results (partial)

<table>
<thead>
<tr>
<th>Scene 15</th>
<th>L=0</th>
<th>L=0+1</th>
<th>L=0+1+2</th>
</tr>
</thead>
<tbody>
<tr>
<td>k-means+SVM</td>
<td>0.722</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SDLM+SVM</td>
<td>0.7687</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$S^2$DLM+SVM</td>
<td>0.7845</td>
<td></td>
<td></td>
</tr>
<tr>
<td>k-means+SPM+SVM</td>
<td>0.7220</td>
<td>0.7900</td>
<td>0.8110</td>
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<tr>
<td>SDLM+SPM+SVM</td>
<td>0.7687</td>
<td>0.8156</td>
<td>0.8227</td>
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<tr>
<td>$S^2$DLM+SPM+SVM</td>
<td>0.7845</td>
<td>0.8189</td>
<td>0.8276</td>
</tr>
</tbody>
</table>
Use Bin-Ratio Information for Category and Scene Classification

Nianhua Xie, Haibin Ling, Weiming Hu, Xiaoqin Zhang
Use Bin-Ratio Information for Category and Scene Classification

Motivations
- partial matching
- co-occurrence information
- histogram normalization

⇒ Ratios between histogram bins

Bin-Ratio Dissimilarity (BRD)

Ratio Matrix $H$ of a histogram $h$

$$H = \left( \frac{h_j}{h_i} \right)_{i,j} = \begin{pmatrix} h_1 & h_2 & h_3 & \cdots & h_n \\ h_1 & h_2 & h_3 & \cdots & h_n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_1 & h_2 & h_3 & \cdots & h_n \\ \end{pmatrix}$$

BRD b/w histograms $p$ and $q$:

$$d_{br}(p,q) = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{(q_j - p_j)^2}{1 + \frac{1}{q_j p_i}}$$

$$\approx n - \|p + q\|^2 \sum_{i=1}^{n} \frac{p_i q_i}{(p_i + q_i)^2}$$

Combination with traditional distance measure ⇒ $L_1$-BRD:

$$d_{l_{br}}(p,q) = \sum_{i=1}^{n} d_{l_{br},i}(p,q) = \|p - q\|_1 - \|p + q\|_2^2 \sum_{i=1}^{n} \frac{|p_i - q_i|}{(p_i + q_i)^2}$$

Experiments

15 Scenes

PASCAL 2008

17 Oxford Flowers

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nilsback &amp; Zisserman 06</td>
<td>71.76±1.76</td>
</tr>
<tr>
<td>Varma &amp; Ray 07</td>
<td>82.55±0.34</td>
</tr>
<tr>
<td>Nilsback &amp; Zisserman 08</td>
<td>88.33±0.3</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>87.45±1.13</td>
</tr>
<tr>
<td>$L_1$-BRD</td>
<td>89.02±0.60</td>
</tr>
<tr>
<td>$\chi^2$ (Zhang et al 07)</td>
<td>74.1</td>
</tr>
<tr>
<td>EMD (Zhang et al 07)</td>
<td>74.3</td>
</tr>
<tr>
<td>PDK (Ling &amp; Soatto 07)</td>
<td>74.5</td>
</tr>
<tr>
<td>$L_1$-BRD</td>
<td>76.7</td>
</tr>
</tbody>
</table>

$L_1$-BRD performs best in 11 out of 20 classes.
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The Role of Features, Algorithms and Data in Visual Recognition

Devi Parikh (TTIC) & Larry Zitnick (MSR)
The Role of Features, Algorithms and Data in Visual Recognition

Human studies

<table>
<thead>
<tr>
<th>Category 1</th>
<th>Category 2</th>
<th>Category 3</th>
<th>Category 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="category_1.png" alt="Image" /></td>
<td><img src="category_2.png" alt="Image" /></td>
<td><img src="category_3.png" alt="Image" /></td>
<td><img src="category_4.png" alt="Image" /></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Category 5</th>
<th>Category 6</th>
<th>Category 7</th>
<th>Category 8</th>
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<tbody>
<tr>
<td><img src="category_5.png" alt="Image" /></td>
<td><img src="category_6.png" alt="Image" /></td>
<td><img src="category_7.png" alt="Image" /></td>
<td><img src="category_8.png" alt="Image" /></td>
</tr>
</tbody>
</table>
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Global Gaussian Approach for Scene Categorization Using Information Geometry

Hideki Nakayama, Tatsuya Harada, and Yasuo Kuniyoshi
The University of Tokyo, JAPAN
Question: Given local features of images (e.g. SIFT, SURF,...), how can we efficiently use them for image categorization?

Our approach: **Sample-specific Gaussian** for representing a distribution of local features.

**Highlights**

1. Our method ≈ BoW < Hybrid
2. Scalable linear approximation based on *Information Geometry* framework
Asymmetric Region-to-Image Matching for Comparing Images with Generic Object Categories

Jaechul Kim and Kristen Grauman
Overview

Asymmetric Region-to-Image Matching for Comparing Images with Generic Object Categories

Jaechul Kim and Kristen Grauman

**Input:** One is segmented, the other is not.

**Region-to-image match:** Fast DP formulation

**Output:** Match score and correspondences

Contributions

- **Asymmetric way** of using segmentation for non-parametric geometric constraint.
- **1~2 orders of magnitude more efficient** dense matching: 1D string representation.
- **10-20% better accuracy in object category recognition** than existing matching algorithms.

Experiments

Exemplar-based nearest neighbor match for object category recognition
Attribute-Centric Recognition for Cross-Category Generalization

Ali Farhadi     Ian Endres
Derek Hoiem
University of Illinois at Urbana-Champaign
Attribute-Centric Recognition for Cross-Category Generalization

Object Models

Basic Categories
Cow, Cat, Dog, …

Parts
Head, Leg

Broad Categories
Four-legged, water animal, Mammal, …

Other Attributes
Facing right, lying down, can bite, is herbivorous

Find and Describe familiar objects.

Find and Describe related unfamiliar objects.
Person Re-Identification by Symmetry-Driven Accumulation of Local Features

M. Farenzena, L. Bazzani, A. Perina, V. Murino, M. Cristani
Person Re-Identification by Symmetry-Driven Accumulation of Local Features (SDALF)

- **Person Re-Identification**: recognizing an individual in diverse locations over different non-overlapping camera views

- Extraction of features inside salient parts selected by the principal *axes of symmetry and asymmetry* of the human body

- We accumulate the features from one or more images into a unique signature

Comparisons with the state-of-the-art