Poster Spotlights

Session: Object Recognition III: Similar Shapes
Wed 16 June 2010, 10:30-12:10 am

Object Matching with A Locally Affine-Invariant Constraint

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In feature matching tasks, geometric inconsistency between corresponding points in two feature point sets need to be penalized.

Key idea: each point can be exactly reconstructed by an affine combination of its neighbors.

This reconstruction is affine invariant.

How to define the geometric cost?

$W_1 + W_2 + W_3 = 1$
Unsupervised Learning of Invariant Features Using Video

David Stavens, Sebastian Thrun
Unsupervised Learning of Invariant Features Using Video

Track patches over time in video…

…generating sets of different views of the same environment location.

From patch sets: learn application-specific feature invariance from data.

Improves performance compared to SIFT and HOG baseline.
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Scale-Hierarchical 3D Object Recognition in Cluttered Scenes

Prabin Bariya and Ko Nishino
Scale variation of local geometric structures

Constraints to cull the space of correspondences

Recognition Results
Linked Edges as Stable Region Boundaries

Michael Donoser, Hayko Riemenschneider and Horst Bischof
- Unsupervised edge detection
- Region support of local gradients
- Returns automatically linked edge lists

Canny Edge Detection

Our method
Many-to-one Contour Matching for Describing and Discriminating Object Shape

Praveen Srinivasan, Qihui Zhu, Jianbo Shi (UPenn)
Many-to-One Contour Matching for Describing and Discriminating Object Shape

Learn shape model from image contours of “lucky” examples:
Examples

“Lucky” back

“Lucky” leg

“Lucky” back + neck

Learned shape from image contours

Our contour shape learning on ETHZ dataset

vs. learning from image gradients:

Lee, Grauman: “Shape Discovery from Unlabeled Image Collections” CVPR 2009

Detections on ETHZ using learned shapes

Latent SVM + large scale shape features on contours

Latent SVM + HOG feature

Giraffe

Mug

Swan
Multi-View Object Class Detection with a 3D Geometric Model

Joerg Liebelt (EADS), Cordelia Schmid (INRIA)
We propose an approach to multi-view object class detection:
• regular grid of object parts,
• part appearance learnt discriminatively from real 2D training images,
• 3D geometry learnt generatively from synthetic CAD models,
• approximate 3D pose estimation.

Main advantages:
• separate training procedures for appearance and geometry,
• no 3D estimation during training required,
• evaluates consistency of 2D part detections with a full 3D model.

We test on 3D Object Category Datasets CAR and BICYCLE.
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Fast Directional Chamfer Matching

Ming-Yu Liu, Oncel Tuzel, Ashok Veeraraghavan and Rama Chellappa
We present a novel approach for **improving the accuracy** of Chamfer matching while reducing its computational complexity from **linear to sublinear**.

Directionally enhanced Chamfer matching cost reduces error rates up to **70%**.

Sublinear time matching algorithm improves speed of traditional methods up to **40x**.

The proposed algorithm is competitive with the state-of-the-art and evaluates up to **2.5 million** hypotheses per second.
Scale-invariant heat kernel signatures for non-rigid shape recognition
Michael Bronstein, Iasonas Kokkinos
Scale-invariant heat kernel signatures

Heat kernel signature (HKS)

\[ HKS(x, t) = (K_{t_1}(x, x), ..., K_{t_n}(x, x)) \]

Scaling effect: not invariant

\[ HKS_{\alpha X}(x, t) = \alpha^2 HKS_X(x, \alpha^2 t) \]

Scale-invariant HKS

**Log scale-space**

\[ \tau = \log_\alpha t \]

\[ K_{\alpha^\tau} \xrightarrow{\text{scaling}} \alpha^2 K_{\alpha^{\tau+2}} \]

**log + d/d\tau**

\[ \log \alpha^2 + \log K_{\alpha^{\tau+2}} \]

\[ \frac{d}{d\tau} \log K_{\alpha^{\tau+2}} \]

**FFT magnitude**

\[ \mathcal{F} \left\{ \frac{d}{d\tau} \log K_{\alpha^{\tau+2}} \right\} = e^{i2\omega} \mathcal{F} \left\{ \frac{d}{d\tau} \log K_{\alpha^{\tau}} \right\} \]

**Feature descriptor**

**Geometric words**

**Bag of features**

Scale 0.7

Heat Kernel Signature

Scale-Invariant Heat Kernel Signature
Object Recognition as Ranking
Holistic Figure-Ground Hypotheses

Fuxin Li*, Joao Carreira*, Cristian Sminchisescu
(first two authors contributed equally)
Object Recognition as Ranking Holistic Figure-Ground Hypotheses

Object Recognition from multiple figure-ground segment hypotheses

Generate multiple object segment hypotheses

Rank object hypotheses using mid-level cues (class independent scoring)

Predict overlap estimate of each segment to specific object class (1 predictor/class)

Sort segments by maximal score.
Aggregates high-rank segments with large spatial overlap.
Choose confident aggregations as final segmentation result.

Detection and recognition in a segmentation framework!

Top scoring results 82.3% in Caltech-101
in hard benchmarks: 37.2% in VOC 2009 Segmentation Challenge

Our semantic segmentations align well with boundaries of objects
Finding Nemo: Deformable Object Class Modelling using Curve Matching

Mukta Prasad, Andrew Fitzgibbon, Andrew Zisserman and Luc Van Gool
Finding Nemo: Deformable Object Class Modelling using Curve Matching

Joint, analytic bundle-adjustment to recover correspondences, cameras and a smooth, deformable shape model.

- Distinct class instances
- Unordered images
- Curve-based correspondences
- Class-based priors and topology
- Occlusion
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Automatic Attribution of Ancient Roman Imperial Coins
Ognjen Arandjelović
High-level problem: learn classes of Roman Imperial Coins

Specific challenge: learn over local feature appearance & their geometric relationship

"Appearance context" features
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Multiple Object Detection by Sequential Monte Carlo and Hierarchical Detection Network

M. Sofka, J. Zhang, K. Zhou, and D. Comaniciu
(Siemens Corporate Research)
Multiple Object Detection by Sequential Monte Carlo and Hierarchical Detection Network

Sequential object detection

\[ \theta_t \] State (pose) of the object
\[ V_t \] Set of observations

Approximate posterior \( f(\theta_{0:t} \mid V_{0:t}) \) by sampling

\[
P(\theta_{0:t} \mid V_{0:t})
\]

Observation

\[ f(V_t \mid \theta_t) = f(y_t = +1 \mid \theta_t \mid V_t) \]

Transition

\[ f(\theta_t \mid \theta_{0:t-1}) = f(\theta_t \mid \theta_j) \]

\( j \in \{0, 1, \ldots, t-1\} \), select automatically

\[
\begin{align*}
&\text{Transventr. plane} \\
&\text{LV 2mm} \rightarrow \text{LV 1mm} \\
&\text{CER 4mm} \rightarrow \text{CER 2mm} \rightarrow \text{CER 1mm} \\
&\text{Transcerebellar plane} \\
&\text{CM 1mm}
\end{align*}
\]
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Putting Local Features on a Manifold

Marwan Torki and Ahmed Elgammal
Putting Local Features on a Manifold

Motivation:
1) Local features are important for recognition.
2) Manifold Learning is a very powerful tool.
3) Previous work on Manifold learning uses wholistic image representation, or assumes full correspondences between features.

Contributions:
1) An approach to learn a smooth image manifold from local features (preserving feature similarity and spatial structure) without the need to establish correspondences.
2) A solution for out-of-sample to embed features from a new image.
3) Application to object categorization and localization.