Predicating What and Where in Social Media Images



San Diego State University

Xiaobai Liu,

Assistant Professor Computer Vision Laboratory Department of Computer Science San Diego State University (SDSU)

Email: <u>xiaobai.liu@mail.sdsu.edu</u>

Computer Vision: What and Where



Computer Vision: What and Where



HTTP:// CV.SDSU.EDU

Liu Xiaobai, PhD

Assistant Professor, Department of Computer Science, San Diego State University, SD, 92182

Office: GMCS 542 Campus-Phone: 619-5944345 EMail: xiaobai Dot liu AT mail DOT sdsu DOT edu

News

July 22, 2016: Our paper on large-scale optimization will appear in the Journal TKDE (IF: 2.067).

July 10, 2016: Our paper on video coding will appear in the Journal FGCS (IF: 2.054).

June 25, 2016: I will chair the session: Maching Learning 8- Data Mining in UCAI'2016. Welcome to Attend!

June 22, 2016: Our paper on Visual Vehicle-to-Vehicle (V3I) was accepted as Oral Presentation by ACM MM'2016

Apr. 10, 2016: Our paper on Hierarchical LSTM model for Scene Parsing was accepted by UCAI'2016.

Apr. 10, 2016: Our paper on Mobile Landmark Search was accepted by UCAI'2016.

Apr. 10, 2016: Our paper on Single-view 3D Scene Reconstruction was accepted by UCAI'2016.

Feb. 29, 2016: Our Paper on Multi-view Human Tracking was accepted by IEEE CVPR'2016!

Feb. 24, 2016: Received the SDSU GREW Fellowship Spring 2016.

Feb. 1, 2016: I will chair the sessions of VIS: Pose Estimation and ML: Deep Learning I in AAAI' 2016. Welcome to Attend!

Jan. 10, 2016: Our Proposal to the SDSU Undergraduate Research Program has been awarded. Congradulations to Jacob Thalman!

Jan. 7, 2016: Received a donation of GPU K40 from the NVIDA Inc. Thanks NVIDA!

Dec. 1, 2015: Our paper on Attributed Grammar was accepted by AAAI' 2016.

Biography

I am working as Assistant Professor of Computer Science at the San Diego State University (SDSU). I am also affiliated with the Center for Vision, Cognition, Learning and Autonomy (VCLA), University of Californiat, Los Angeles (UCLA). In prior to joining SDSU, I worked as a Postdoctoral Research Scholar at the University of California, Los Angeles (UCLA) with Professor Song-Chun Zhu (from July 2013 to August 2015) and Professor Alan L. Yuille (from June 2011 to July 2013). I received my PhD degree from the Huazhong University of Science and Technology (HUST) in November, 2012. I was a visiting Doctoral Student at the National University of Singapore (NUS), Singapore, working Professor Shuicheng Yan from 2008-2011.

Computer Vision & Machine Learning

Outline of this Talk

Part –I: 2D reconstruction (What)

(weakly supervised image parsing)

- Label-to-Region
- Label-to-region by search
- Image Label Competition
- Tree-structure sparsity

Part-II: 3D reconstruction (Where)

- Single-image Reconstruction (demo 1-3)
- > 3D Human tracking (demo 4-6)

Nominated as one of two **Best Paper Candidates** in Content Track

I. Label to Region by Bi-Layer Sparsity Priors

• X. Liu, B. Cheng, S. Yan, T. Chua, J. Tang and H. Jin., Label to Region by Bi-Layer Sparsity Priors. Proc. ACM Conference on Multimedia (MM, Full Paper), 2009

Online Photos

Photo-sharing websites

- ✓ Twitter
- ✓ Flickr
- Facebook
- ✓ eBay
- ✓ …
- Potentials
 - Content-based image retrieval
 - > Visual Recommendation
 - Dr.Tsou's homepage

Task: Label to Region

Label to Region for a single Image is Challenging!

Task: Label to Region

Simultaneous Region Partition and Labeling in Batch Mode

Related Work

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Supervised Learning Techniques

[C.Galleguillos et al., 2008][Jeon et al., 2003][Kang et al., 2006][Zhang et al., 2007]

Label-to-Region is valuable in Computer Vision community.

Label to Region: Our Approach

sky, road, aeroplane

sky, grass, tree, aeroplane

Solution: for each pair of images, assign shared labels, if any, to shared regions!

Cross-Image Correspondence

Label to Region: Correspondence

Step-I: Over-Segmentation

Label to Region: Our Approach

Step-2: cross-image correspondence

Using Coefficients as Relevance

Criteria:

- Select as few patches as possible;
- Select patches from as few images as possible:

 $\arg\min_{\alpha,\epsilon,\gamma} |\alpha||_1 + ||\epsilon||_1 + |\gamma||_2 \quad s.t. \quad y = A\alpha + \epsilon, \ \gamma = B\alpha$

Bi-Layer Sparse Representation

Label to Region: correspondence

Label to Region: Our Approach

Step 1: Initialization

• Over-segmentation

Step 2: Select one of the input images as reference image

- Step 2.1: recover cross-image correspondence: bi-layer sparse representation
- Step 2.2: bi-directional label propagation

Step 3: Post-Processing

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• Derive semantic regions and associated labels.

Label to Region: Results

MSRC dataset

Label to Region: Accuracies

Dataset	SVM-I	SVM-2	SVM-3	SVM-4	One-Layer	Bi-Lay	yer
MSRC	0.22	0.20	0.24	0.23	0.47	0.63	0.81
COREL	0.29	0.32	0.33	0.32	0.51	0.61	0.76

The SVM-based algorithm is implemented with different values for the parameter of maximal patch size, namely, SVM-1: 150 pixels, SVM-2: 200 pixels, SVM-3: 400 pixels, and SVM-4: 600 pixels.

Contributions

- Label-to-Region task
- Label propagation
- Bi-Layer sparsity Model

Limitations

- Can only handle labels corresponds with local region, e.g., road;
- Process a set of images at the same time;
- Cannot handle partially annotated images or noisy tags;

II. Image Label Completion

Partially annotations or noisy labels

Label Completion via Nonnegative Decomposition

$$\label{eq:constraint} \begin{split} \min_{W,Y} \ \alpha Tr(WBW^T) + \beta Tr(CYLY^TC^T) + \gamma ||\tilde{Z}_0 \circ (CY)||^2 + ||X-WY||^2, \\ s.t. \ W, Y \geq 0, \end{split}$$

X. Liu, et al. IEEE Transactions on Image Processing, 2010

III. Label-to-region by Search

[Liu et al. IEEE CVPR'2010]

IV. Tree Structure Sparsity

Bi-Layer Sparse representation

[X. Liu, ACM Transaction on MCCAP 2012]

IV. Tree Structure Sparsity

From Bi-Layer to Tree Structure

[X. Liu, ACM Transaction MCCAP 2012]

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[Liu et al. CVPR'2014], [Liu et al.AAAI'2016], [Liu IJCAI'2016]

Failure Cases: foreground objects

Synthesized Views

Demo 2: Scene Construction from Monocular Video (captured by a mobile phone camera)

Input video sequence

Families of Parallel lines

Layout Recovered

Recovered 3[[]

Notations	R1: layout	R3: affinity
R2: siding	R₄: mesh	Rs: terminal

b

Demo 3: Scene Construction from Monocular Video

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Demo 4: Geo-Localization of moving persons (Indoor)

Liu et al.AAAI'2016

Demo 5: Geo-Localization of moving persons (outdoor)

3D Trajectories

Demo 6: Multiple-View Multiple Person Tracking

Summary of this talk

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Question & Answer