Local Regularity-driven City-scale Facade Detection from Aerial Images

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Acknowledgments

- NSF grant IIS-1248076
- NSF grant IIS-1144938
- Data provided by Google
The problem

- Unsupervised detection
- 200+ facades per image
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- 200+ facades per image
Motivation

- Huge amount of multi-modal, multi-dimensional data
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Existing work only extracts a handful of facades from street-views
Single-view facade detection helps matching / SfM
Broad applications (geo-coding, SLAM, scene understanding)
Overview – Edge based Regularity Analysis
Overview – Edge based Regularity Analysis
Overview – Edge based Regularity Analysis

- Facade region has higher regularity
- Edge images are sufficient to capture such regularities
Facade region has higher regularity

Edge images are sufficient to capture such regularities
Determine the vertical and horizontal facade orientation

- Vertical orientation known from vanishing point
Overview – Edge based Regularity Analysis

Determine the vertical and horizontal facade orientation

- Vertical orientation known from vanishing point
- Horizontal orientation to be detected
Overview – Edge-based Regularity Analysis

- Dense local regularity computation (facade likelihood)
- Dense dominant local horizontal orientation estimation
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- Group local regions with high regularity and consistent orientation
Overview – Edge-based Regularity Analysis

- Dense local regularity computation (facade likelihood)
- Dense dominant local horizontal orientation estimation
- Group local regions with high regularity and consistent orientation
• Vertical Edge alignment regularity
• Vertical Edge distance regularity
Vertical Edge Alignment Regularity

Facade regions → Sparse distribution

Non-facade regions
Desirable attributes of sparsity measurement

- **Robin Hood** – stealing from rich giving to poor **DECREASES** sparsity

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1 Hurley and Rickard, “Compare Measures of Sparsity”, 2008
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- **Scaling** and **Cloning** invariant

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Distribution Sparsity (Inequality, Dispersion, Variability)

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Gini = \(1 - 2 \sum_{k=1}^{N} \frac{c(k)}{|c|_1} \left( \frac{N-k+0.5}{N} \right)\), where \(c(1) \leq c(2) \leq \ldots \leq c(N)\)

\[Gini = 0.09\]  \[Gini = 0.25\]  \[Gini = 0.53\]  \[Gini = 0.78\]

\(^1\) Hurley and Rickard, “Compare Measures of Sparsity”, 2008
Extract vertical distances between edges
Vertical Edge-distance Regularity

- Extract vertical distances between edges
Vertical Edge-distance Regularity

- Extract vertical distances between edges
- High responses to parallel elements
Facade Likelihood

- Naive Bayes assumption

\[ P(f_1, f_2 \ldots, | x = \text{Facade}) = \prod_i P(f_i | x = \text{Facade}) \]
Naive Bayes assumption

\[ P(f_1, f_2 \ldots, | x = Facade) = \prod_{i} P(f_i | x = Facade) \]
Gini score: 0.25
Discover the Horizontal Direction

Gini score: 0.15

Horizontal Orientation

Gini
Discover the Horizontal Direction

Gini score: 0.16

[Graph showing Gini score vs. horizontal orientation]

J. Liu and Y. Liu (PSU)
Discover the Horizontal Direction

Gini score: 0.43

Gini

Horizontal Orientation
Discover the Horizontal Direction

Gini score: 0.24

Gini

Horizontal Orientation
Discover the Horizontal Direction

Gini score: 0.22

Gini

Horizontal Orientation
Discover the Horizontal Direction

Gini score: 0.43

Gini

Horizontal Orientation
Facade Detection via Regional Expansion

\[ F^* = (X_{Min}, X_{Max}, Y_{Min}, Y_{Max}, \dot{\theta}_h, \dot{\theta}_v) = \arg \max_F \sum_{i=1}^{I} \sum_{j=1}^{J} s(x_{ij}, y_{ij}) \cdot a_{ij} \]
Facade Detection via Regional Expansion

$$\mathbf{F}^* = (X_{\text{Min}}, X_{\text{Max}}, Y_{\text{Min}}, Y_{\text{Max}}, \hat{\theta}_h, \hat{\theta}_v) = \arg \max_{\mathbf{F}} \sum_{i=1}^{I} \sum_{j=1}^{J} s(x_{ij}, y_{ij}) \cdot a_{ij}$$

$$\sum_{j} s(x_{ij}, y_{ij}) a_{ij} > \tau_r \cdot \max_k \left\{ \sum_{j} s(x_{kj}, y_{kj}) a_{kj} \right\}, \forall i = 1, \ldots, I$$

$$\sum_{i} s(x_{ij}, y_{ij}) a_{ij} > \tau_r \cdot \max_k \left\{ \sum_{i} s(x_{ik}, y_{ik}) a_{ik} \right\}, \forall j = 1, \ldots, J$$
- Multiple random initialization followed by iterative expansion to maximize local regularity
Multiple random initialization followed by iterative expansion to maximize local regularity

IQP to remove overlapping: \( \arg \max_x x'Mx, \quad x \in \{0, 1\}^n \)
Multiple random initialization followed by iterative expansion to maximize local regularity

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Experiments

- Images from NYC, Rome and SF
- 3000+ facades
Results and Comparisons

- Comparison against [Park, et al., ACCV10]
- Area based evaluation
Application: Cross-view Matching

- Matching facades with similar orientation
- Resolve relative depth ambiguity
- Frontal-view image patch matching with no rotation/scaling
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- Matching facades with similar orientation
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We have proposed and validated a novel and robust local regularity measure using Gini score on urban scenes.

Our algorithm detects and localizes facades in city-scale aerial images.

The output of our algorithm leads to feasible facade matching and alignment across views.
Efficient integral histogram [F. Porikli, CVPR05] for dense feature computation

- pre-compute $C_\theta(i,j)$ for all $\theta$
- $h_\theta(i,j) = C_\theta(i,j + k) - C_\theta(i,j)$