Cross-View Geo-Localization: Ground-to-Aerial Image Matching

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Geo-Localization

- Pixel-Wise Geo-Localization
  - Given a query image, geo-localize each pixel by aligning an image with the geodetically accurate reference image.

- Image-Based Geo-Localization
  - Given a query image, determine its GPS location by matching it with geo-tagged reference images.

Contents

- Pixel-Wise Geo-localization
  - Geodetic Alignment of Aerial Video Frames
- Image-Based Geo-Localization
  - Same View (Street-View to Street-View)
    - Generalized Maximum Clique (PAMI, 2014)
    - Constraint Dominant Sets (PAMI, 2017)
  - Cross-View Geo-Localization
    - Bird’s Eye-View to Street View (CVPR, 2017)
    - Aerial to Ground View (ICCV, 2019)

Geodetic Alignment of Aerial Video Frames

Y. Sheikh, S. Khan, M. Shah and R. Cannata

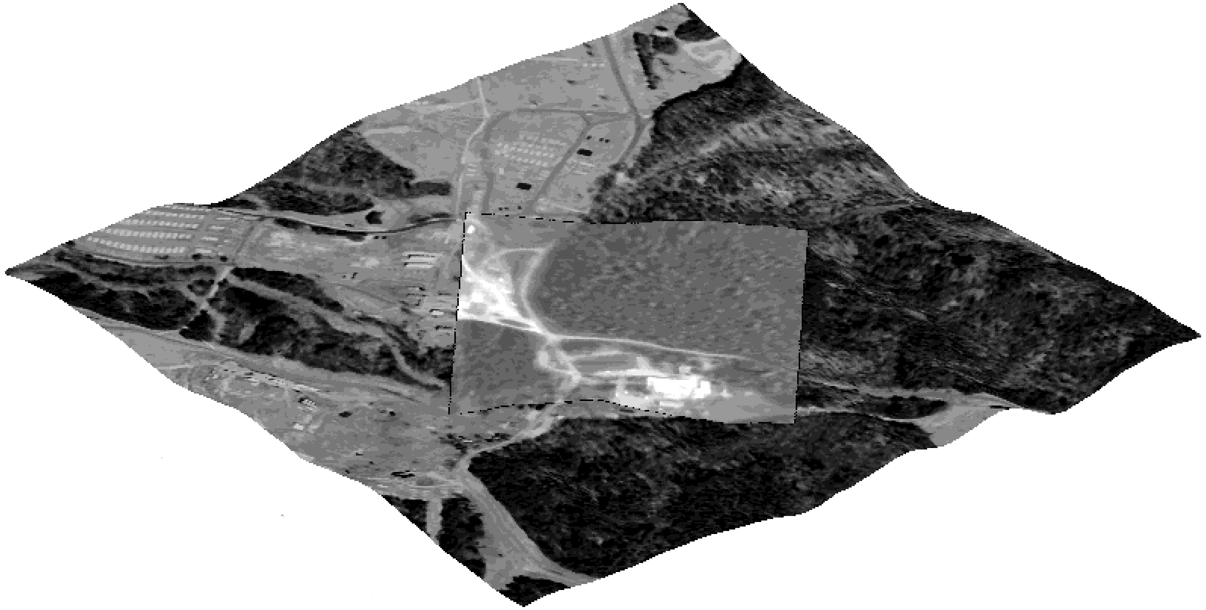
2003

Associate Professor
CMU/FaceBook

geoRegistration

Data Overview

- Aerial Video Data
- Reference Data
- Telemetry



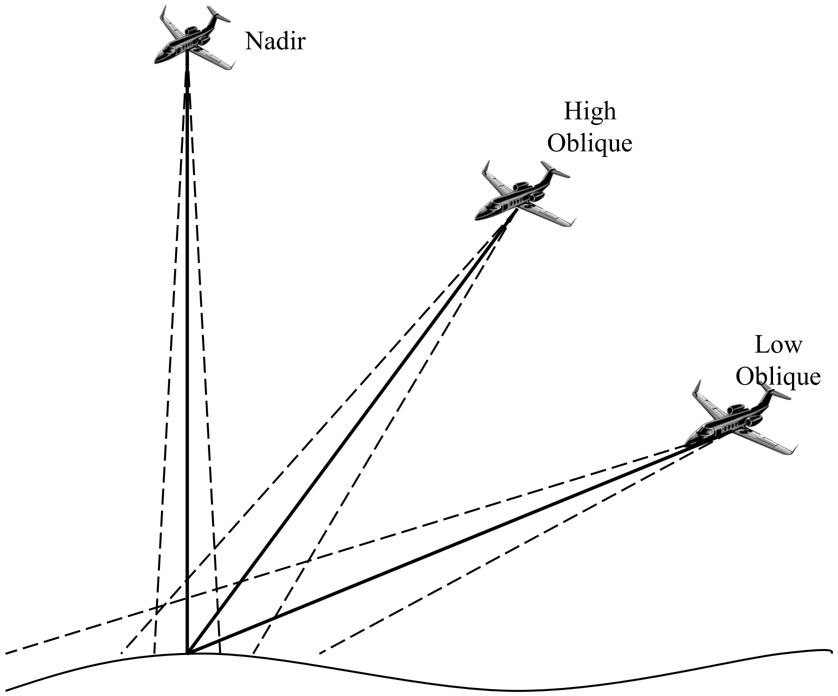
*geo*Registration

Different Viewpoints

Nadir

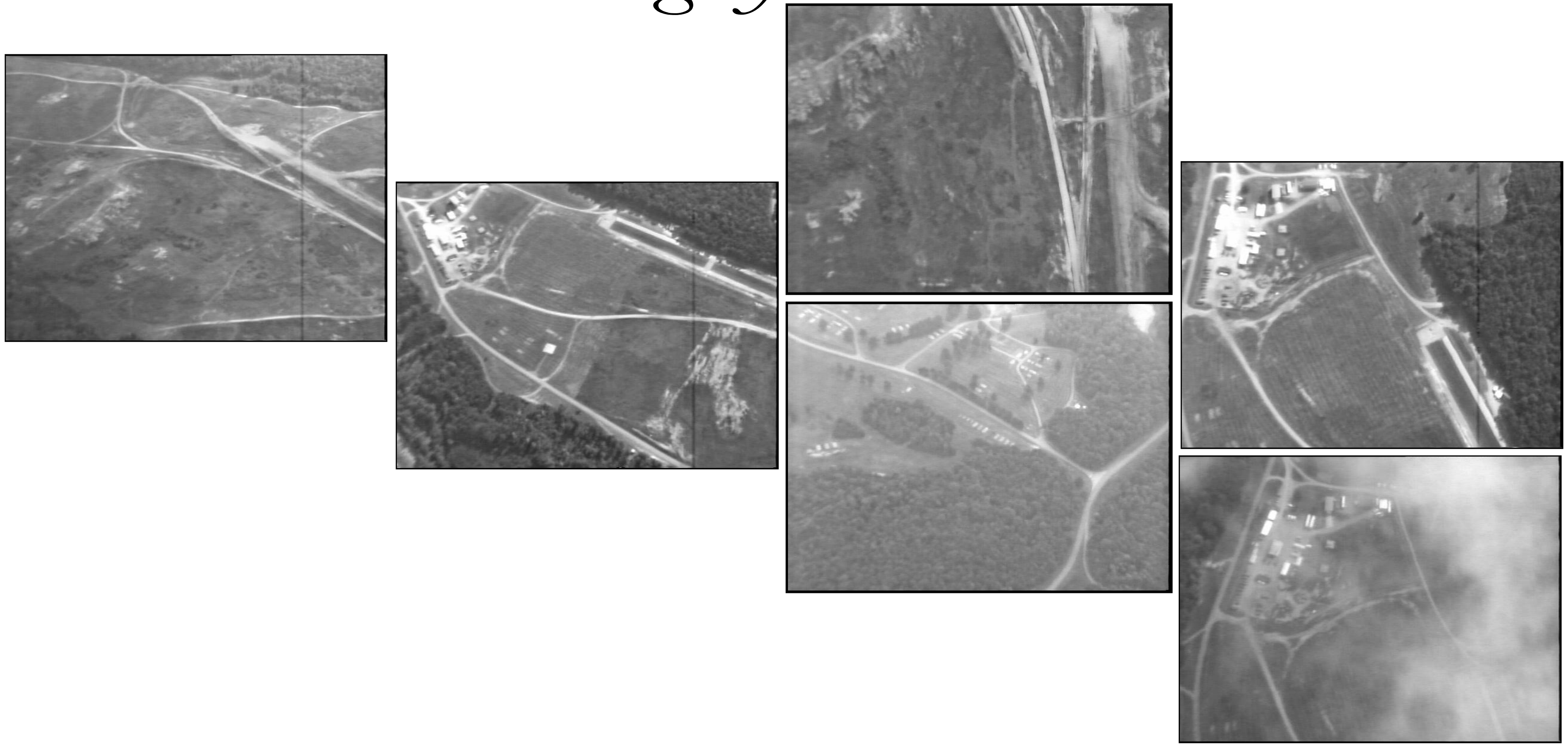
High Oblique

Low Oblique



geoRegistration

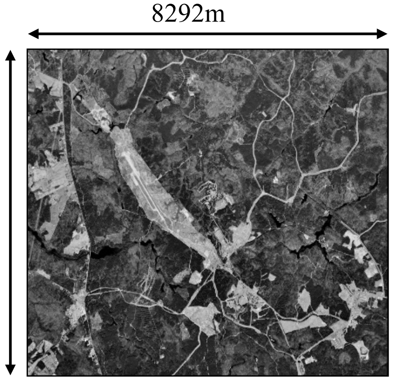
Aerial Video Imagery



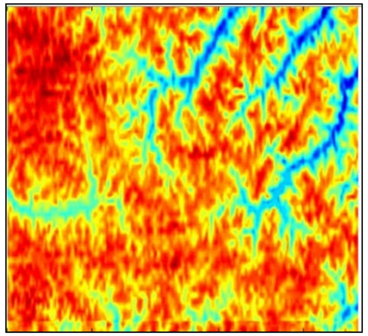
*geo*Registration

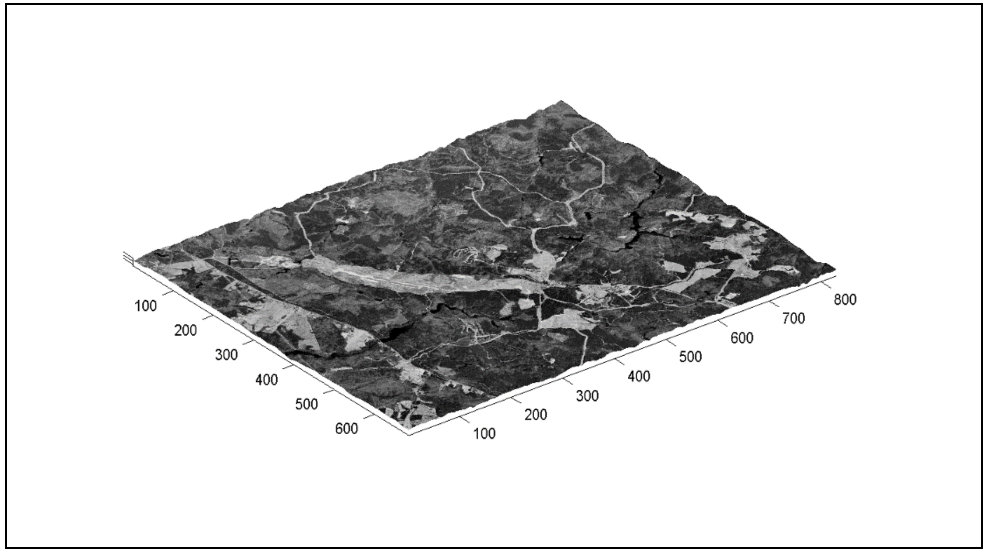
Reference Data

DOQ
(Digital Ortho Quad



DEM
(Digital Elevation Map)

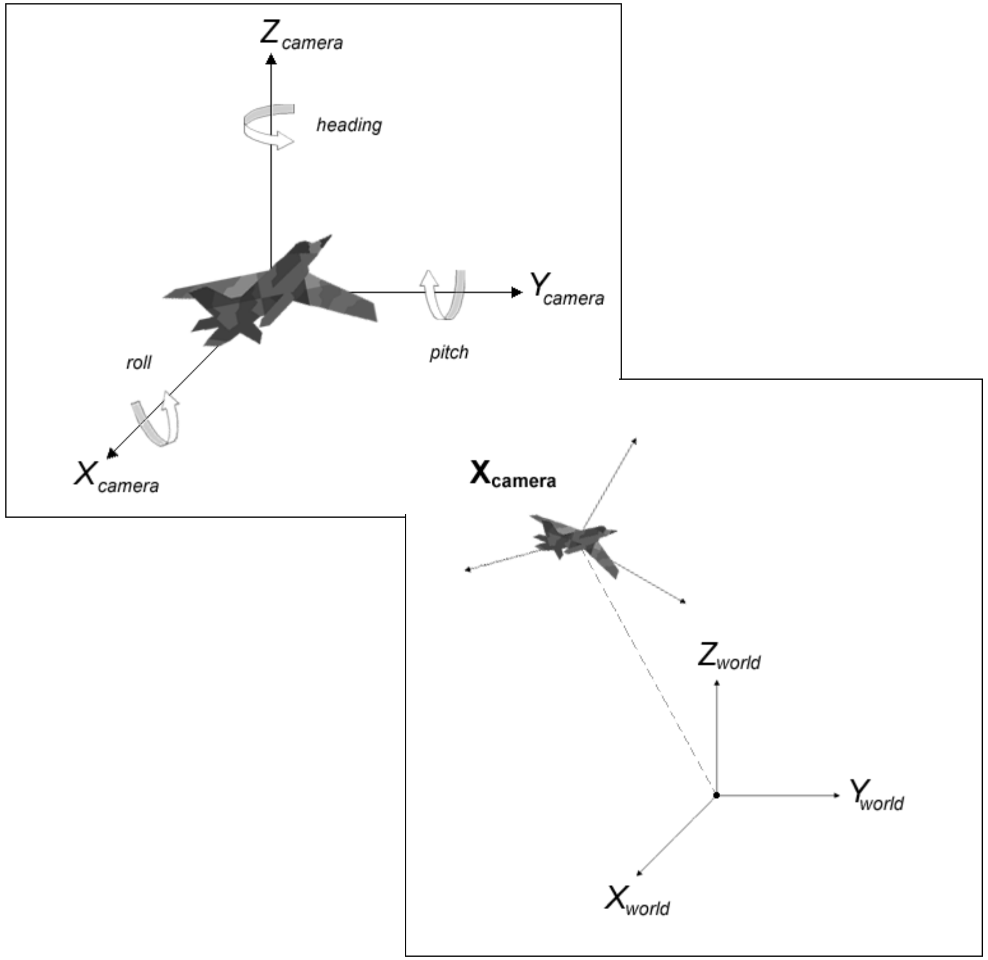




*geo*Registration

Telemetry Data

- Vehicle Longitude
- Vehicle Latitude
- Vehicle Height
- Vehicle Heading
- Vehicle Roll
- Vehicle Pitch
- Camera Elevation Angle
- Camera Scan Angle
- Camera Focal Length

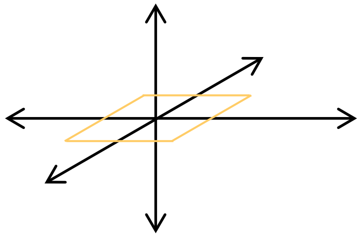


Sensor Model

$$\mathbf{X}_{\mathbf{camera}} = [X_{camera} \quad Y_{camera} \quad Z_{camera}]^{\mathrm{T}}$$

$$\mathbf{X}_{\mathbf{world}} = [X_{world} \quad Y_{world} \quad Z_{world}]^{\mathrm{T}}$$

$$\mathbf{X}_{\mathbf{camera}} = \Pi_t \mathbf{X}_{\mathbf{world}}$$



$\Pi_t = f$ (camera elevation, camera scan, vehicle pitch, vehicle roll, vehicle heading, vehicle elevation)

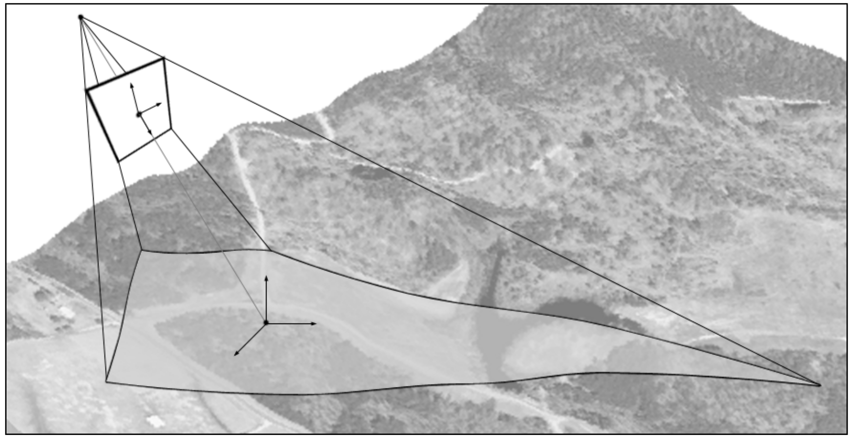
$$\Pi_t = \begin{bmatrix} \cos\omega & 0 & -\sin\omega & 0 \\ 0 & 1 & 0 & 0 \\ \sin\omega & 0 & \cos\omega & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\tau & \sin\tau & 0 & 0 \\ -\sin\tau & \cos\tau & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\phi & 0 & -\sin\phi & 0 \\ 0 & 1 & 0 & 0 \\ \sin\phi & 0 & \cos\phi & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\beta & \sin\beta & 0 \\ 0 & -\sin\beta & \cos\beta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\alpha & \sin\alpha & 0 & 0 \\ -\sin\alpha & \cos\alpha & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & \Delta T_x \\ 0 & 1 & 0 & \Delta T_y \\ 0 & 0 & 1 & \Delta T_z \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Sensor Model

$$\Pi_c = P\Pi_t$$

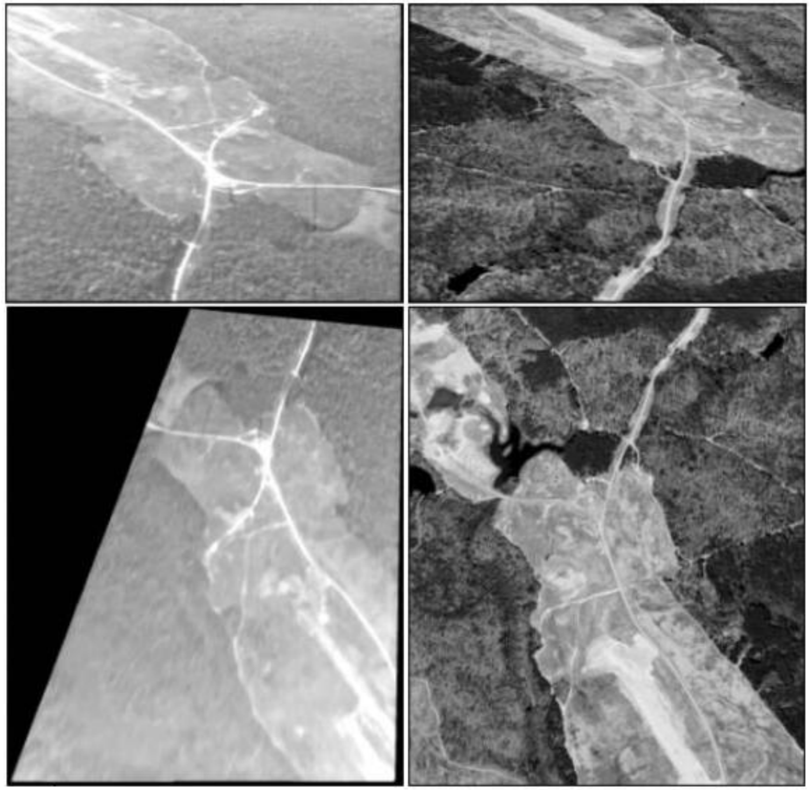
$$\Pi_c = PG_yG_zR_yR_xR_zT$$

$$\mathbf{x}_{\mathbf{video}} = \Pi_c\mathbf{X}_{\mathbf{world}}$$



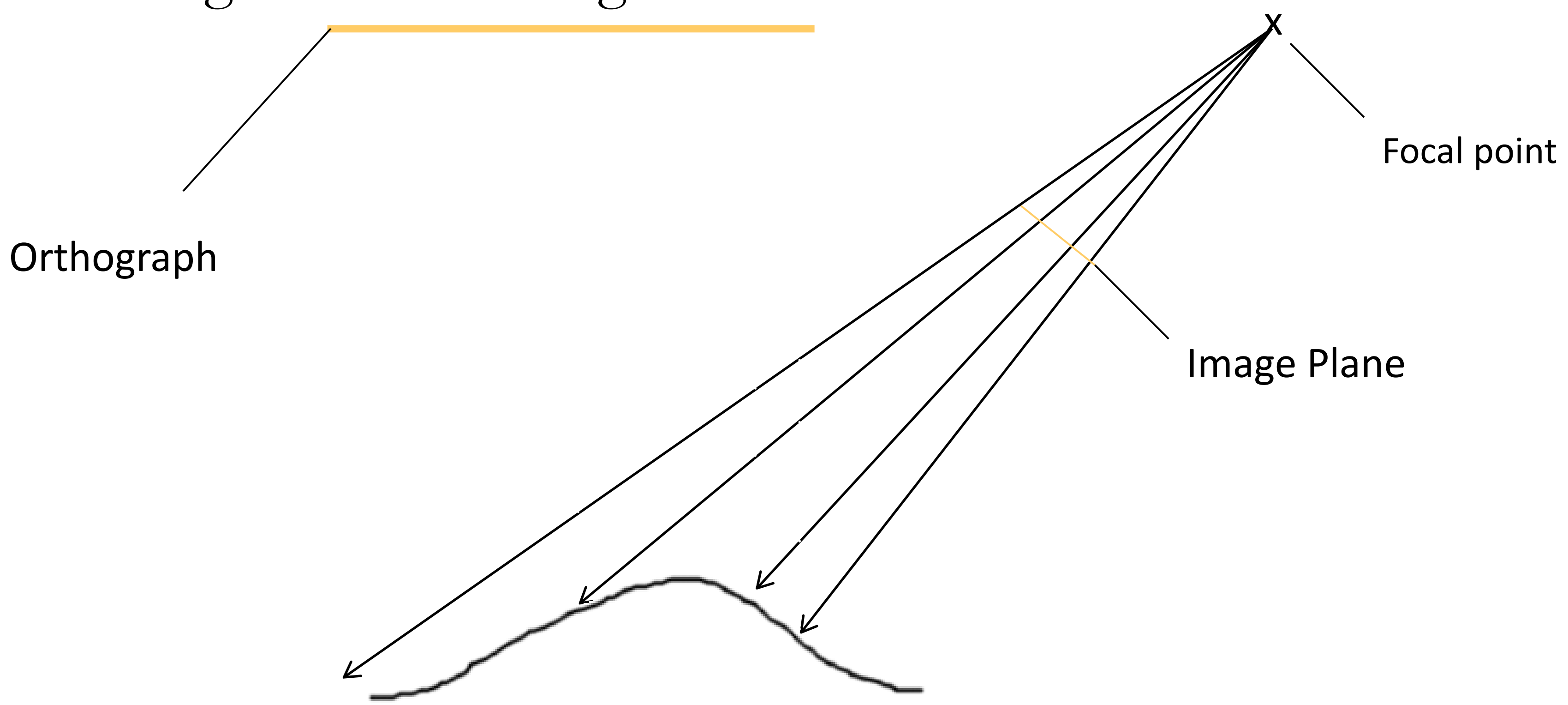
*ortho*Rectification

- Bringing both imageries onto a common view projection (**Bridging the gap**)
- Accounts for gross misalignment
- Not accurate due to telemetry noise



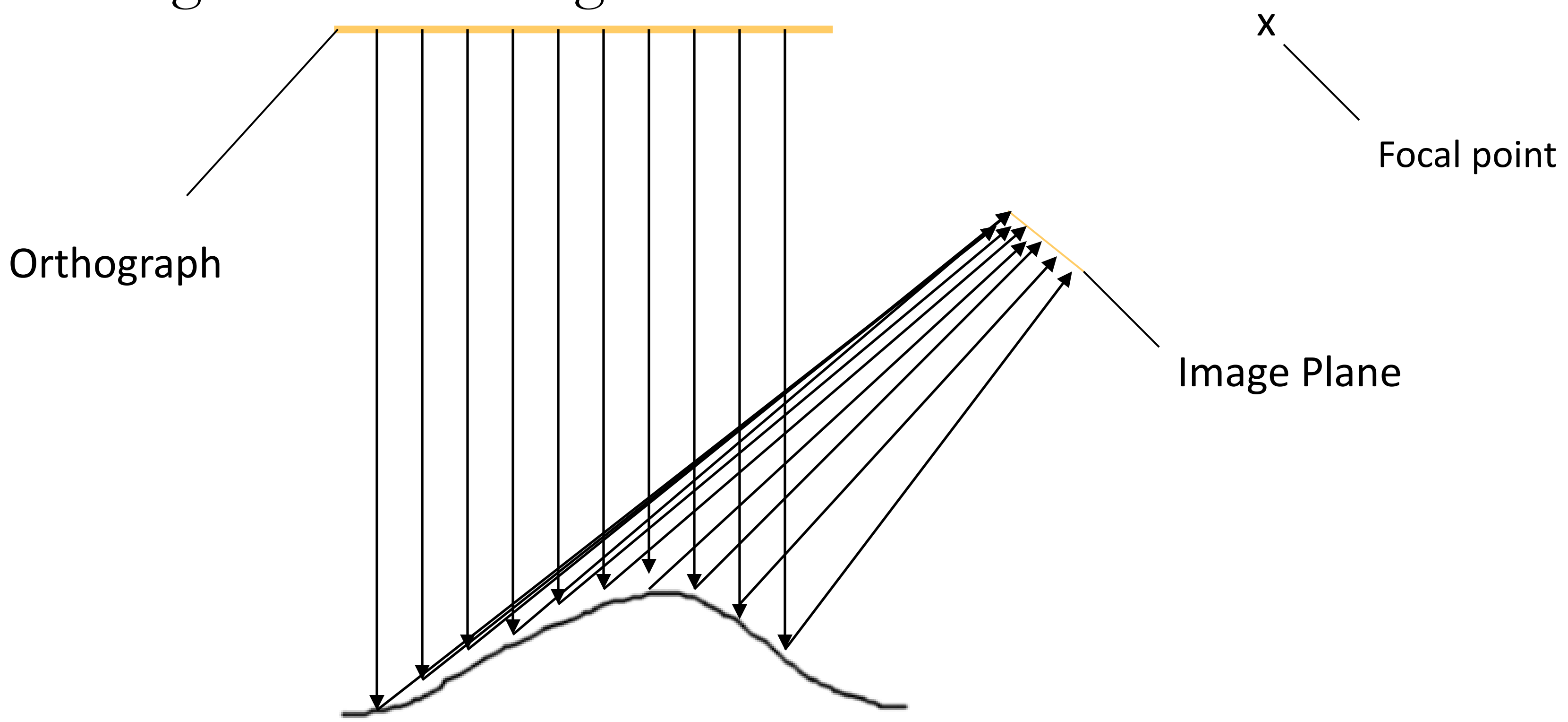
Rectification

Creating the OrthoImage



*ortho*Rectification

Creating the OrthoImage



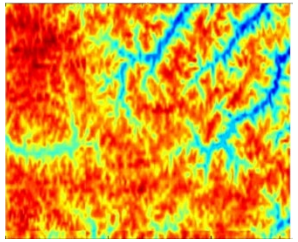
*ortho*Rectification

Sensor File + Mission Images + Reference Eniv. = Orthorectification

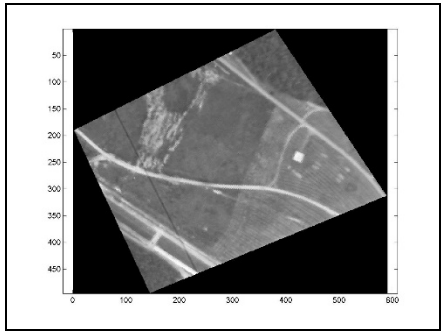
OTTER	system_id
TV	sensor_type
0001	serial_number
9.400008152666640300e+08	image_time
3.813193746469612200e+01	vehicle_latitude
-7.734523185193877700e+01	vehicle_longitude
9.949658409987658800e+02	vehicle_height
9.995171174441039900e-01	vehicle_pitch
1.701626418113209000e+00	vehicle_roll
1.207010551753029400e+02	vehicle_heading
1.658968732990974800e-02	camera_focal_length
-5.361314389557259100e+01	camera_elevation
-7.232969433546705000e+00	camera_scan_angle
480	number_image_lines
640	number_image_samples
1.000000000000000000e+00	u_axis_scale_factor
1.000000000000000000e+00	v_axis_scale_factor
3.812941913638164900e+01	ground_ref_pt_lat
-7.733710187470967400e+01	ground_ref_pt_lon
-1.418041566542428400e-09	ground_ref_pt_hgt
1.732050807568877200e+02	position_error
1.000000000000000000e+02	vehicle_lat_sigma
1.000000000000000000e+02	vehicle_lon_sigma
1.000000000000000000e+02	vehicle_hgt_sigma
5.000000000000000000e-01	vehicle_heading_sigma
5.000000000000000000e-01	vehicle_pitch_sigma
5.000000000000000000e-01	vehicle_roll_sigma
6.186380463322359200e-04	focal_length_sigma
5.000000000000000000e-01	gimbal_azimuth_sigma
5.000000000000000000e-01	gimbal_elevation_sigma

+

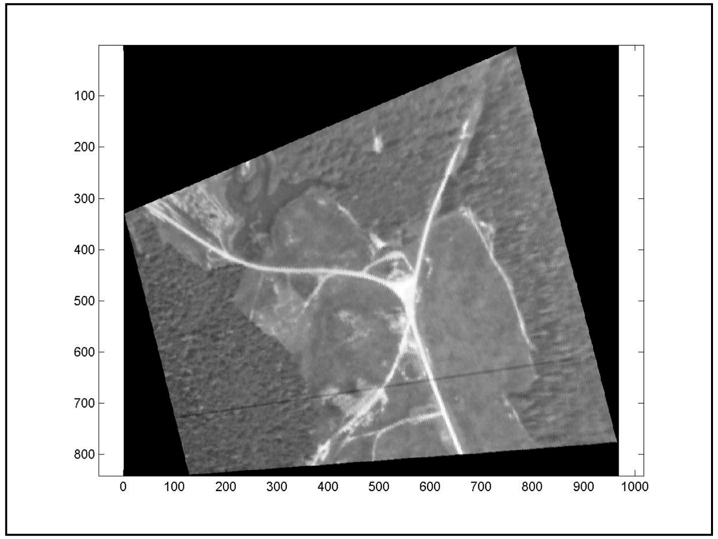
+



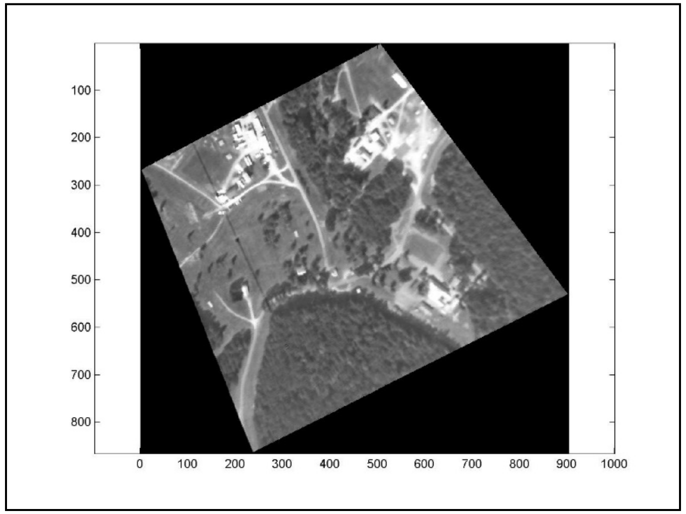
=



*ortho*Rectification



*ortho*Rectification



Reference Image
(DOQ)

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Geo-localization Using Image Matching

- No Meta-Data (Telemetry)
- No Sensor Model
- No Geodetically Accurate Reference Image
  - Only Geo-tagged images
- Image level coarse geo-localization

"Where Am I?"

- Problem:

  Image Localization

Input

Output

Mere Visual Information(Images)   Location in Terms of λ (Lon.) and φ (Lat.)

“Where Am I?”

- Problem:

  Image Localization

Input

Output

Mere Visual Information(Images)

Location in Terms of λ (Lon.) and φ (Lat.)

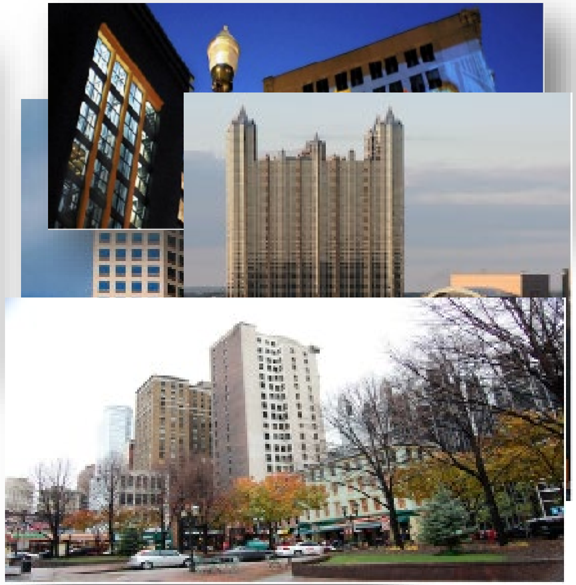
φ=40.4419, λ=-79.9986

Google Maps Street View Dataset

- Reference Set: GSV ~100k
- Test Set:
  - 521 GPS- Tagged from **Pittsburgh, PA and Orlando, FL.**
  - Downloaded From Flickr, Panoramio, Picasa, etc.

picasa.google.com

Panoramio.com



Flickr.com

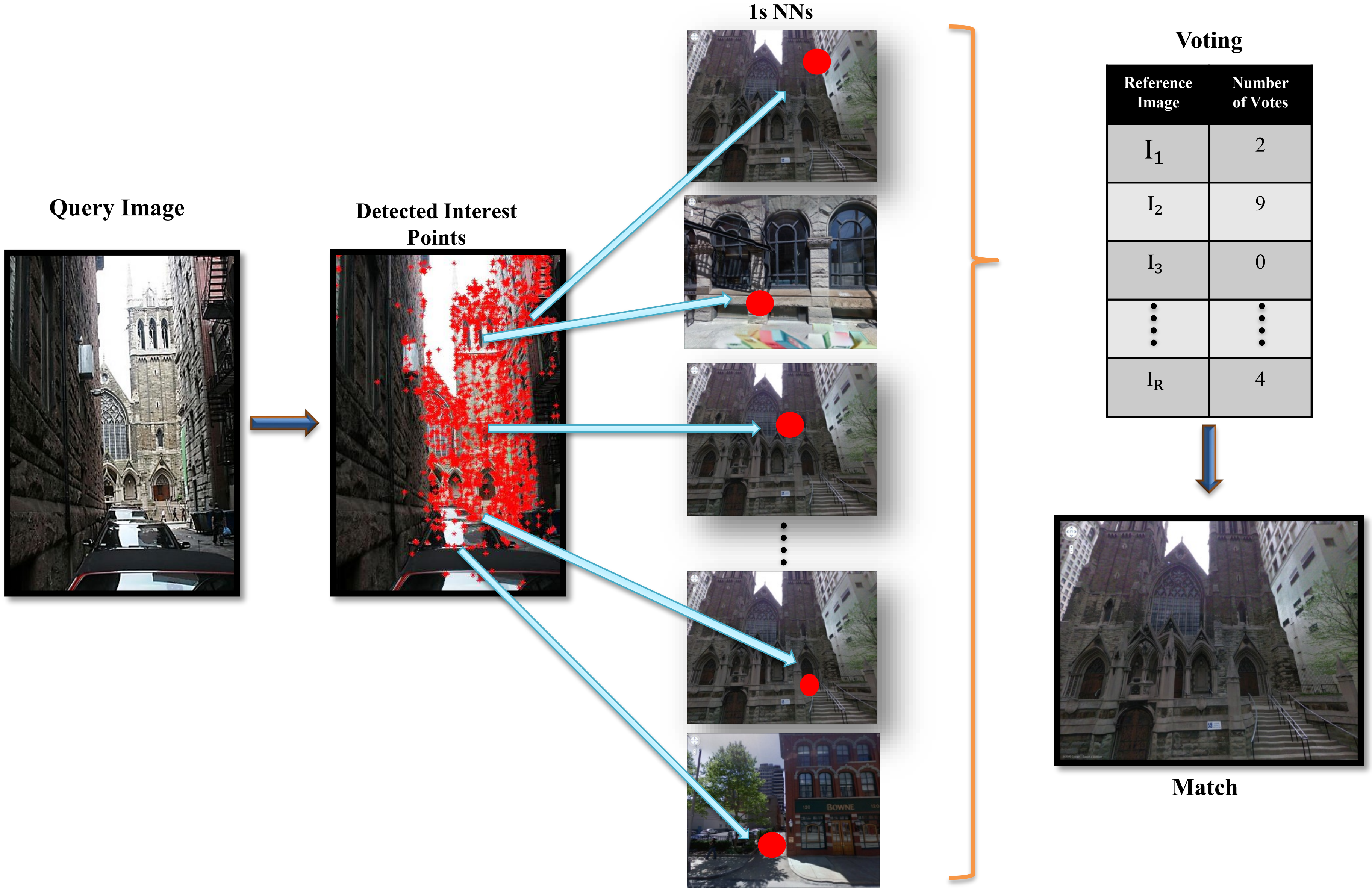
Image Geo-localization Based on Multiple Nearest Neighbor Feature Matching Using Generalized Graphs.

Amir Zamir and Mubarak Shah

In ***T-PAMI***, 2014.

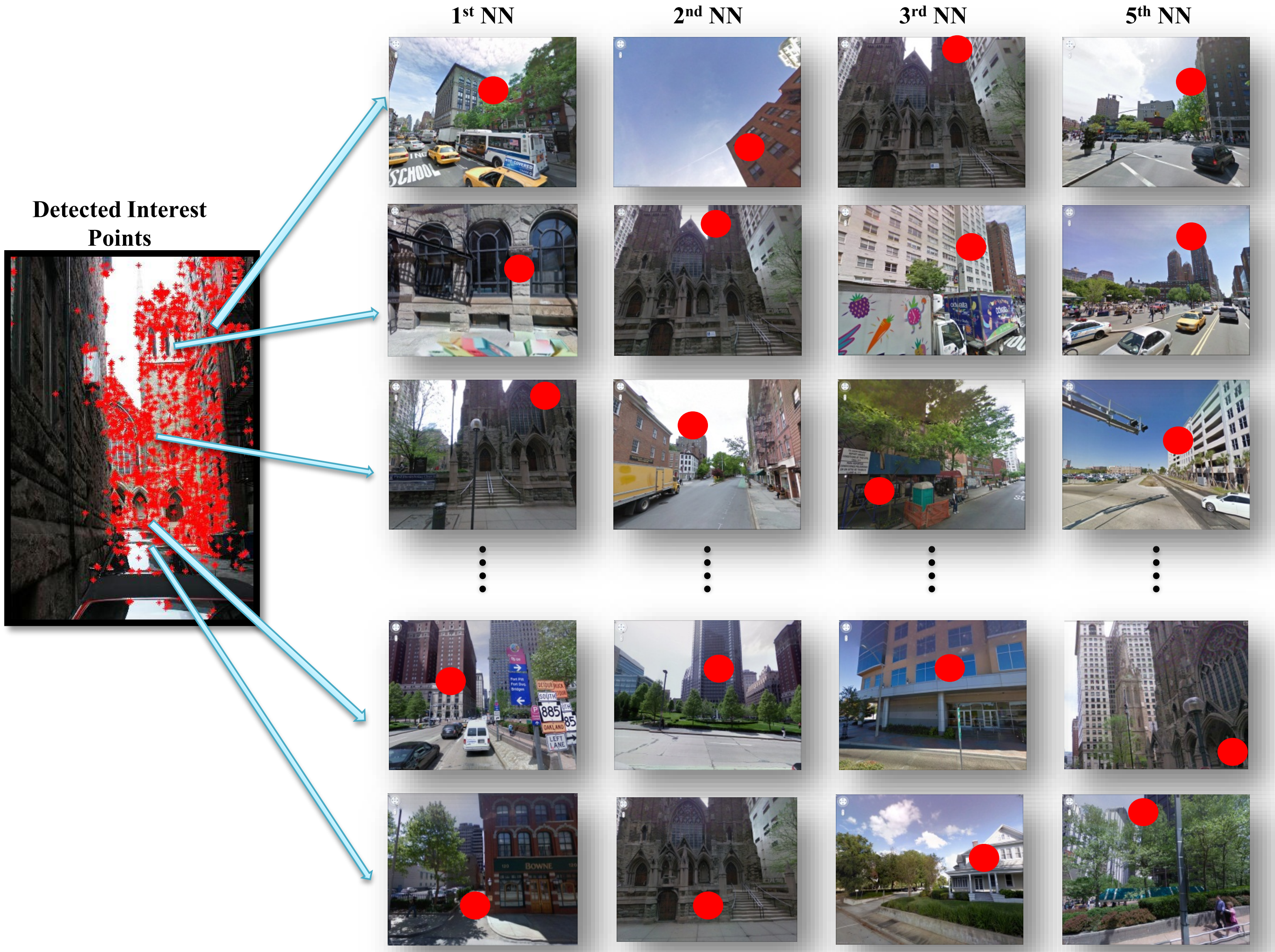
Asst Professor; EPFL

I: Localization Recognition Using Local Features

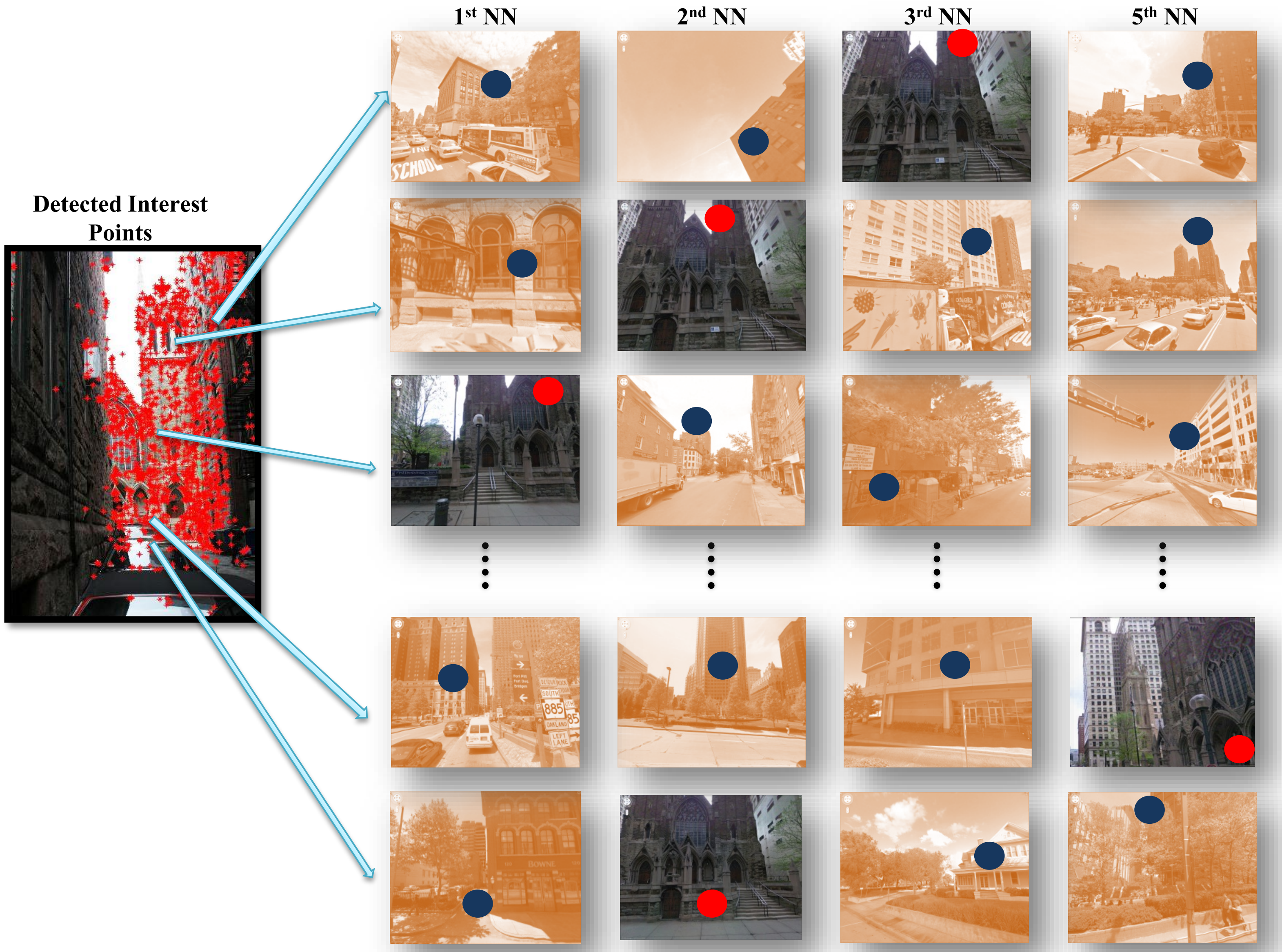


Reference Image	Number of Votes
I_1	2
I_2	9
I_3	0
⋮	⋮
I_R	4

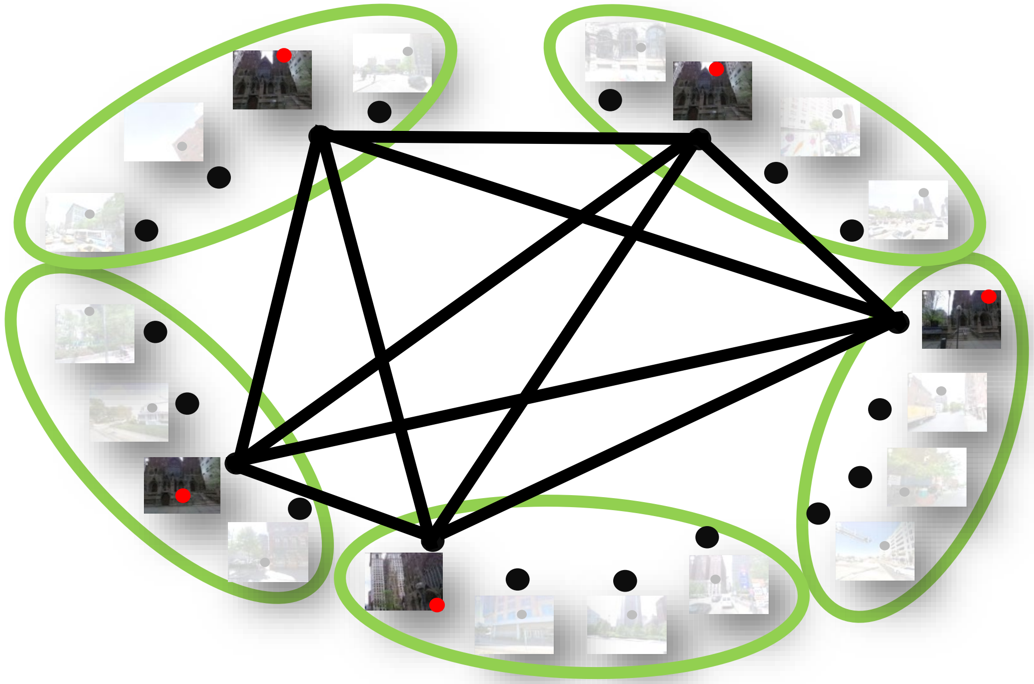
Using Multiple Nearest Neighbors



Using Multiple Nearest Neighbors



Generalized Minimum Clique



- Subset of NNs with maximum agreement in local and global features

Geo-localization Results

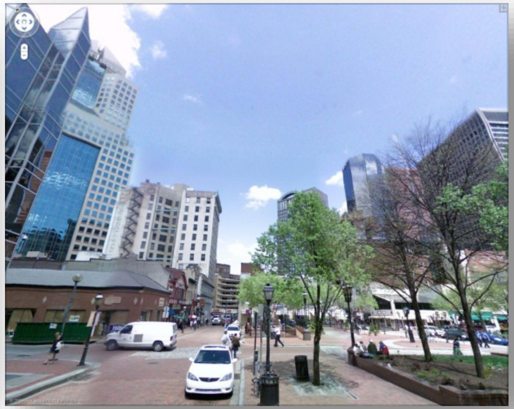
Query

Match – Error: 7.6 m

Query

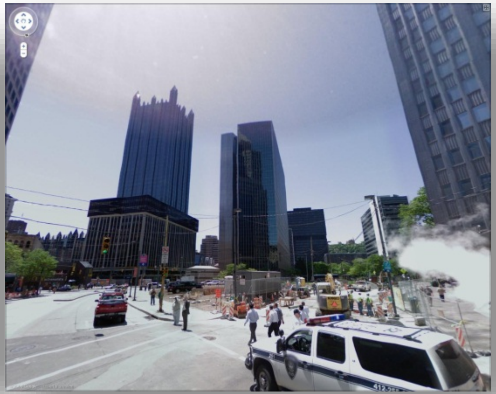
Match – Error: 6.9 m

Query



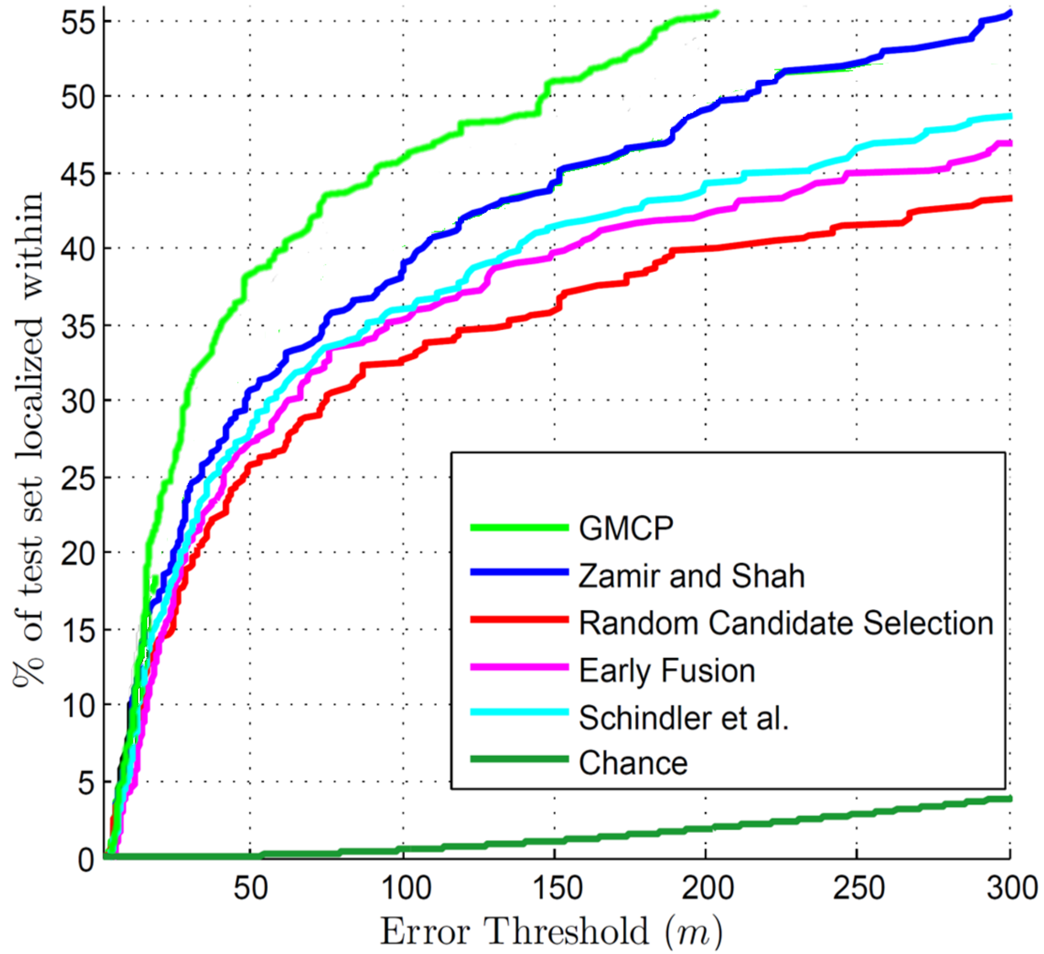
Match – Error: 308.1 m

Query



Match – Error: 59.3 m

Geo-localization Results



Limitations

- GMCP selects exactly one NN per query feature; sensitive to outliers
- A very simple voting scheme
- GMCP is a binary-variable NP hard problem

Image Geo-Localization Using Constraint Dominant Sets

Eyasu Mequaanint, Qualcom

Yonatan Tariku. , Qualcom

Haroon Idrees, RetailNext

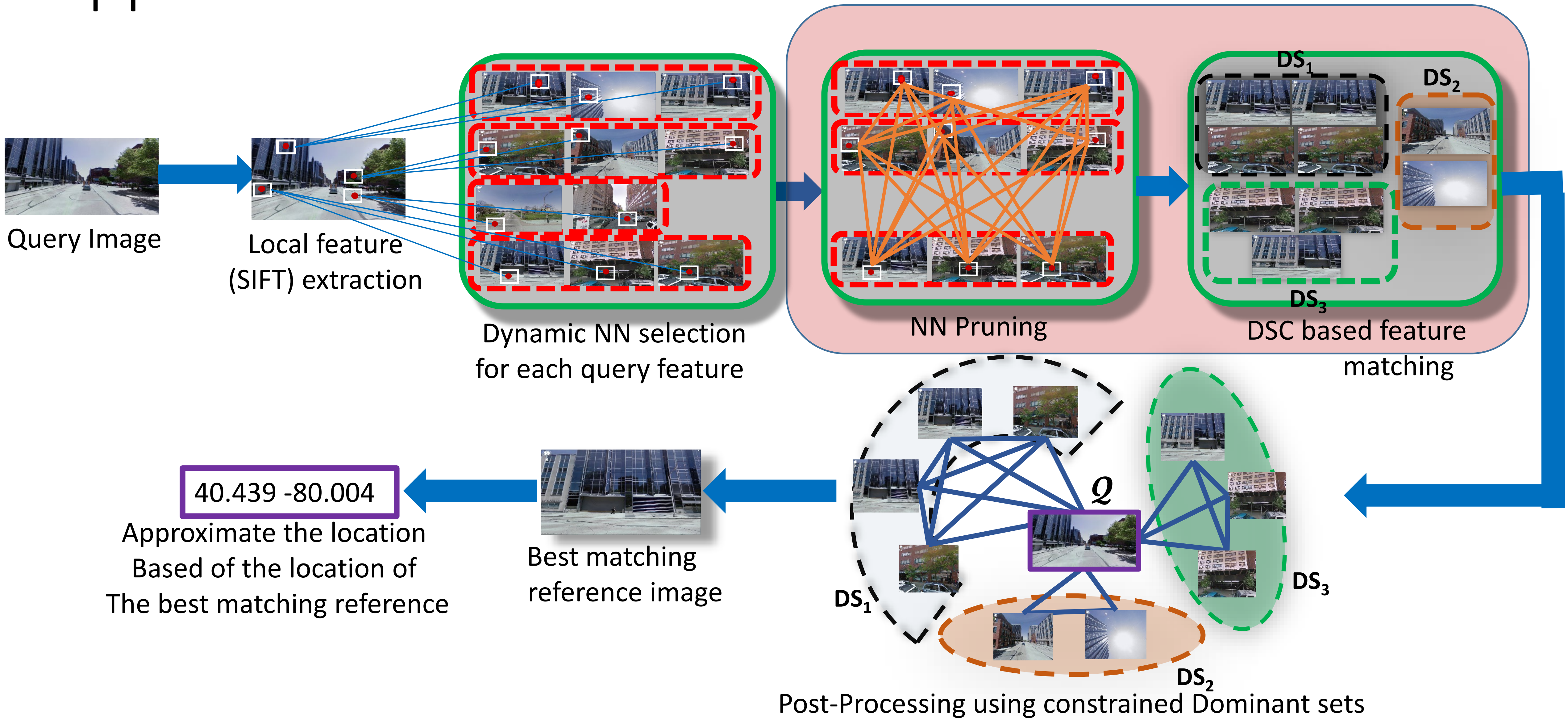
Eyasu Zemene,Yonatan Tariku Tesfaye, Haroon Idrees, Andrea Prati, Marcello Pelillo, and Mubarak Shah

T-PAMI, 2017.

Goal

- Fast
- Accurate
- Handle outliers
- Scalable to large scale

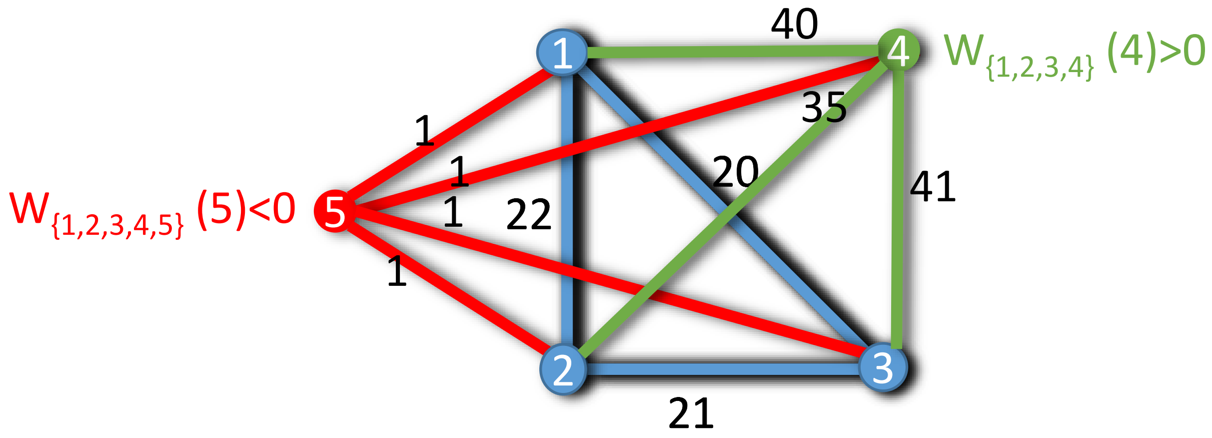
Approach


Query Image
Local feature
(SIFT) extraction
Dynamic NN selection
for each query feature
NN Pruning
DS_1
DS_2
DS_3
DSC based feature
matching
Q
DS_1
DS_3
DS_2
Post-Processing using constrained Dominant sets
Best matching
reference image
40.439 -80.004
Approximate the location
Based of the location of
The best matching reference

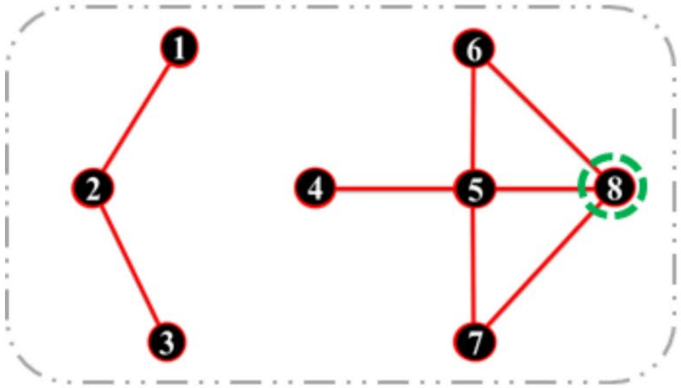
Dominant Sets

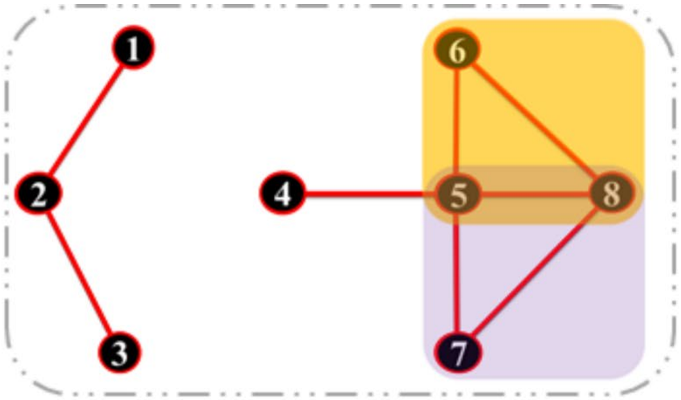
- Dominant set is an edge-weighted generalization of a clique
- Dominant set is a subset of vertices, which is
  - Coherent and
  - Compact

Dominant Sets



Constraint Dominant Sets





Dominant Sets

- Edge-weighted generalization of maximal cliques
- Given a (symmetric) affinity **A**, consider,

$$\begin{array}{ll} \text{maximize} & f(\mathbf{x}) = \mathbf{x}'\mathbf{A}\mathbf{x} \\ \text{subject to} & \mathbf{x} \in \Delta \end{array}$$

Where $\Delta = \{x \in \mathbb{R}^n : \sum_{i=1}^{n} x_i = 1 \text{ and } x_i \geq 0, \text{ for all } i = 1, \ldots, n\}$

- If **x** is a local maximizer, its support, $\sigma(\mathbf{x})$, is a dominant set
- DS's caputer both *internal* and *external* coherence conditions for a cluster

M. Pavan and M. Pelillo, "Dominant sets and pairwise clustering," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 1, pp. 167–172, 2007.

Constrained Dominant Sets (CDS)

Given a query $\mathcal{Q} \subseteq \mathrm{V}$ and a parameter $\alpha > 0$, define the following parameterized family of quadratic program:

$$maximize\ \ f_{\mathcal{Q}}^{\alpha} = x^T\,(A - \alpha I_{\mathcal{Q}}\,)x \qquad (1)$$
$$\text{Subject to } x \in \Delta$$

Where $I_{\mathcal{Q}}$ is the diagonal matrix whose **diagonal elements are set to 1** in correspondence to the vertices contained in $\mathrm{V} \setminus \mathcal{Q}$ and to 0 otherwise.

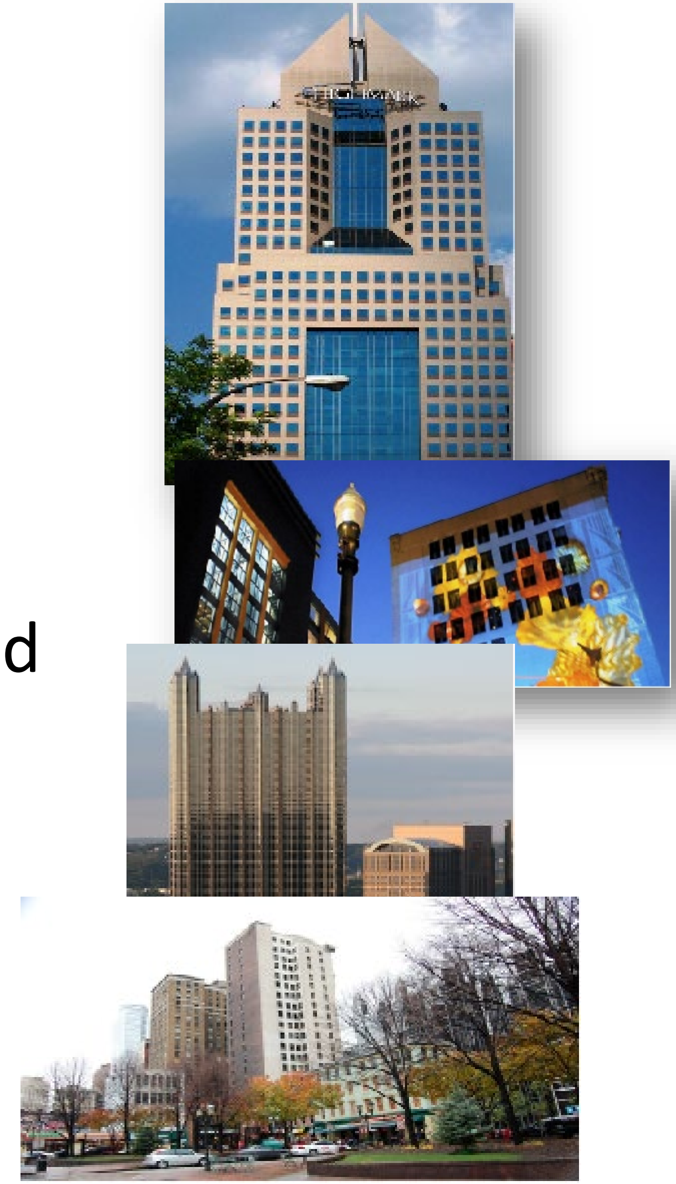
Experimental Results

Dataset I: Orlando & Pittsburgh:

- Reference images:
  - 102K Google street view images from **Pittsburgh, PA** and **Orlando, FL**
- Test Set:
  - 644 GPS-Tagged unconstrained images
  - Downloaded From Flickr, Panoramio, Picasa, …

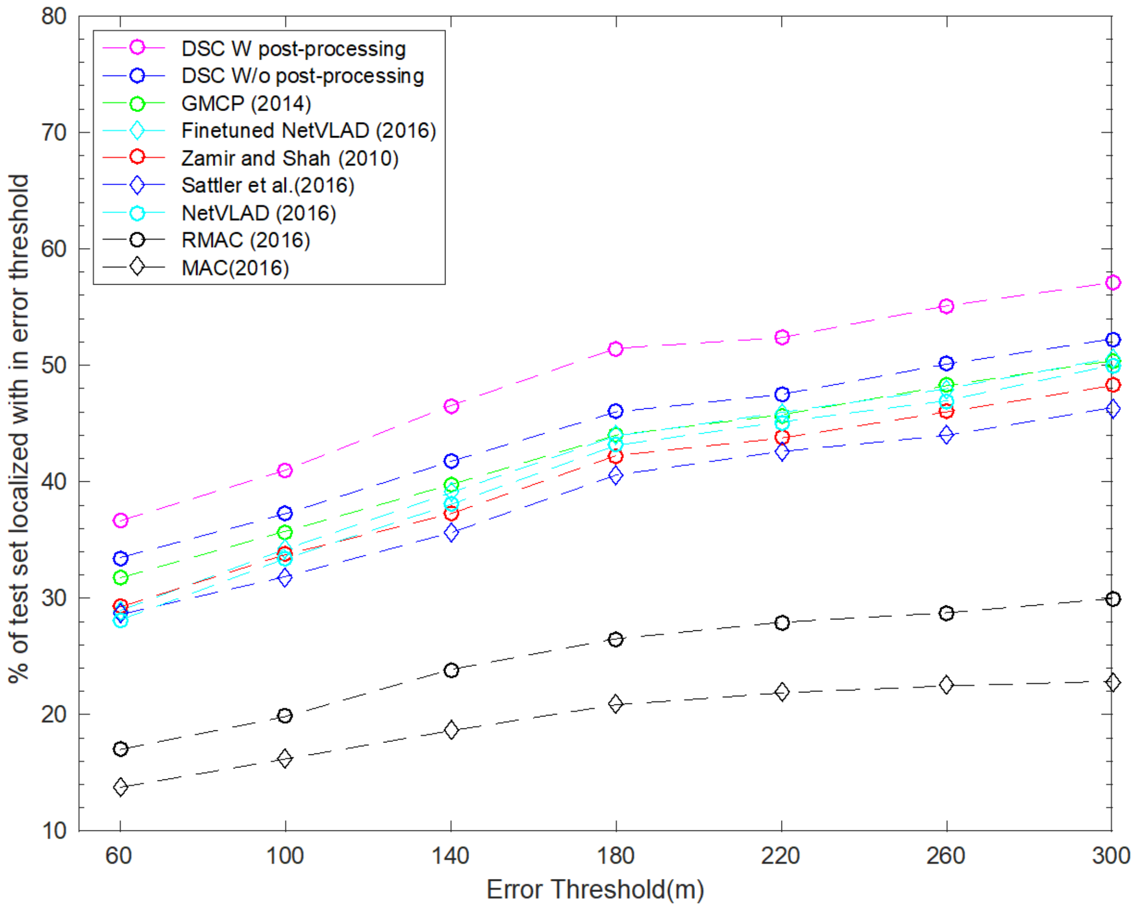
Dataset II: *WorldCities* Dataset: (NEW)*

- **Reference images** (300K Google street view images):
- 14 different cities from different parts of the world:
  - USA: Los Angeles, Phoenix, Houston, San Diego, Las Vegas, Dallas, Chicago
  - Australia: Sydney and Melbourne
  - Europe: Amsterdam, Frankfurt, Rome, Milan and Paris
  - **Test Set**
    - 500 GPS-Tagged unconstrained images
    - Downloaded From Flickr, Panoramio, Picasa…



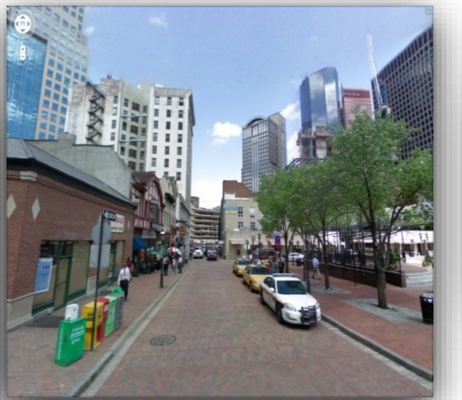
Overall Results

- Dataset 2: WorldCities (14 different cities from Europa, North America, Australia)



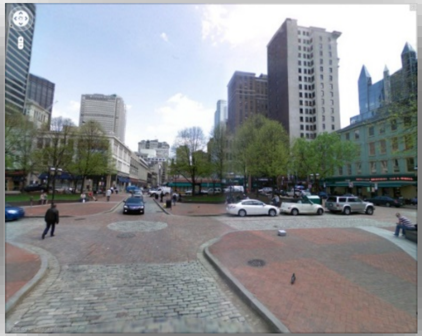
Qualitative Image Localization Results

Query



Match – Error: 70.01 m

Query



Match – Error: 5.4 m

Query

Match – Error: 10.4 m

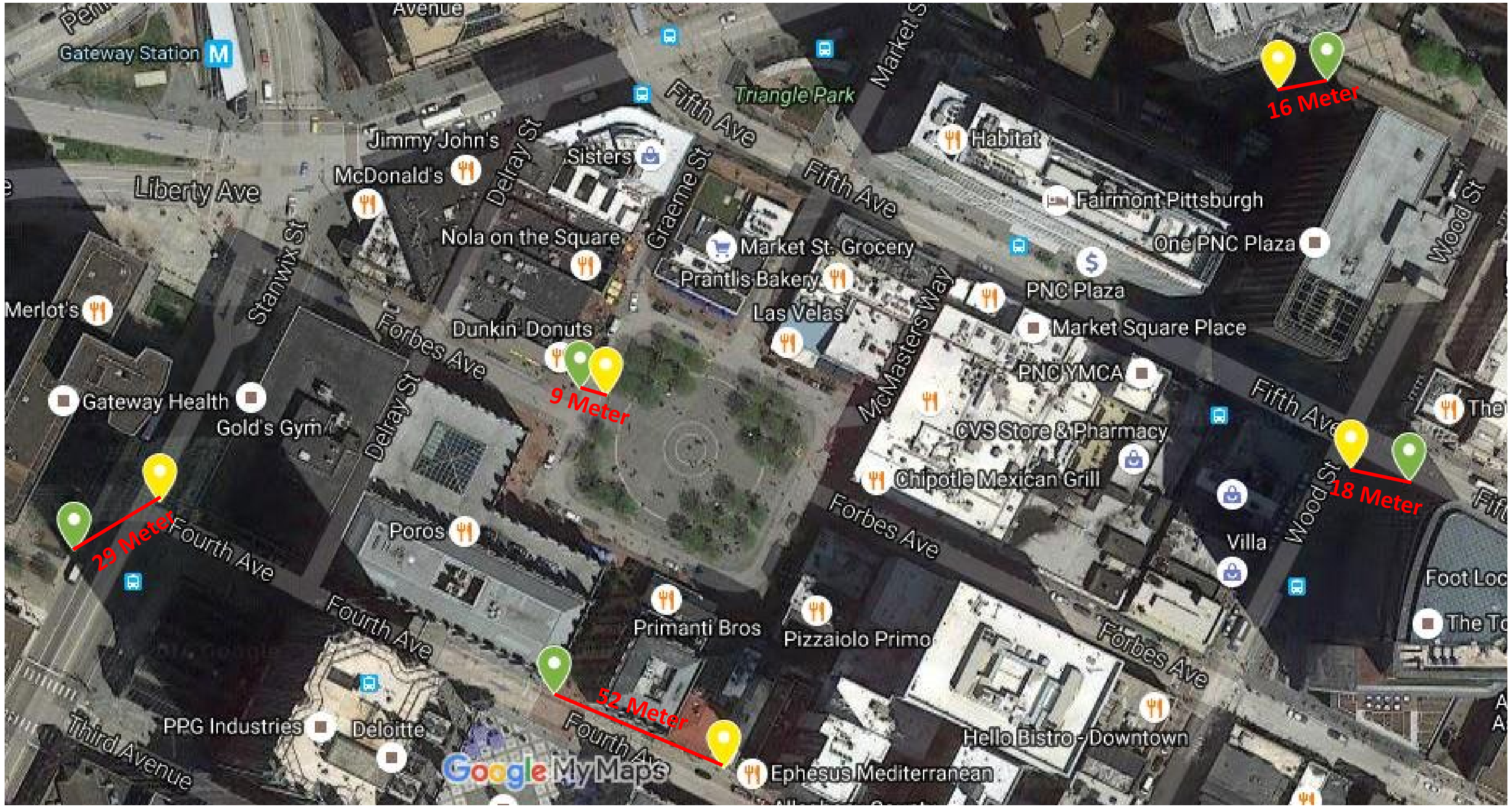
Query

Match – Error: 7.5 m

Query

Match – Error: 62.7 m

Qualitative Image Localization Results



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Cross-View Challenges

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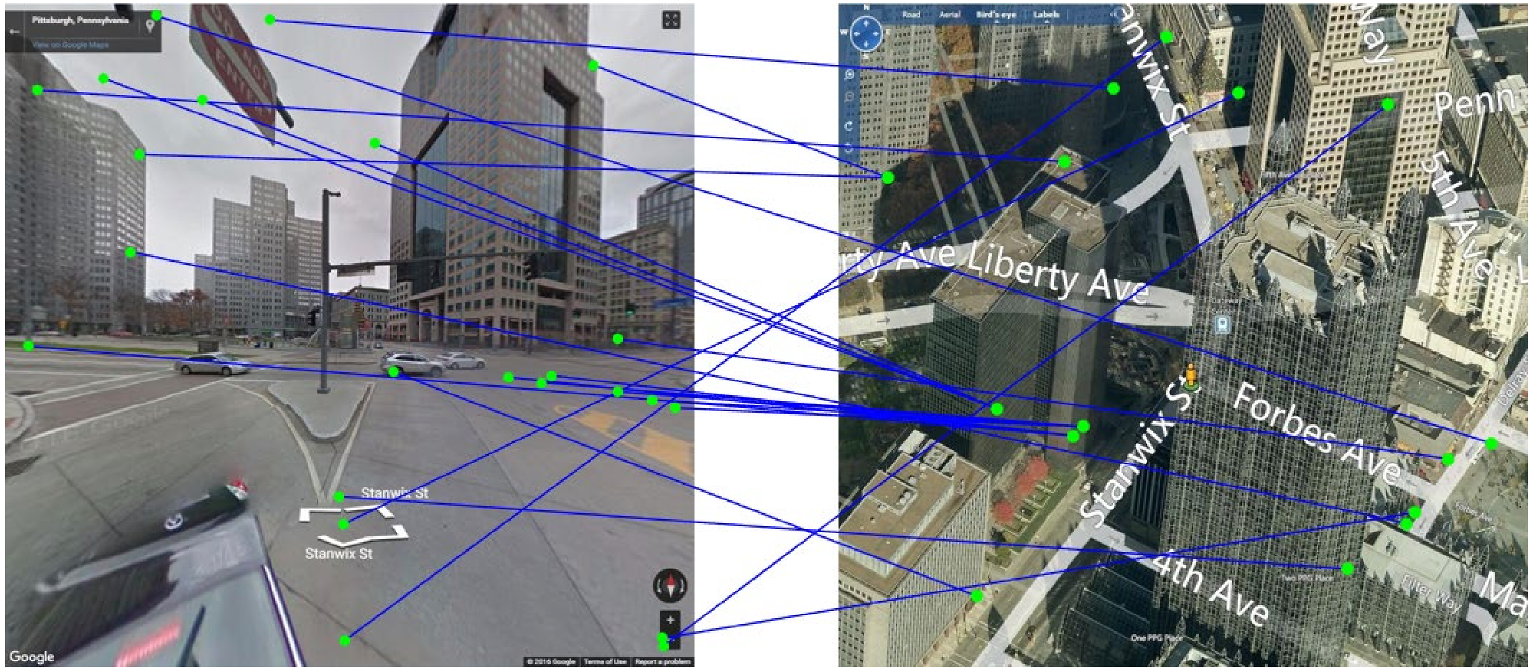
- Images from different viewpoints are visually different
- The images may be captured with different lighting
- The mapping from one viewpoint to the other may be complex
- Traditional features e.g. SIFT, HOG etc. may be very different



Retrieval Features

- Local Features (SIFT) (same view)
- **Buildings Features** (cross view)

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Cross-View Image Matching for Geo-localization in Urban Environments

Yicong Tian, Google

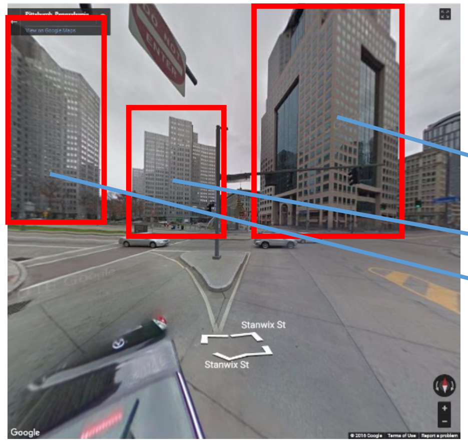
Yicong Tian, Chen Chen, Mubarak Shah
Center for Research in Computer Vision,
University of Central Florida

CVPR-2017

Chen Chen, UNC Charlotte

Proposed Approach

Query Image → Building Detection → Building Matching → Retrieve k NNs for each query building → Dominant sets selection → Geo-localization



Query image (street view)

Reference images (bird's eye view)

Data Collection

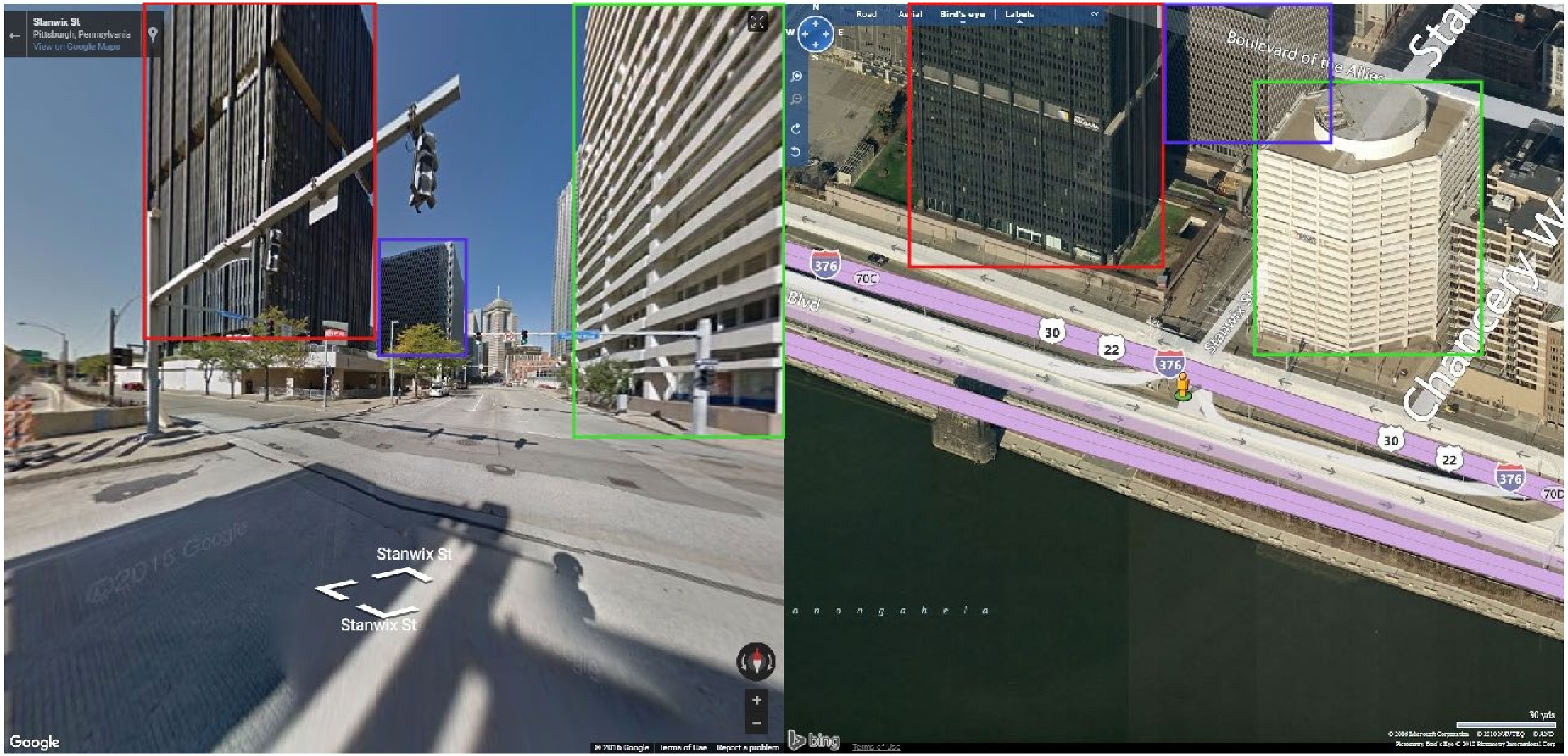
- A new dataset of street view and bird’s eye view image pairs
  - Pittsburg
  - Orlando
- Generated a list of GPS coordinates along streets
- For each GPS location
  - Four pairs with different headings
  - Utilized DualMaps
  - Automatically saved screenshots
- Annotations
  - By four undergraduates and high school students
  - ~300 hours work in total

Data Collection - Pittsburg

- 1,586 GPS locations

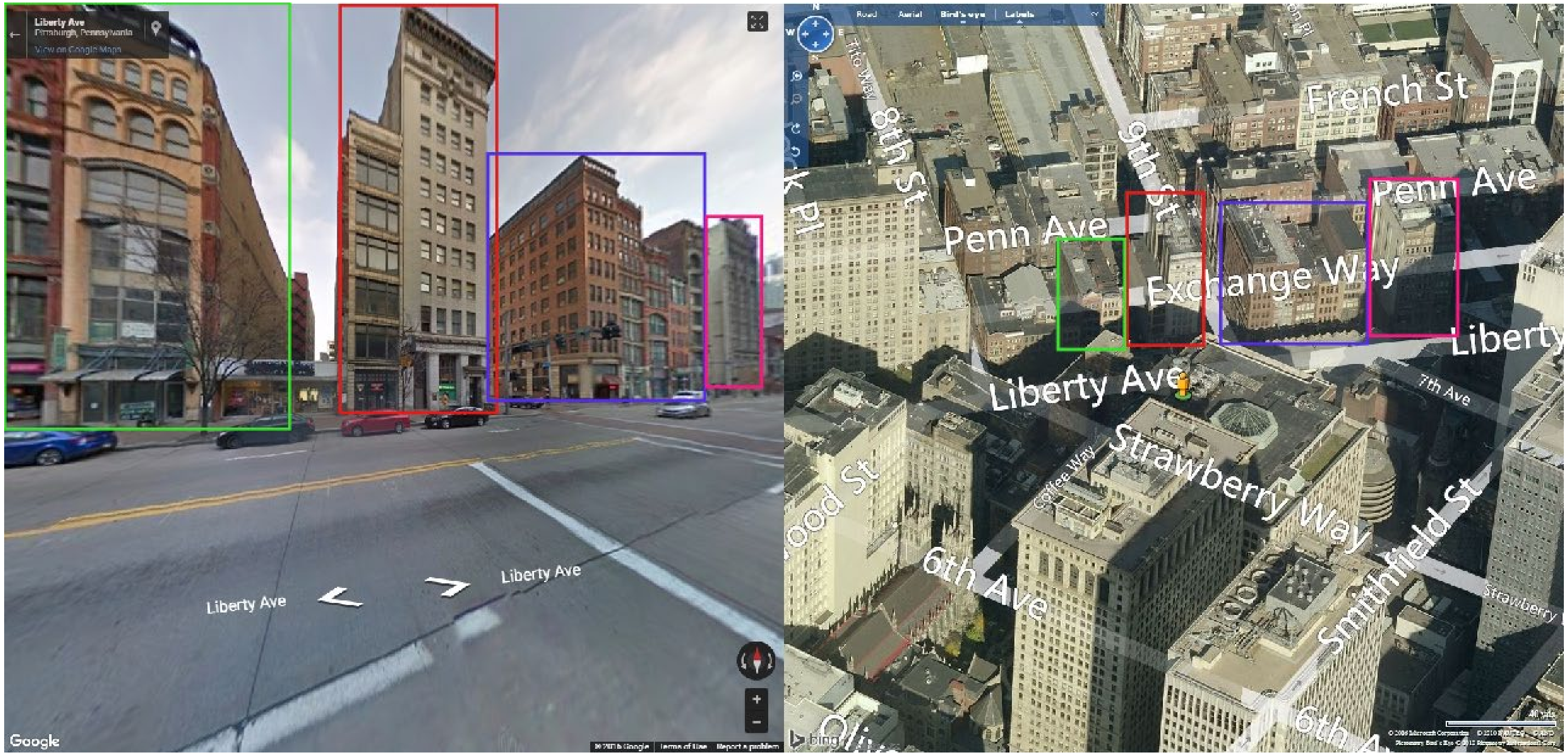
Data Collection - Pittsburg

- Example image pair with annotations



Data Collection - Pittsburg

- Example image pair with annotations

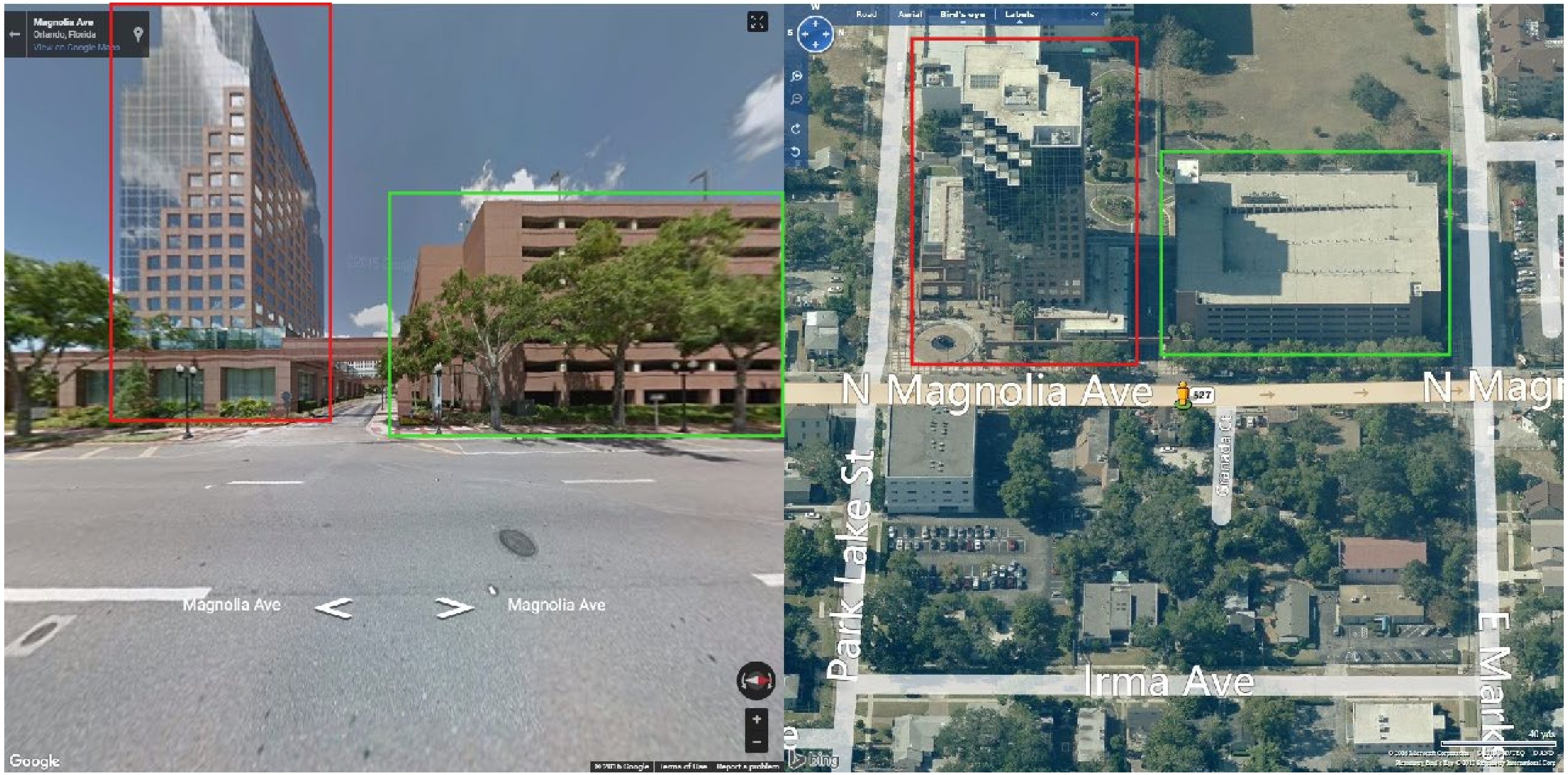


Data Collection - Orlando

- 1,324 GPS locations

Data Collection - Orlando

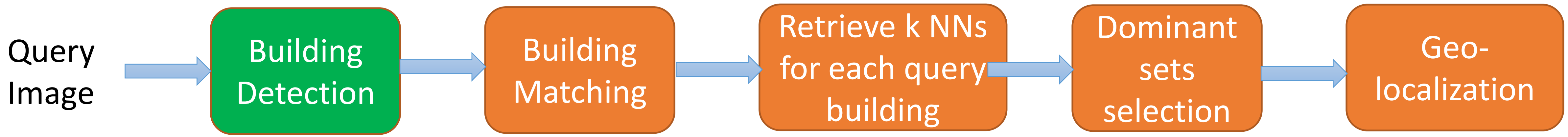
- Example image pair with annotations



Data Collection - Orlando

- Example image pair with annotations

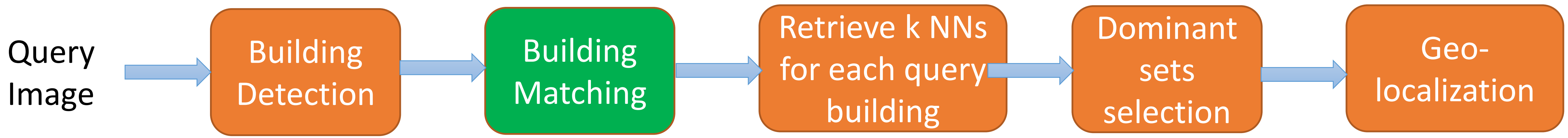
Proposed Approach



Building Detection (Faster R-CNN)

- Street view images
  - Training: 6,682 images
    - With 15,648 annotated boxes
  - Test: 1,903 images
- Bird’s eye view images
  - Training: 6,968 images
    - With 39,511 annotated boxes
  - Test: 1,916 images
- Each model takes 10 hours to train

Proposed Approach



Building Matching

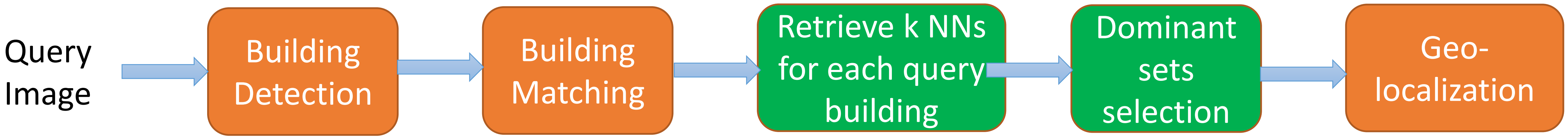
- Train a Siamese network
- In the learned feature space,
  - Matching image pairs are close to each other
  - Unmatched image pairs are far apart
- Contrastive loss

$$\mathcal{L}(x, y, l) = \frac{1}{2} l D^2 + \frac{1}{2}(1 - l) \max\left(0, (m - D^2)\right)$$

l: label (1 or 0)
D^2: square of Euclidean distance between features
m: margin

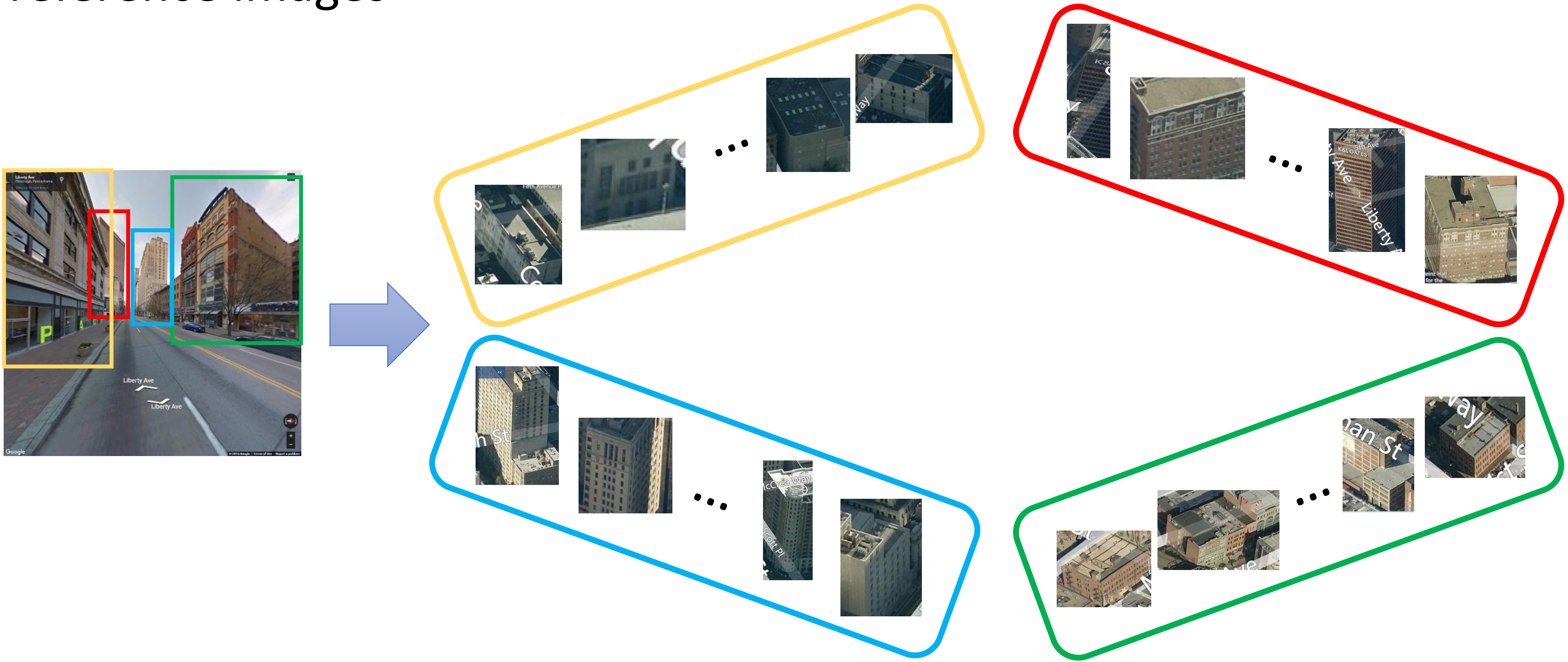
Proposed Approach

UCF Center for Research in Computer Vision



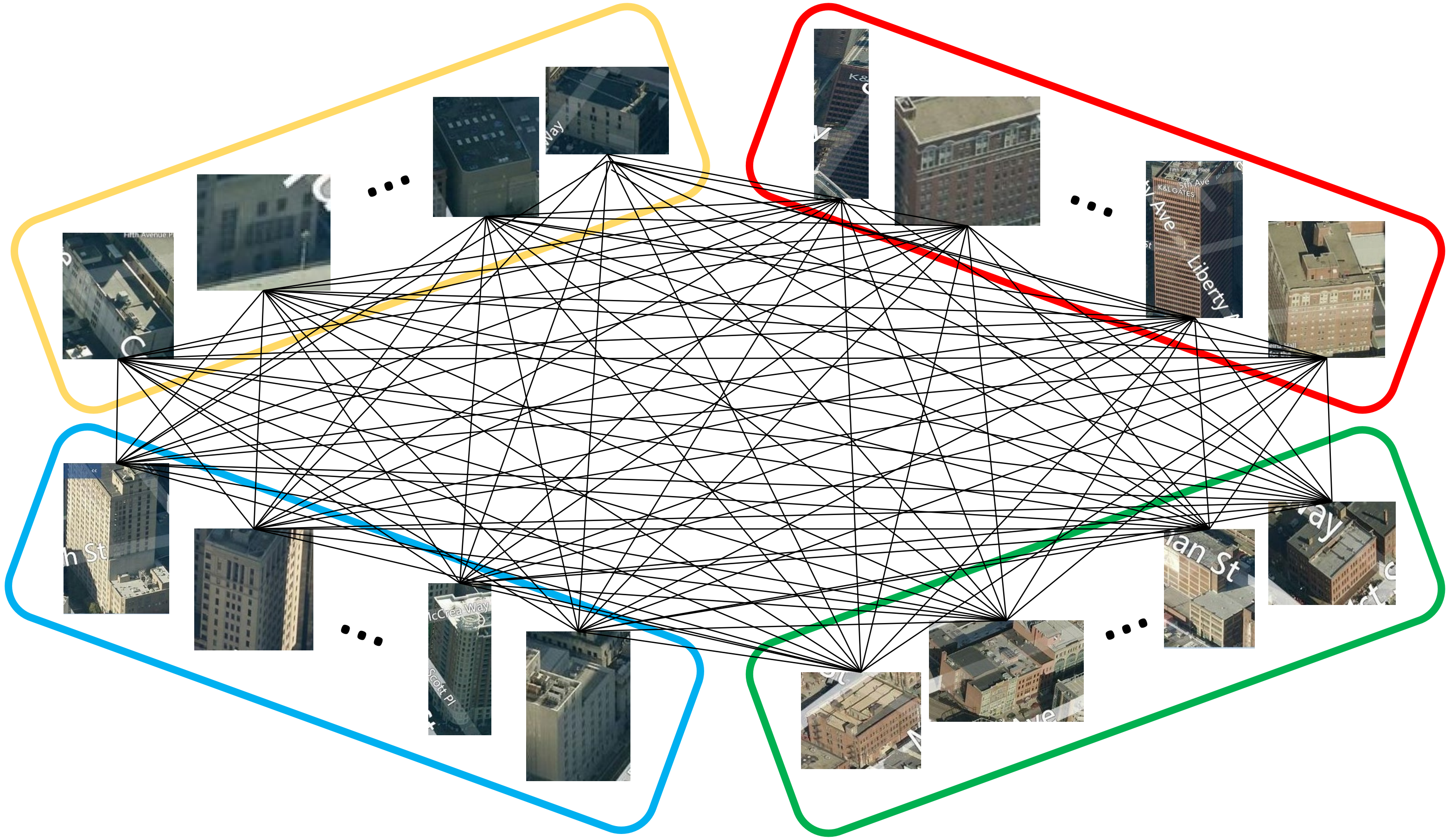
Geo-localization Using Dominant Sets

- For each building in the query image, select k nearest neighbors from reference images



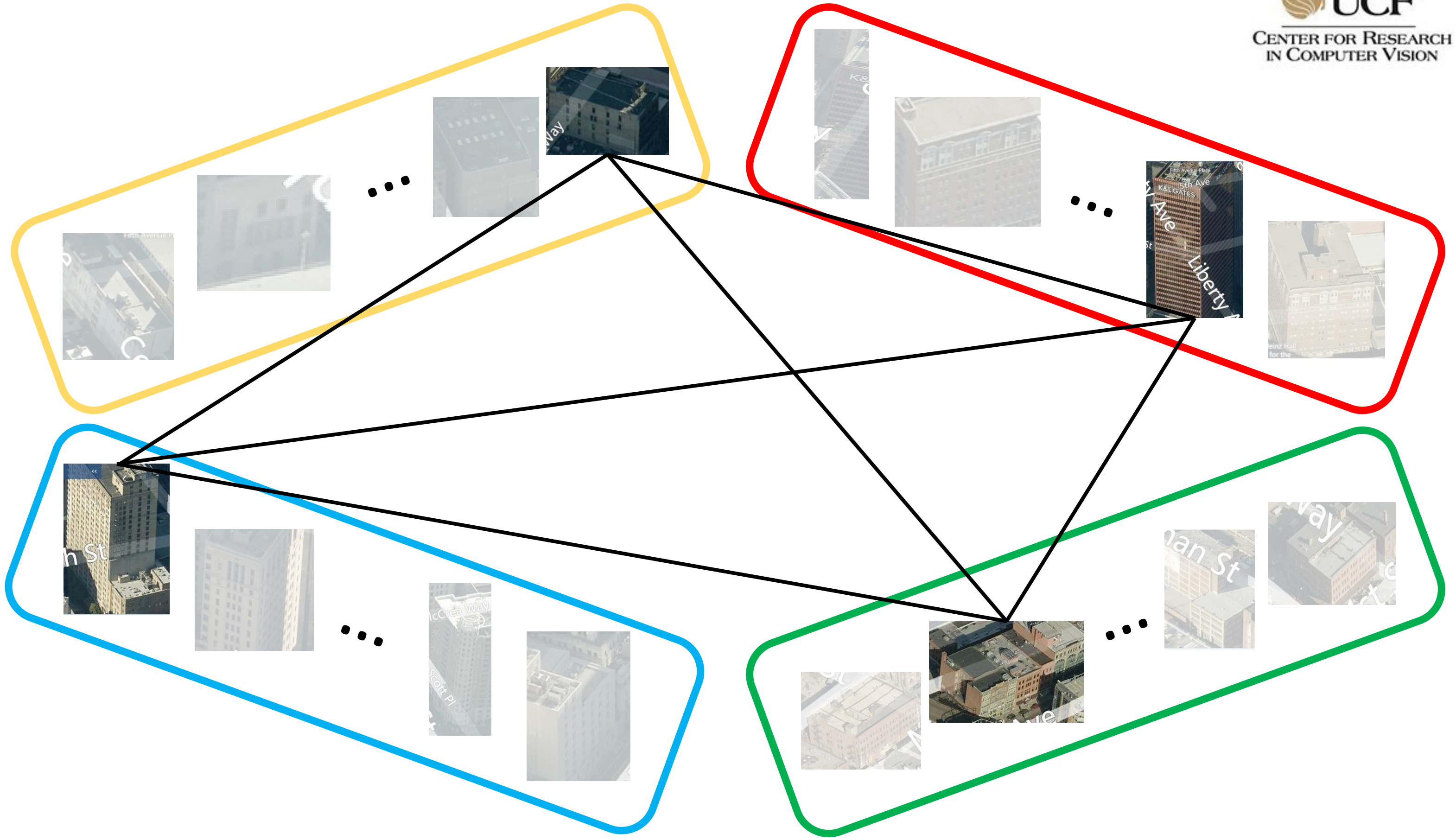
Geo-localization Using Dominant Sets

- Build a graph $G = (V, E, \omega)$ using selected reference buildings



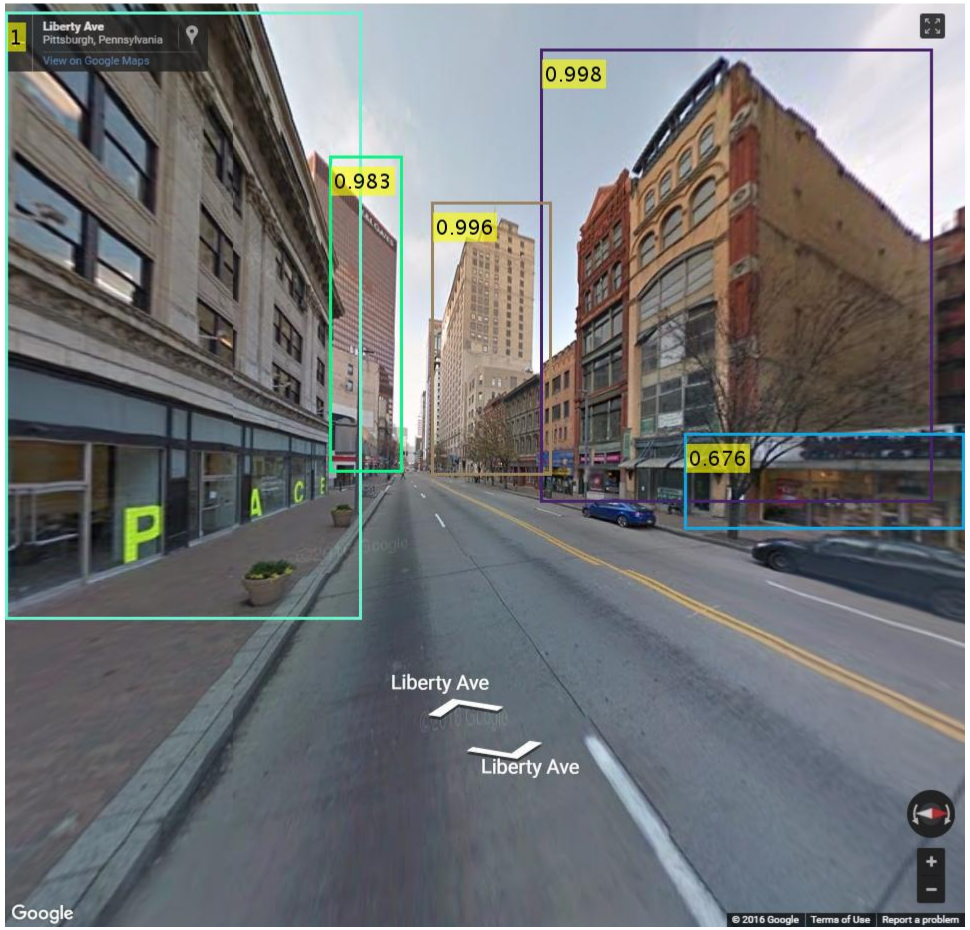
Geolocalization

- The nodes in dominant set form a coherent set
- At most one node is selected from each cluster



Experimental Results

Building detection in street view images



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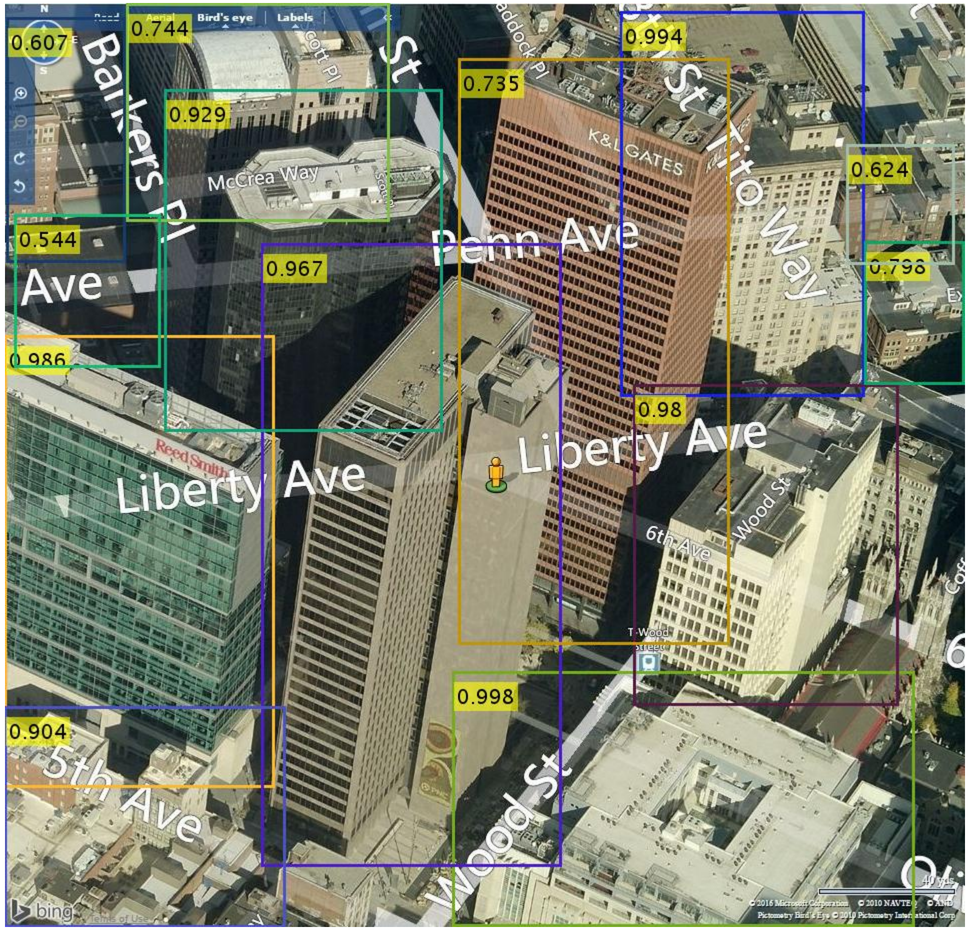
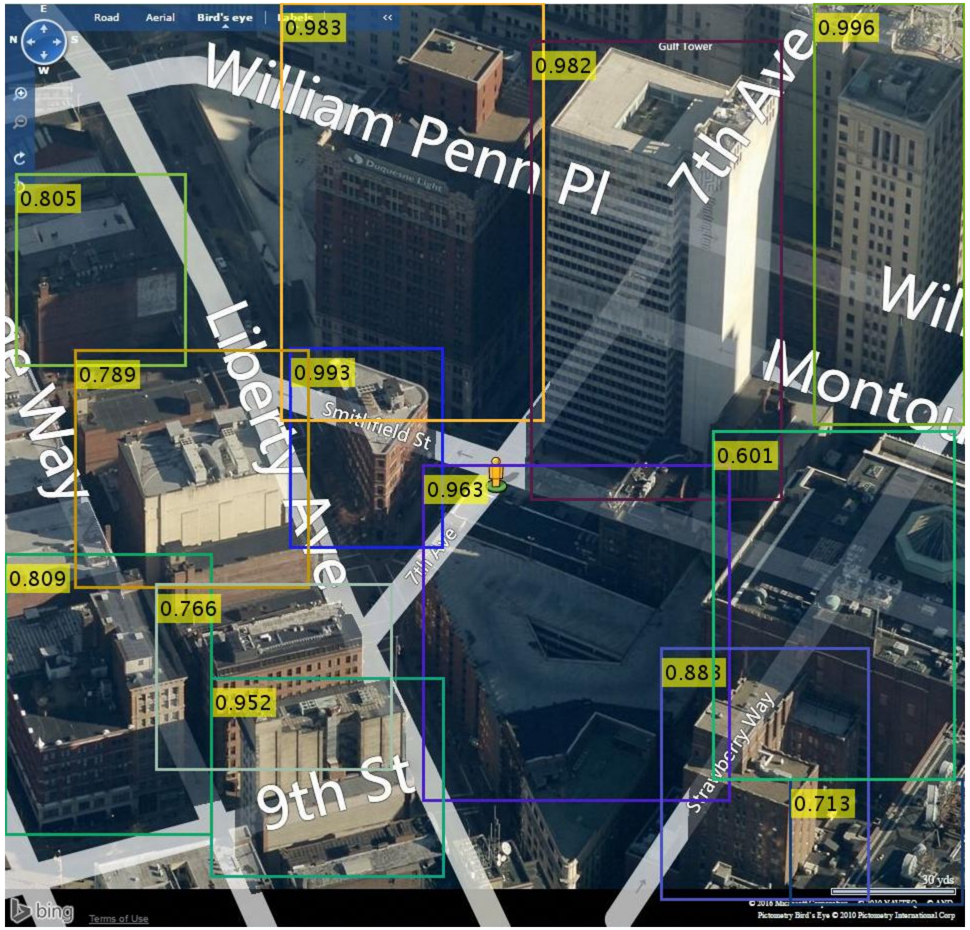
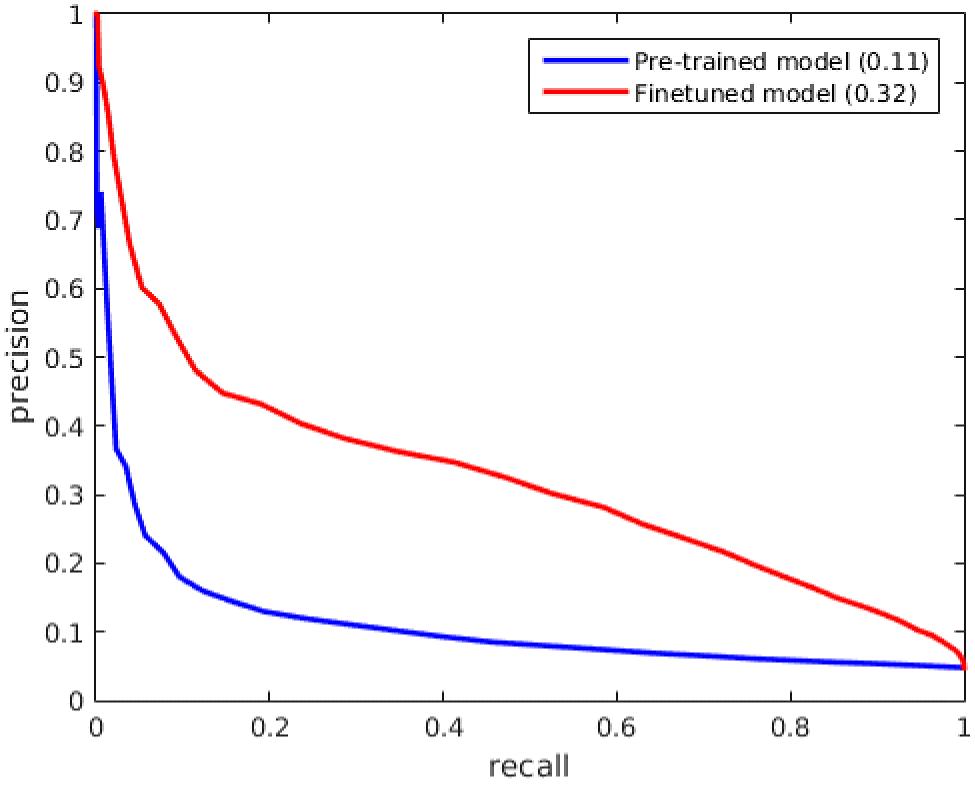
Building detection in bird's eye view images



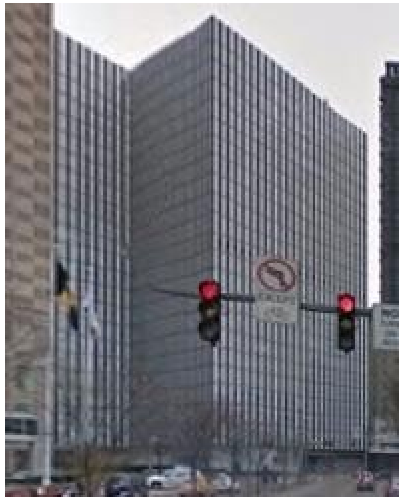


Building matching

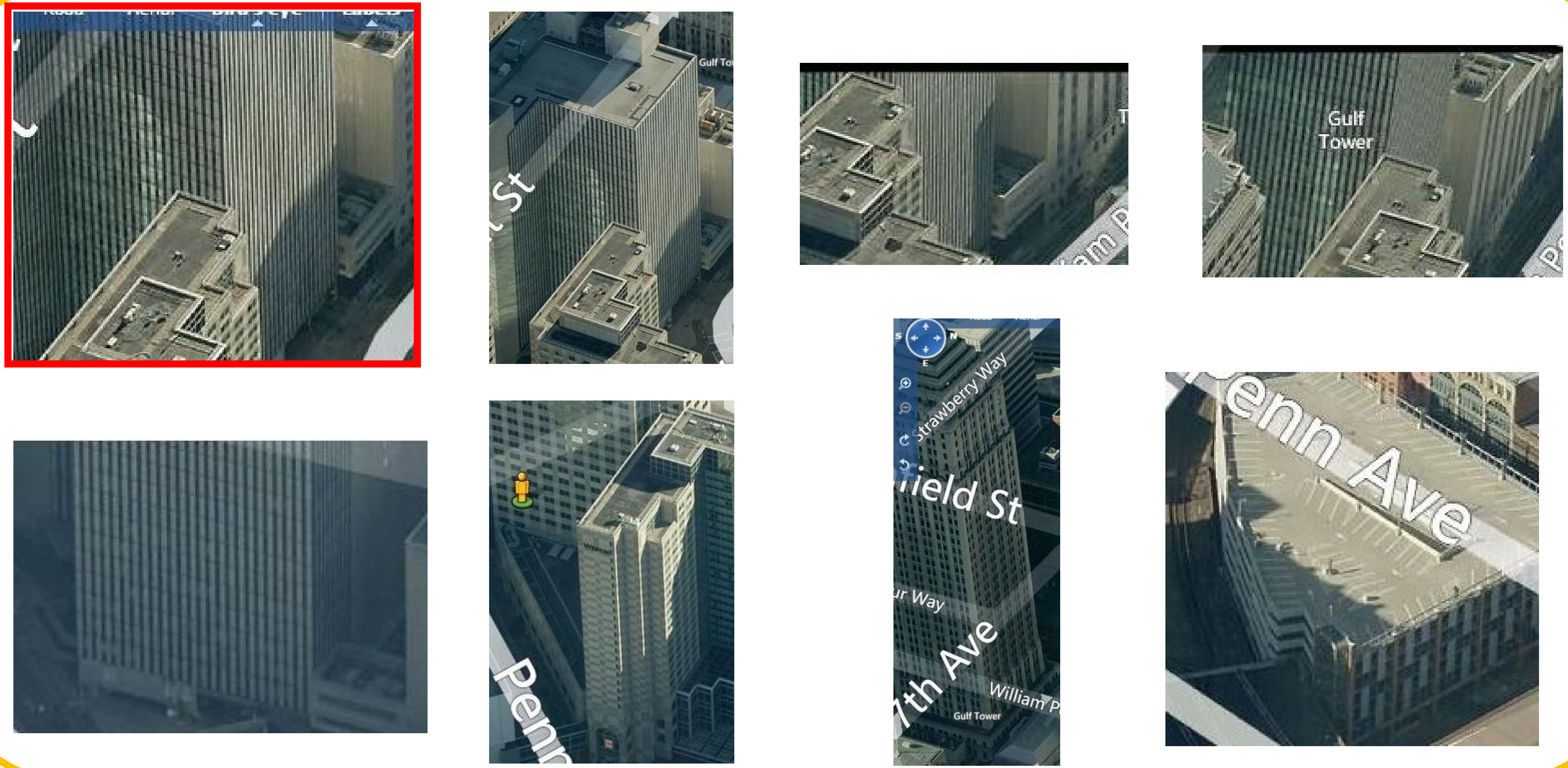
- Precision-recall curve on test image pairs



Building matching



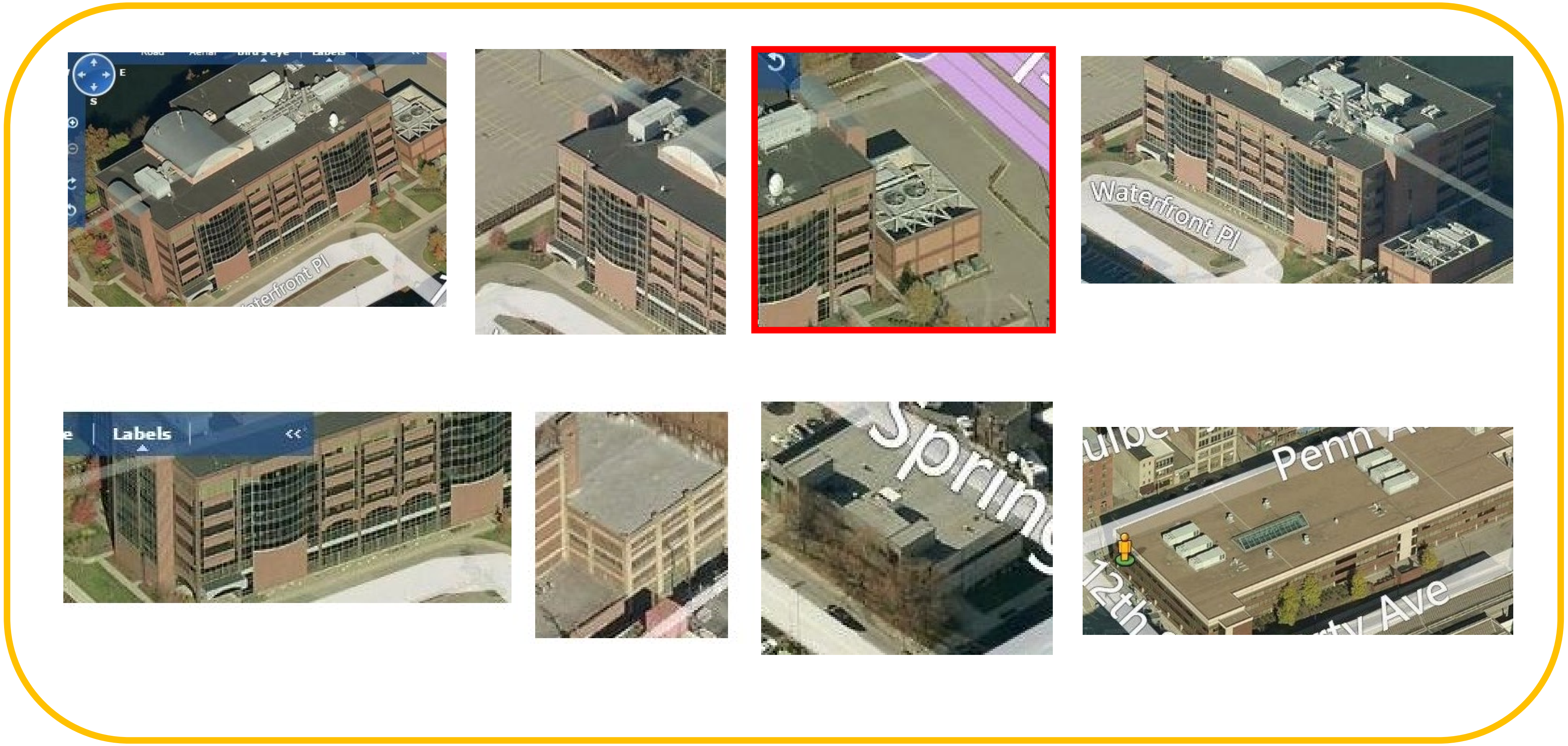
Query image
(street view)



From ~40,000 candidate image patches (Buildings)
(bird's eye view)

Building matching

Query image
(street view)



From ~40,000 candidate image patches (Buildings)
(bird’s eye view)

Building matching

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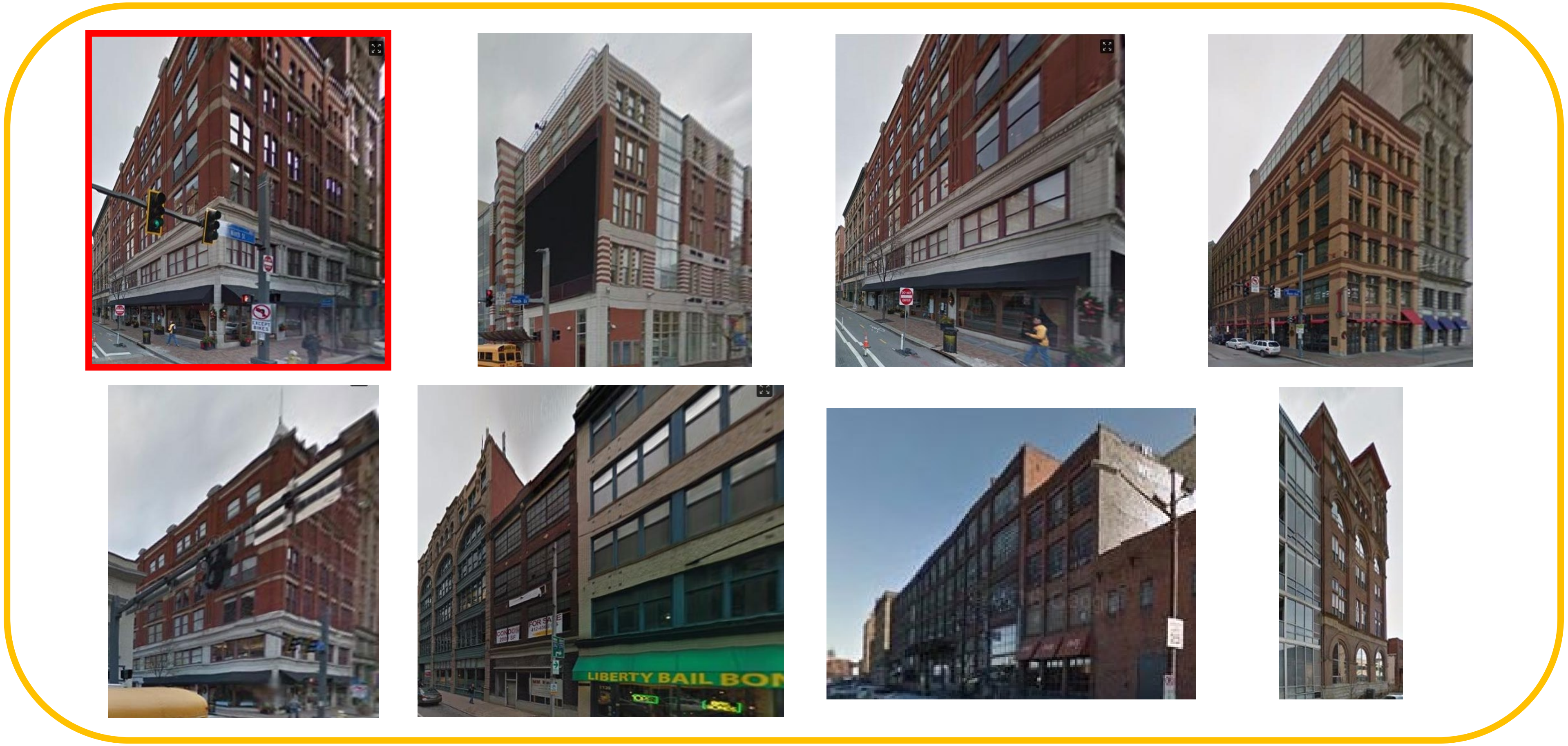
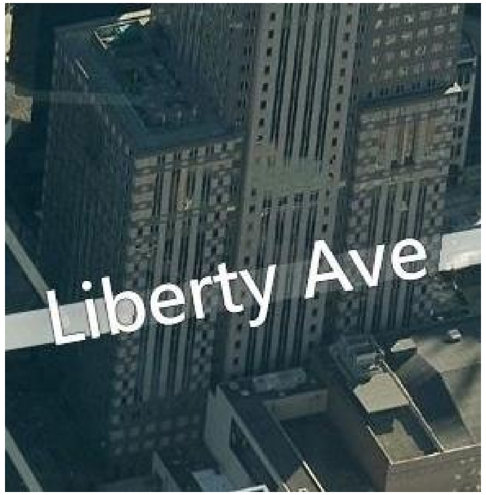
Query image (bird's eye view)



From ~10,000 candidate image patches (Buildings) (street view)

Building matching

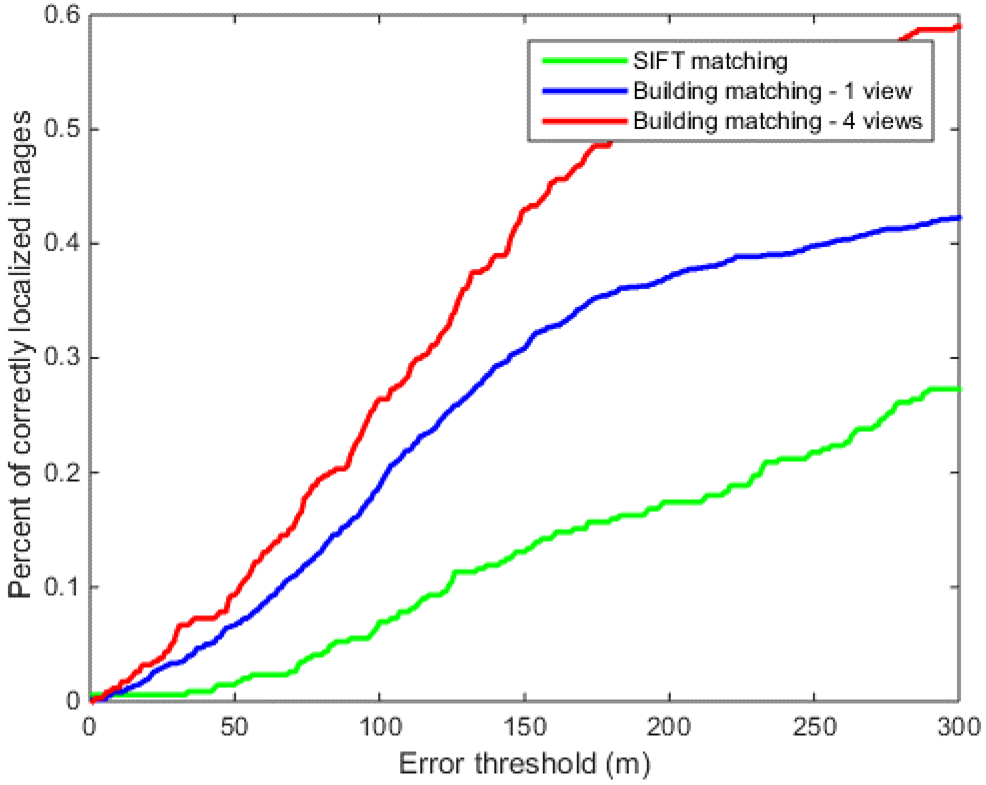


Query image
(bird's eye view)

From ~10,000 candidate image patches (Buildings)
(street view)

Geo-localization

- Query image: street view
- Reference images: bird's eye view
- k: 100



Summary

- Geo-localization Using Cross View Image Matching
  - Detect Buildings
  - Match Buildings
  - Retrieve k-nearest neighbors for each query
  - Dominant Set Selection

Cross-View Image Matching for Geo-localization in Urban Environments

Yicong Tian, Chen Chen, Mubarak Shah
Center for Research in Computer Vision, University of Central Florida

CVPR-2017

Retrieval Features

- Local Features (SIFT)
- Building Features
- **Global Image Features**

Bridging the Domain Gap for Ground-to-Aerial Image Matching

Krishna Regmi

Krishna Regmi & Mubarak Shah
University of Central Florida

https://www.youtube.com/watch?v=gmAhQXCYCEQ&list=PLd3hlSJsX_IkSnnrMtzsMHl1q6vimipvp&index=1

Introduction

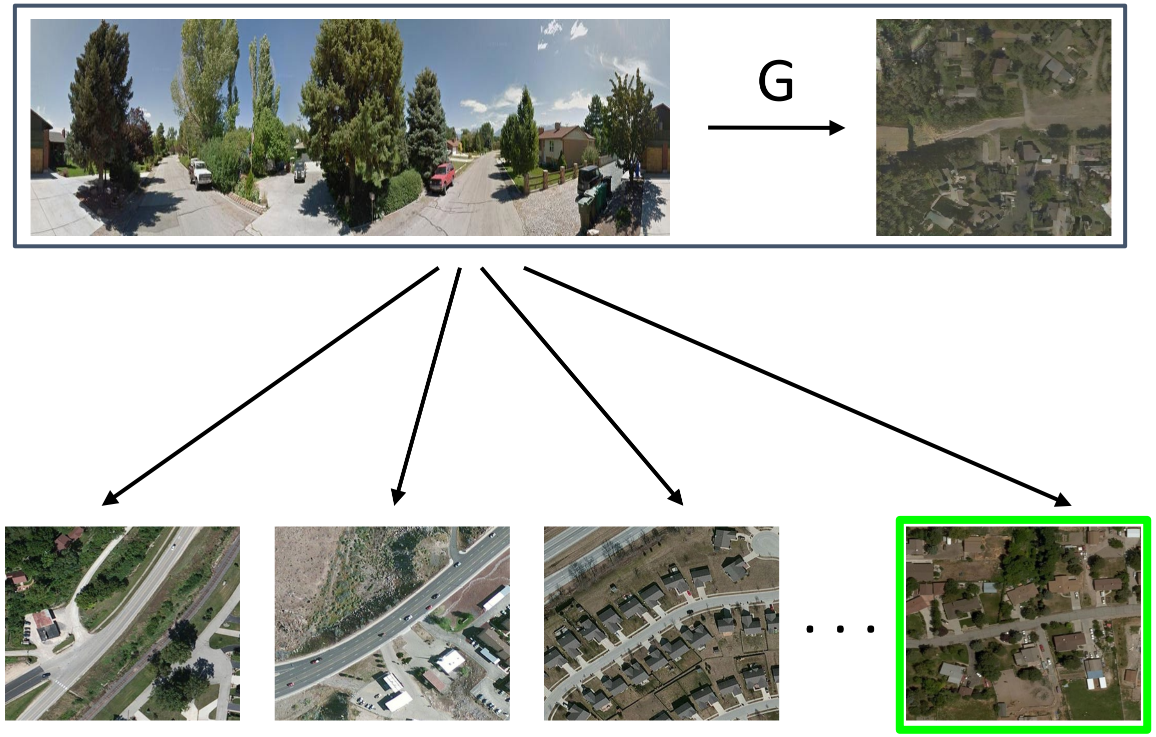
Cross-view image matching

Drastic viewpoint differences

Bridge the domain gap - use GANs
(synthesize target-view images)

Joint Feature Learning and Feature fusion

Multi-scale feature aggregation

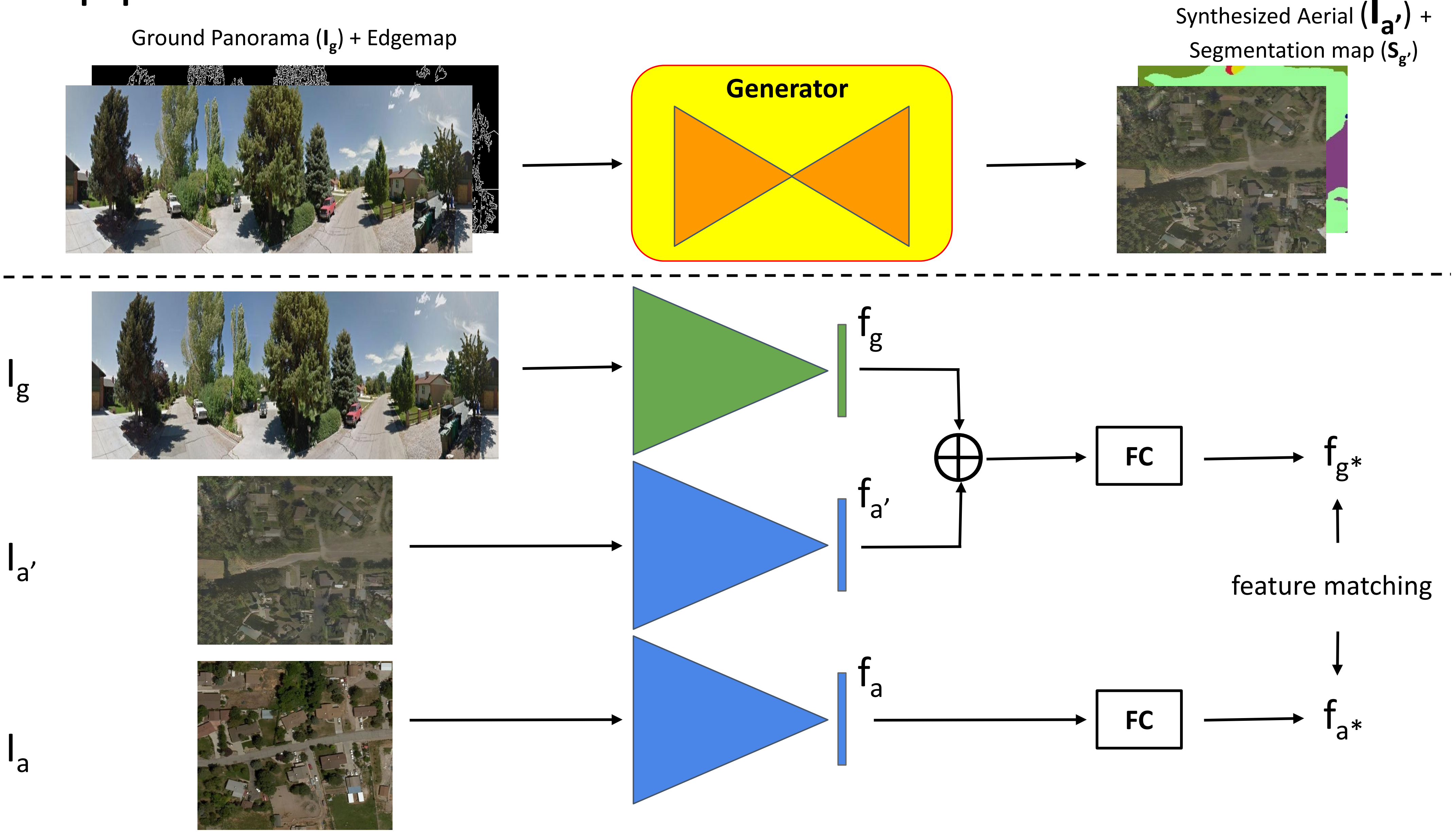


Our Approach

Cross-view image synthesis followed by

Joint Feature Learning and Feature Fusion

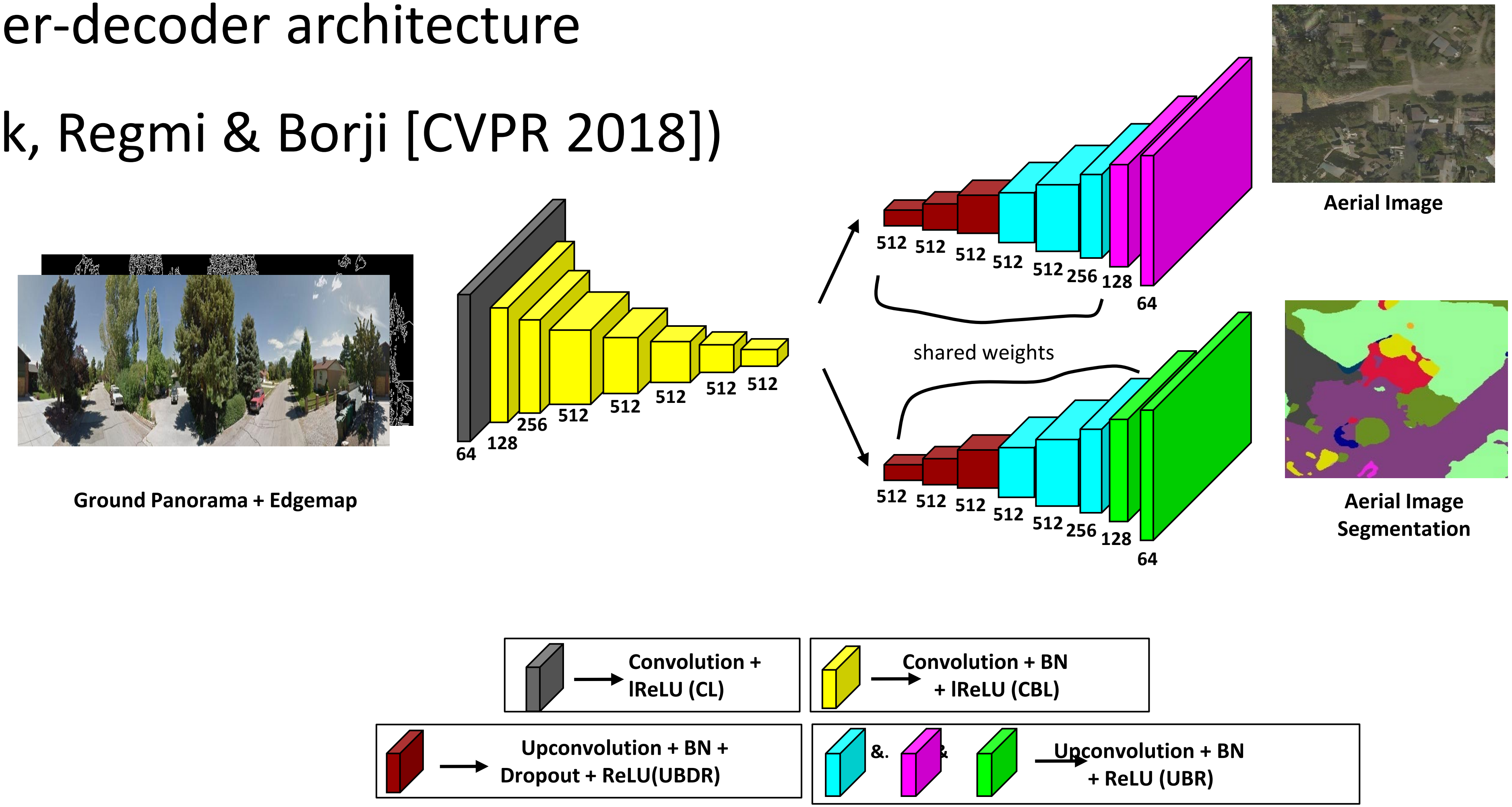
Our Approach



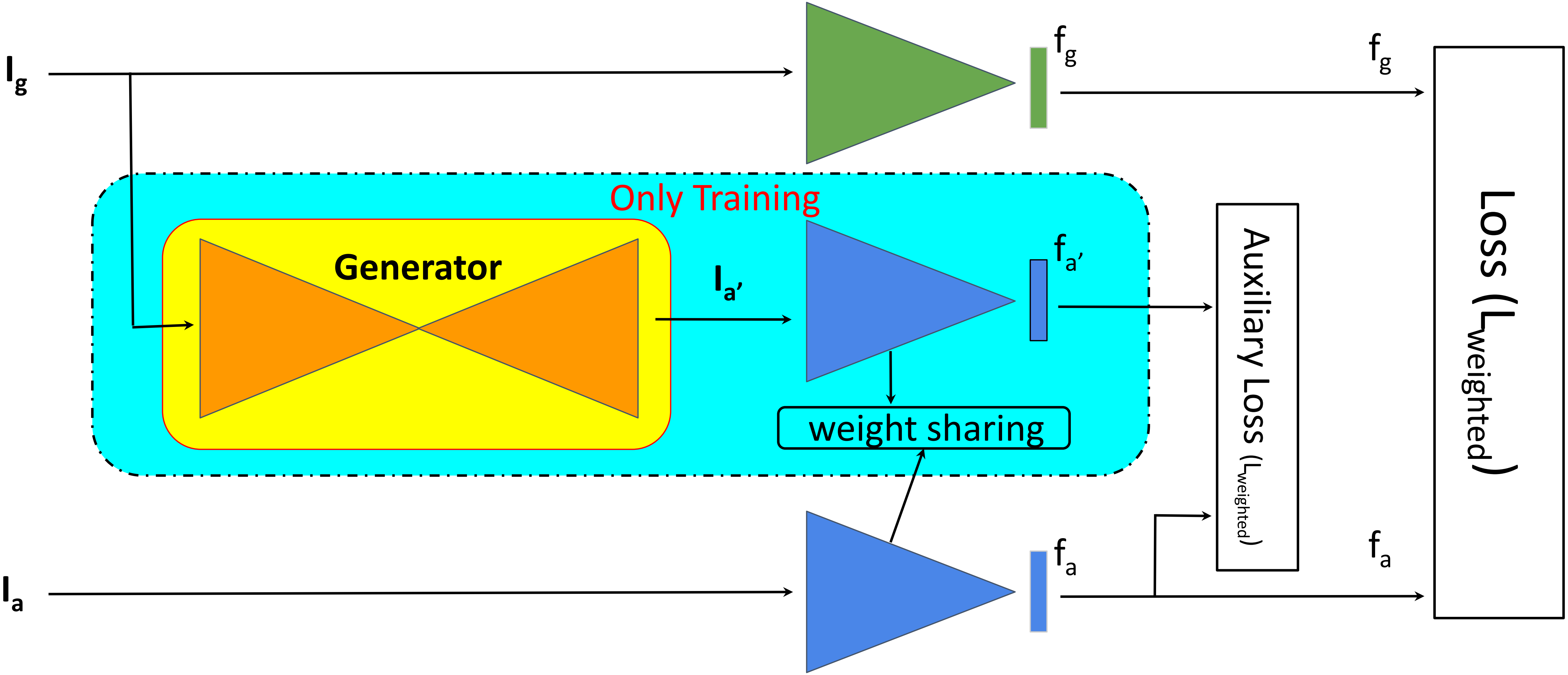
Generator Architecture

Encoder-decoder architecture

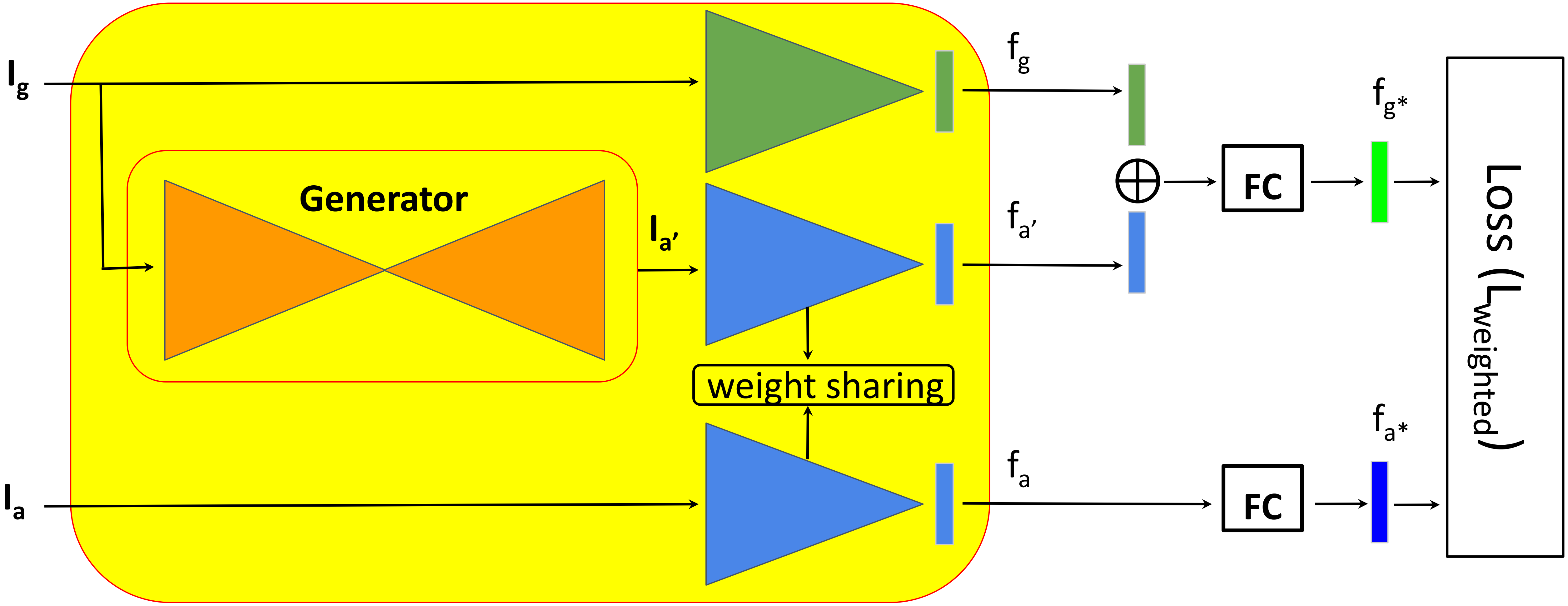
(X-Fork, Regmi & Borji [CVPR 2018])



Joint Feature Learning



Feature Fusion



Loss Functions

Triplet Loss: $$L_{triplet} = max(0, m + d_p - d_n)$$

$$= max(0, m + d) \quad \text{where, } d = d_p - d_n$$

Soft-Margin Triplet Loss: $$L_{soft} = ln(1 + e^{d})$$

Weighted Soft-Margin Triplet Loss: $$L_{weighted} = ln(1 + e^{\alpha d})$$

Loss for Joint Feature Learning:

$$L_{joint} = \lambda_1 L_{weighted}(I_g, I_a) + \lambda_2 L_{weighted}(I_{a'}, I_a)$$

Datasets

Satellite - ground panorama pairs

CVUSA Dataset:

Train/Test: 35,532/8,884 pairs

Covers rural areas

UCF OP Dataset: (Orlando Pittsburgh)

Train/Test: 1,910/722 pairs

Newly collected

Covers urban areas

GPS info available

Results: CVUSA Dataset

Quantitative Results (CVUSA Dataset)

Method	Top-1	Top-10	Top-1%
Two-stream baseline ($I_{a'}$, I_a)	10.23%	35.10%	72.58%
Two-stream baseline (I_g, I_a)	18.45%	48.98%	82.94%
Joint Feat. Learning ($I_{a'}$, I_a)	14.31%	48.75%	86.47%
Joint Feat. Learning (I_g, I_a)	29.75%	66.34%	92.09%
Feature Fusion	**48.75%**	**81.27%**	**95.98%**
Workman et al. [41]	-	-	34.3%
Zhai et al. [46]	-	-	43.2%
Vo and Hays [39]	-	-	63.7%
CVM-Net-I [18]	22.53%	63.28%	91.4%
CVM-Net-II [18]	11.18%	43.51%	87.2%

Recall Accuracy (CVUSA Dataset)

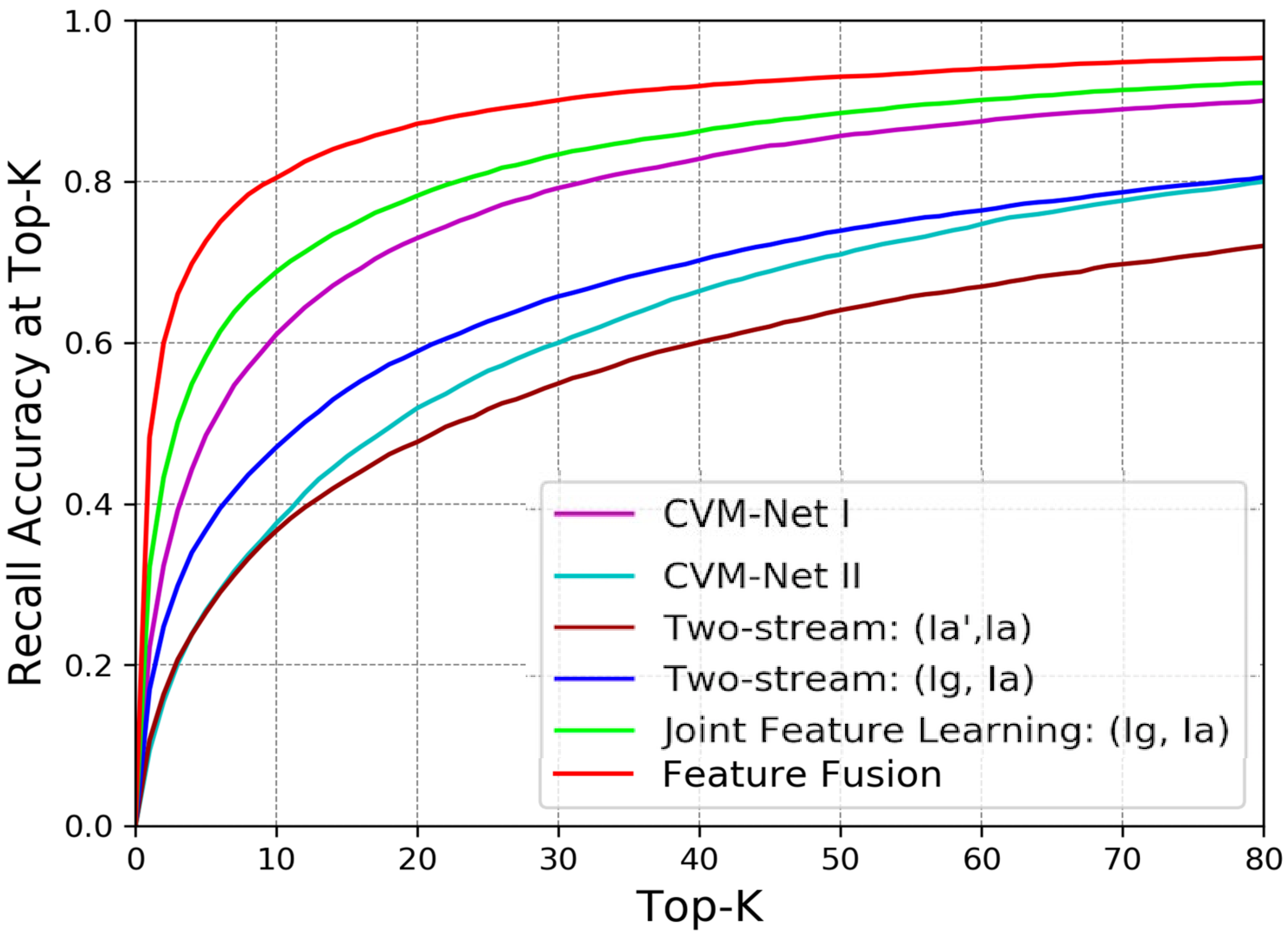
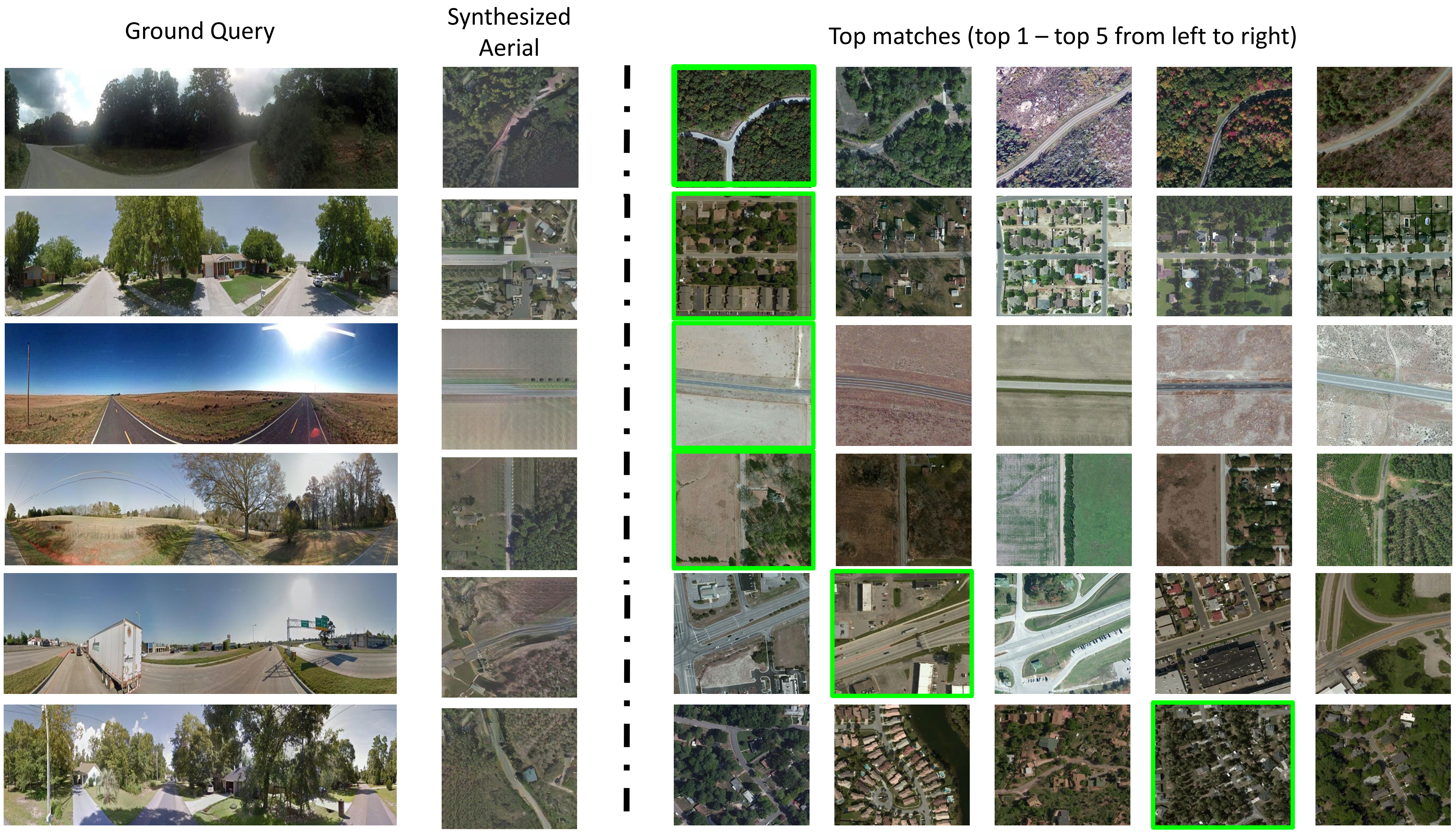


Image Retrieval (CVUSA Dataset)



Failure Cases

Ground Query	Synthesized Aerial	Top-1 match	Correct match (Ground Truth)	Retrieved position
				13
				37
				532
				1700

Results: OP Dataset

Retrieval Performance (OP Dataset)

Two-stream (I_g, I_a)	Joint Feat. Learning	Feature Fusion
30.61%	38.36%	45.57%

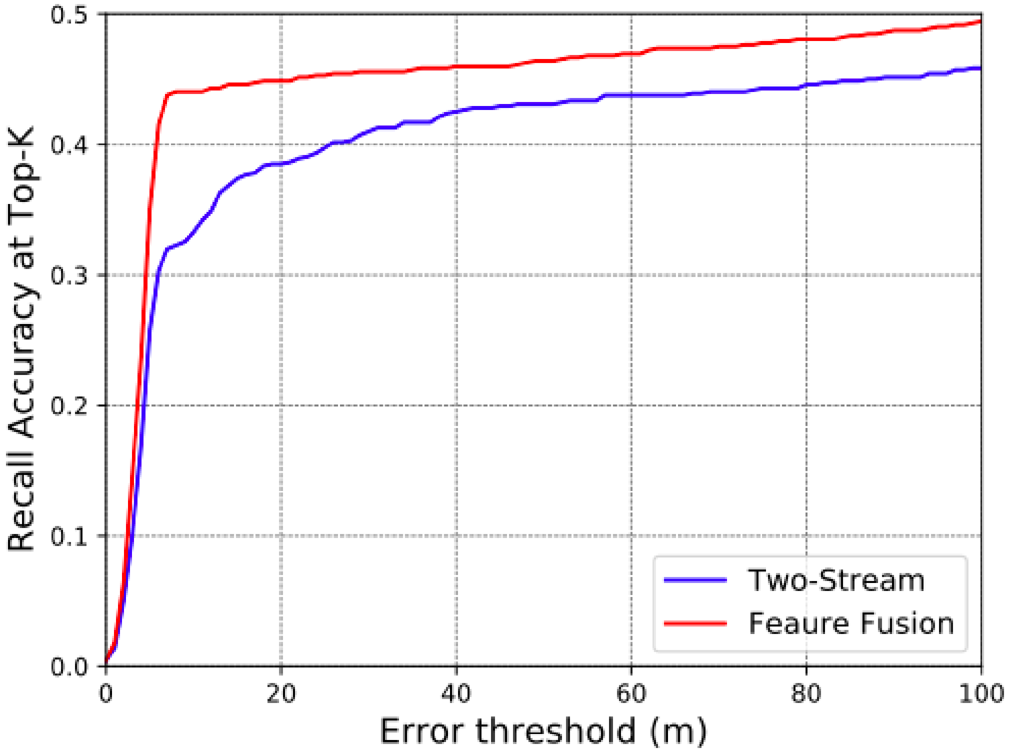
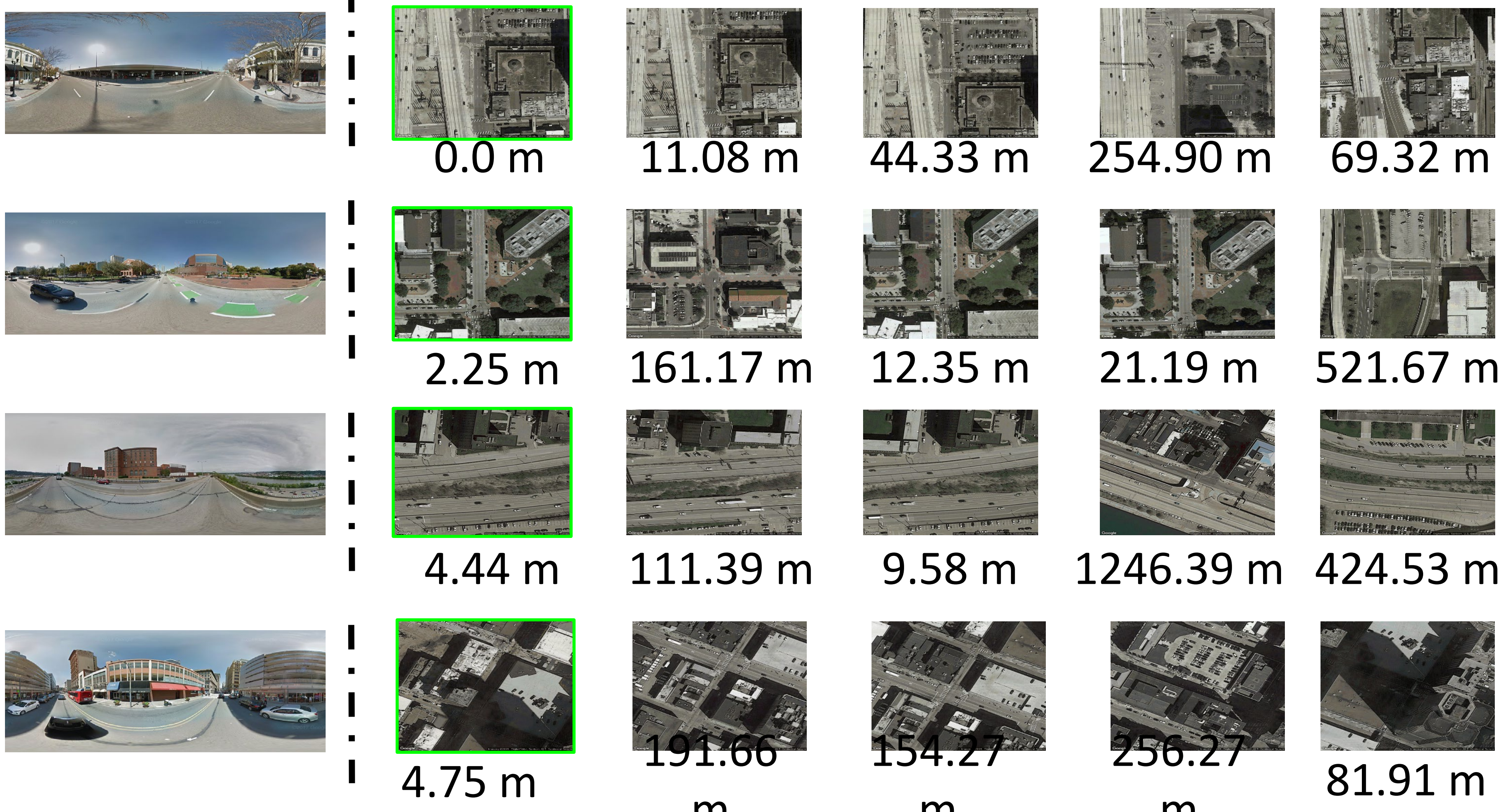


Image Retrieval (OP Dataset)

Ground Query | Top matches (top 1 – top 5 from left to right)



Aerial-to-Ground (A2G) Image Matching

Reverse problem

Synthesize the ground panorama from aerial image

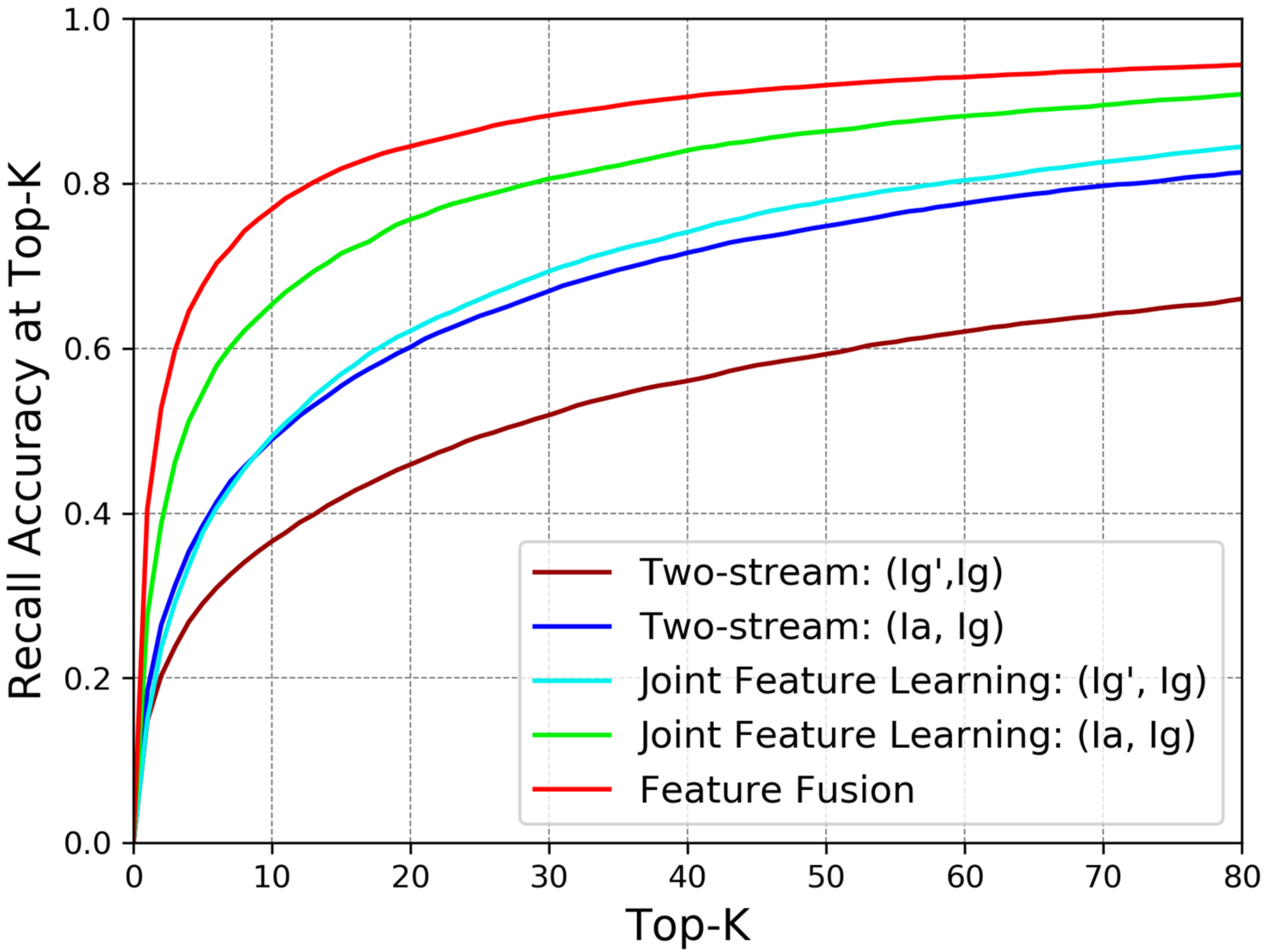
Quantitative Results - A2G (CVUSA Dataset)

Method	Top-1	Top-10	Top-1%
Two-stream baseline ($I_{g'}$, I_g)	15.04%	37.31%	67.99%
Two-stream baseline (I_a, I_g)	16.99%	47.06%	82.11%
Joint Feat. Learning ($I_{g'}$, I_g)	16.46%	50.26%	86.26%
Joint Feat. Learning (I_a, I_g)	27.39%	65.29%	91.46%
Feature Fusion	**44.99%**	**79.37%**	**95.66%**

Image Retrieval - A2G (CVUSA Dataset)

Aerial Query | Synthesized Ground Panorama | Top matches (top 1 – top 5 from left to right)

Recall Accuracy - A2G (CVUSA Dataset)



Summary

- Novel and practical approach to cross-view image matching
- Domain gap is bridged by synthesized images
- Significant improvement on Top-1 and Top-10 accuracies over SOTA on CVUSA.
- This approach can be used for other view transformation tasks where the transformations can be in horizontal or vertical directions.

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ICCV 2019
Seoul, Korea

Bridging the Domain Gap for Ground-to-Aerial Image Matching

Krishna Regmi

Krishna Regmi & Mubarak Shah
University of Central Florida

Summary

- Pixel-Wise Geo-localization
  - Geodetic Alignment of Aerial Video Frames
- Image-Based Geo-Localization
  - Same View (Street-View to Street-View)
    - Generalized Maximum Clique (PAMI, 2014)
    - Constraint Dominant Sets (PAMI, 2017)
  - Cross-View Geo-Localization
    - Bird’s Eye-View to Street View (CVPR, 2017)
    - Aerial to Ground View (ICCV, 2019)

Thank You