



Combining Satellite Imagery and GPS Data for Road Extraction

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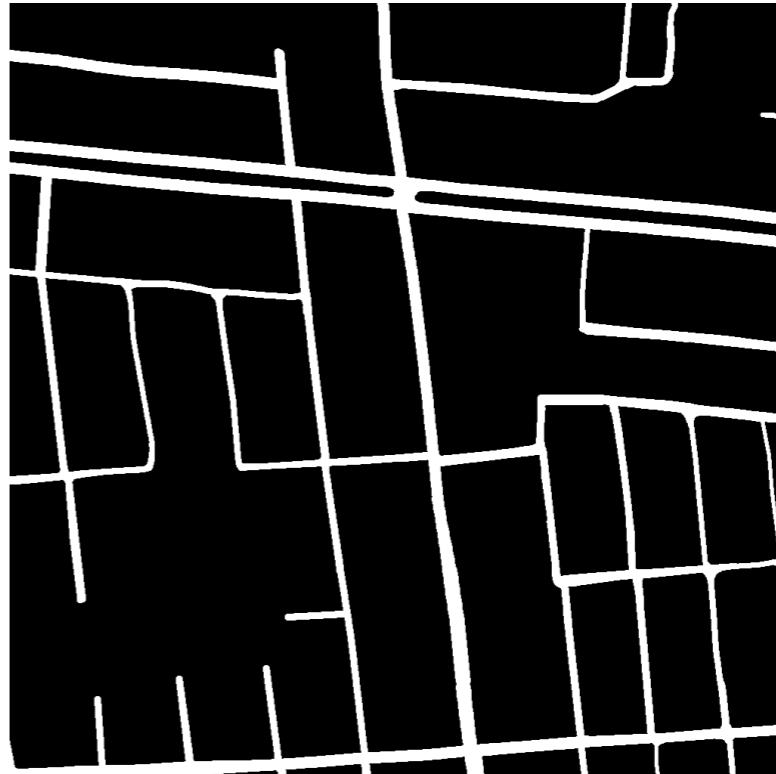
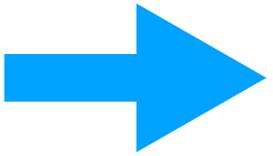
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Outline

- **Task Description**
- **Previous Solutions**
- **Proposed Method**
 - **The dataset we used**
 - **Training Details**

Task Description

- Automatically extracting roadmap from satellite images.
- The manual methods are costly, error-prone, and easily become outdated.
- It is a binary classification or segmentation problem.



Previous Solutions

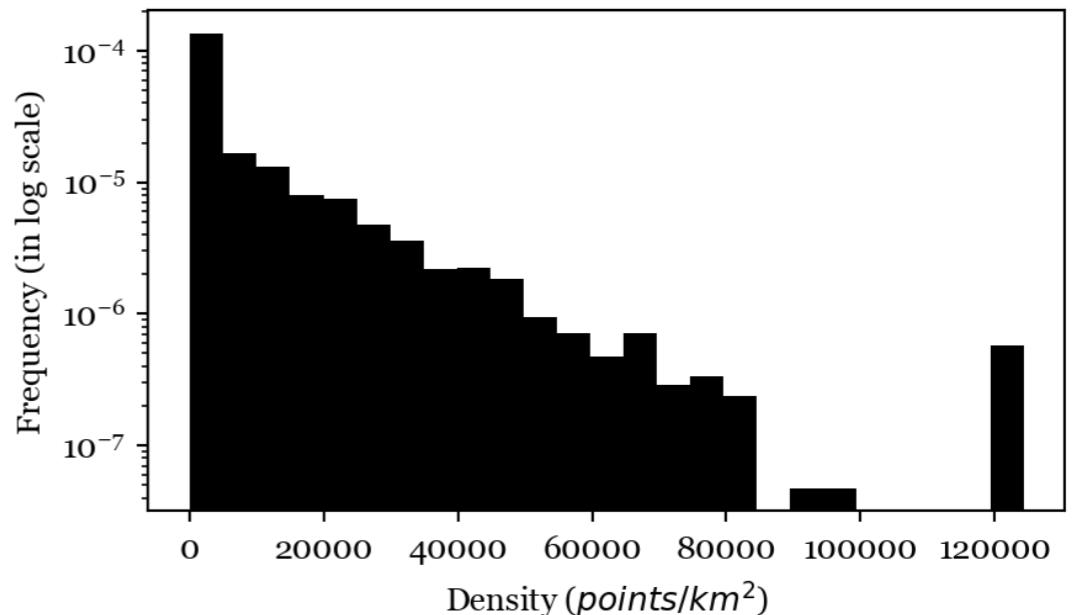
- GPS: Kernel Density Estimation (KDE), ...
- Satellite Images & CNN-based methods:
 - Classification model: AlexNet, VGG, ResNet, ...
 - Segmentation model: Fully Convolutional Network (FCN), **U-Net**, ...

Challenges & Opportunities

- Challenges in previous methods:
 - **GPS-only:** noisy, incomplete and inaccurate roadmaps
 - **Satellite-only:** easily influenced by dense vegetation, building shadow, dirty roads and so on
- Opportunities: **GPS + Satellite + Deep Learning = ?**
 - GPS is increasingly abundant
 - GPS can help satellite images fill the prediction gaps
 - Satellite images can help make GPS prediction more accurate

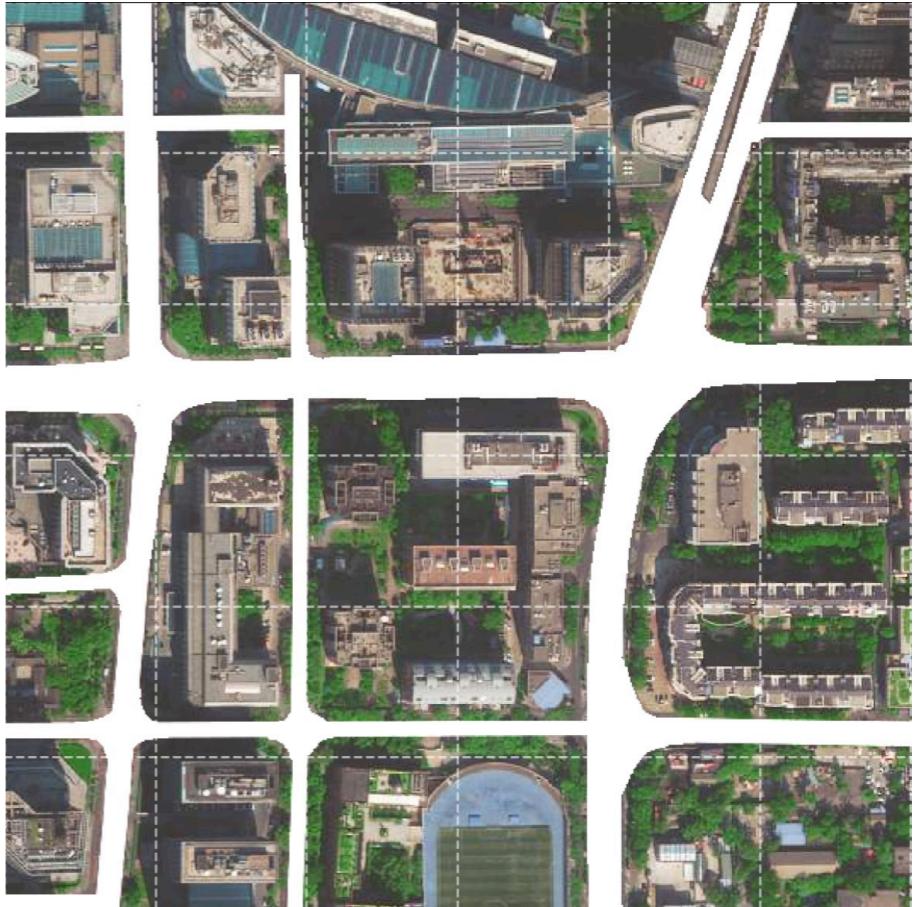
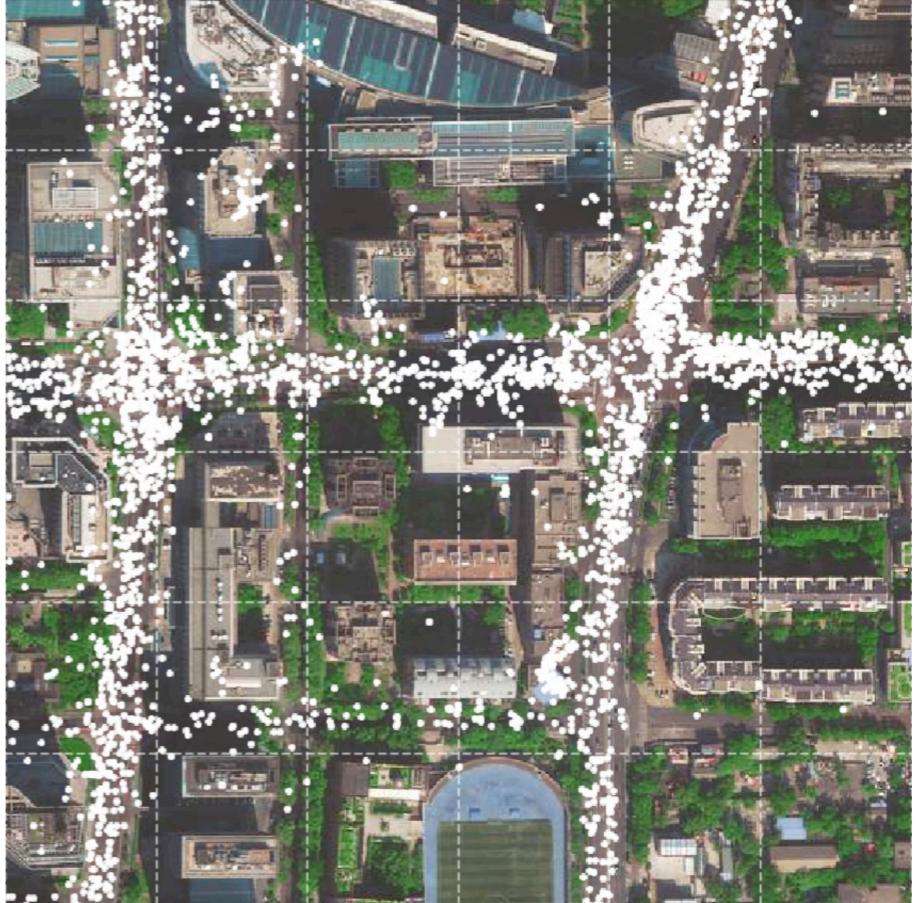
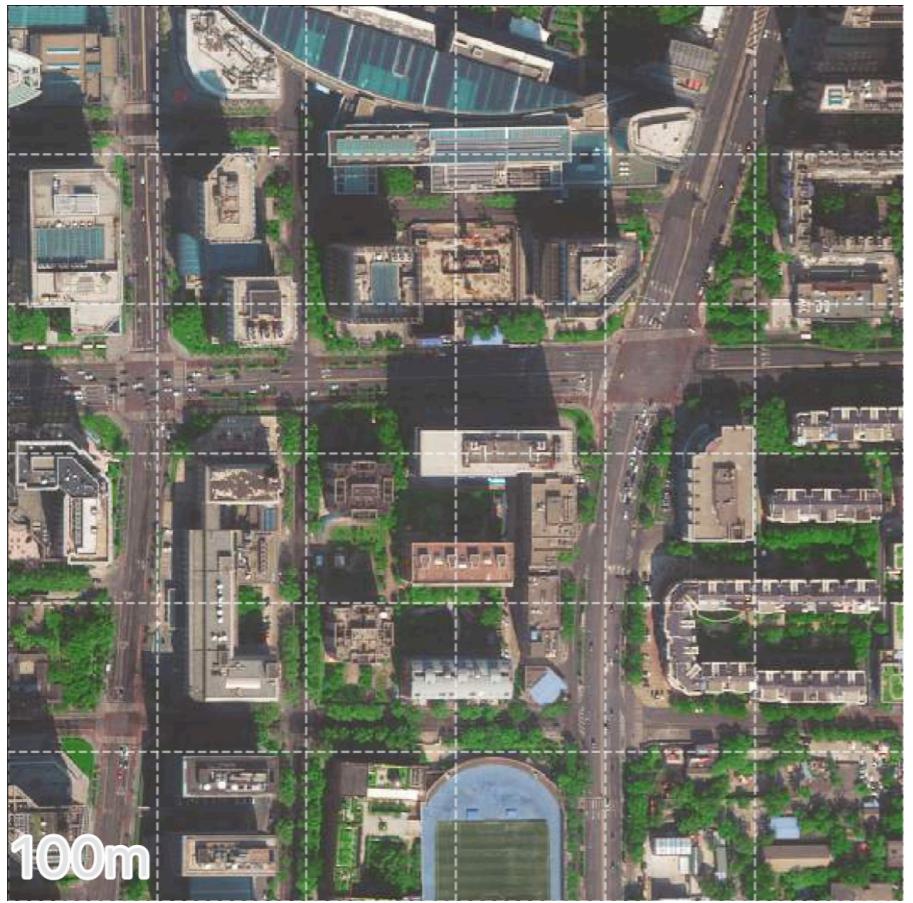
The GPS data we used

- The GPS data
 - 65-taxi and 192-hour data
 - The sampling interval is 10s.
 - The spatial resolution is 0.00001 degree of latitude and longitude (about 1m in Beijing).
 - We render GPS data in points and lines.



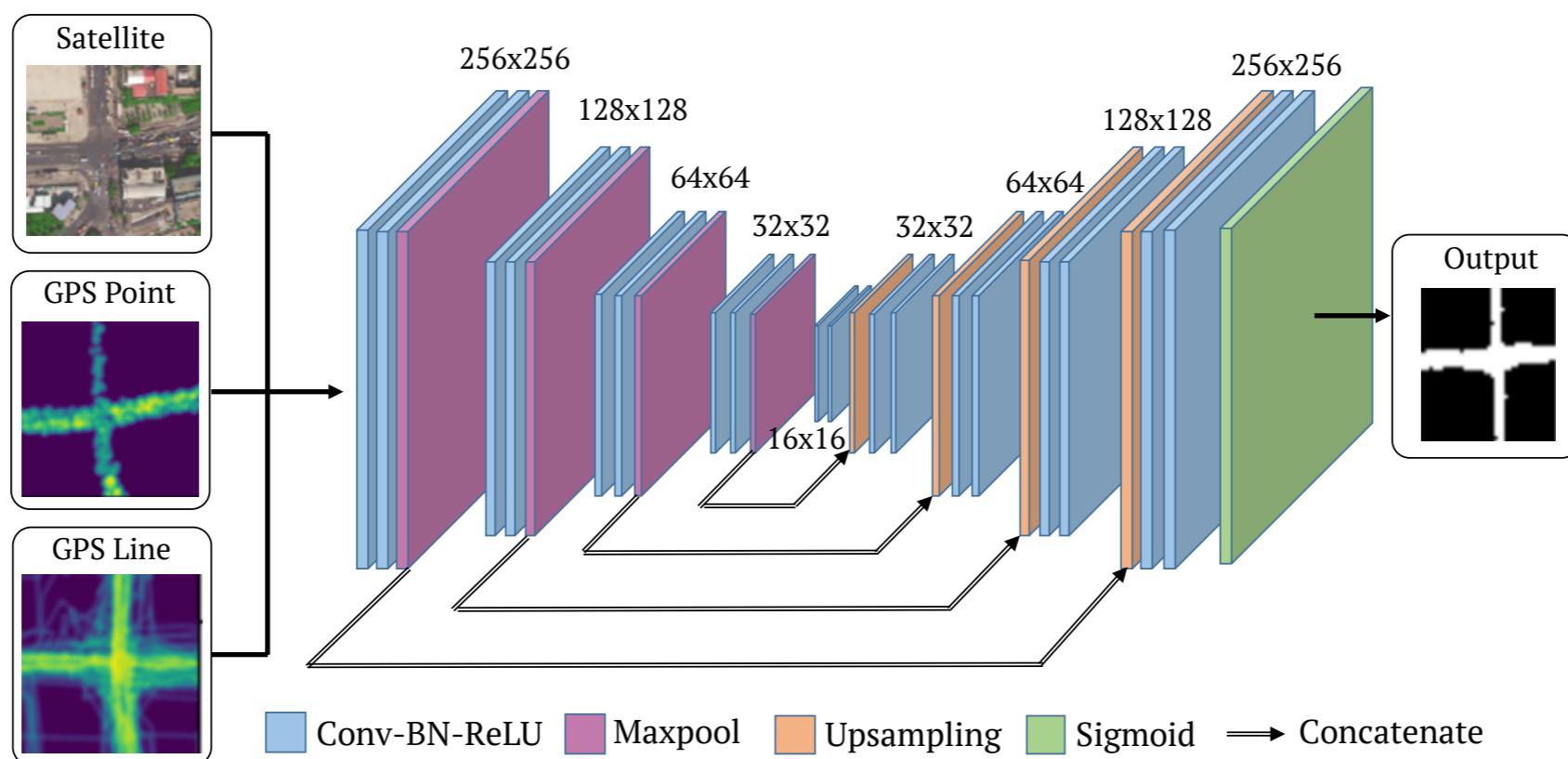
The satellite images we used

- The Satellite Image data:
 - 120 images from *Fifth Ring Road* in Beijing
 - 1024×1024 with resolution of 1m per pixel
 - Labelled manually
 - Road pixel coverage is 13.1%



The model we used

- We used U-Net as skullbone.
- The number of input channels is extended from 3 to 5.
- The input size is 256×256.



Training Details

- Use PyTorch in 2 Nvidia 1080Ti GPUs in about 50 hours
- 5-fold cross validation
- Data enhancement including rotation, flipping, cropping, and HSV tuning
- If the loss does not decrease over 4 epochs, we decrease the learning rate to 1/5 in the next epoch. We terminate training when the loss stops decreasing over 10 epochs or the learning rate is smaller than 1e-7.
- Loss function is $L = (1 - \lambda)L_{ce} - \lambda log(L_j)$, where

$$L_{ce} = -\frac{1}{N} \sum N_{i=0} (y \log y' + (1 - y) \log(1 - y')) \quad L_j = \frac{1}{N} \sum N_{i=0} \frac{y_i y'_i}{y_i + y'_i - y_i y'_i}$$

Results

	Method	Input	mIoU	Recall	Precision	Recall
CNN	RGB	RGB	31.36	38.73	39.24	38.98
	RGB+Line	RGB+Line	43.45	60.92	51.51	55.82
	RGB+Point	RGB+Point	43.79	64.12	50.59	56.56
	RGB+Line+Point	RGB+Line+Point	44.02	64.96	50.48	56.81
	Line+Point	Line+Point	36.08	47.46	54.03	50.53
KDE	Line	Line	31.64	39.42	61.61	48.08
	Point	Point	34.06	46.27	56.34	50.82

Results Illustration



true positive = green, false positive = red, false negative = blue



Thanks for your listening

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