Inferring Road Information from Crowd-sourced Vehicle Sensor Data

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Acknowledgments

❑ Research collaborators

- o Dr. Andrew Fox
- o Dr. Eric He
- o Dr. Fan Bai (General Motors)

❑ Research Sponsor

- o General Motors

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Motivation

❑**T**he increasing computing, communication and sensing capabilities can help intelligent transportation systems (ITS)

❑Two Examples

o **Inferring road maps from Global Positioning System (GPS) data**

o **Detecting road potholes from accelerometer data**

Inferring Road Maps from GPS Data

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Map Usage
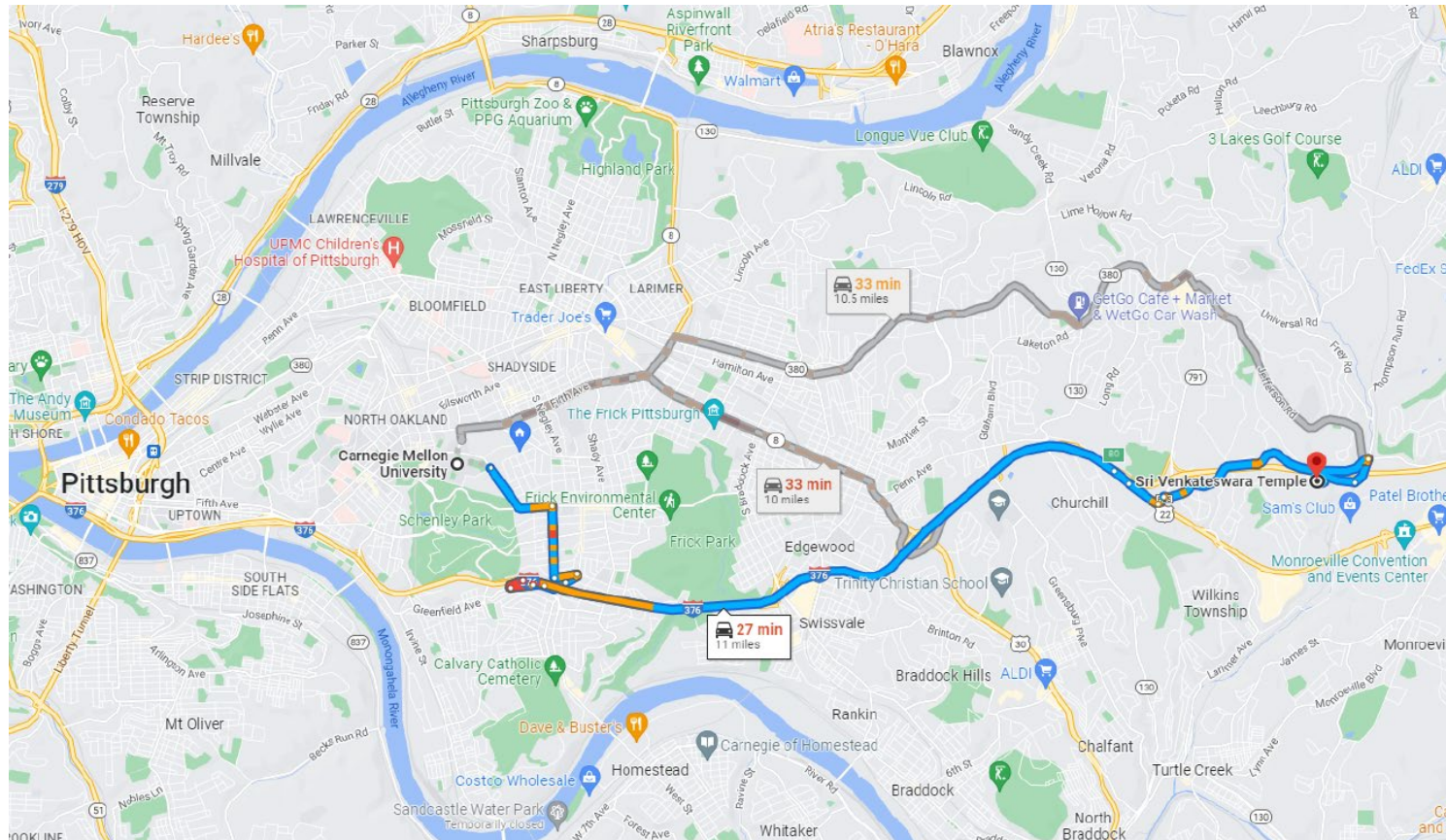
Courtesy of Google Maps

Google Map for going from CMU to the Sri Venkateswara Temple in Pittsburgh
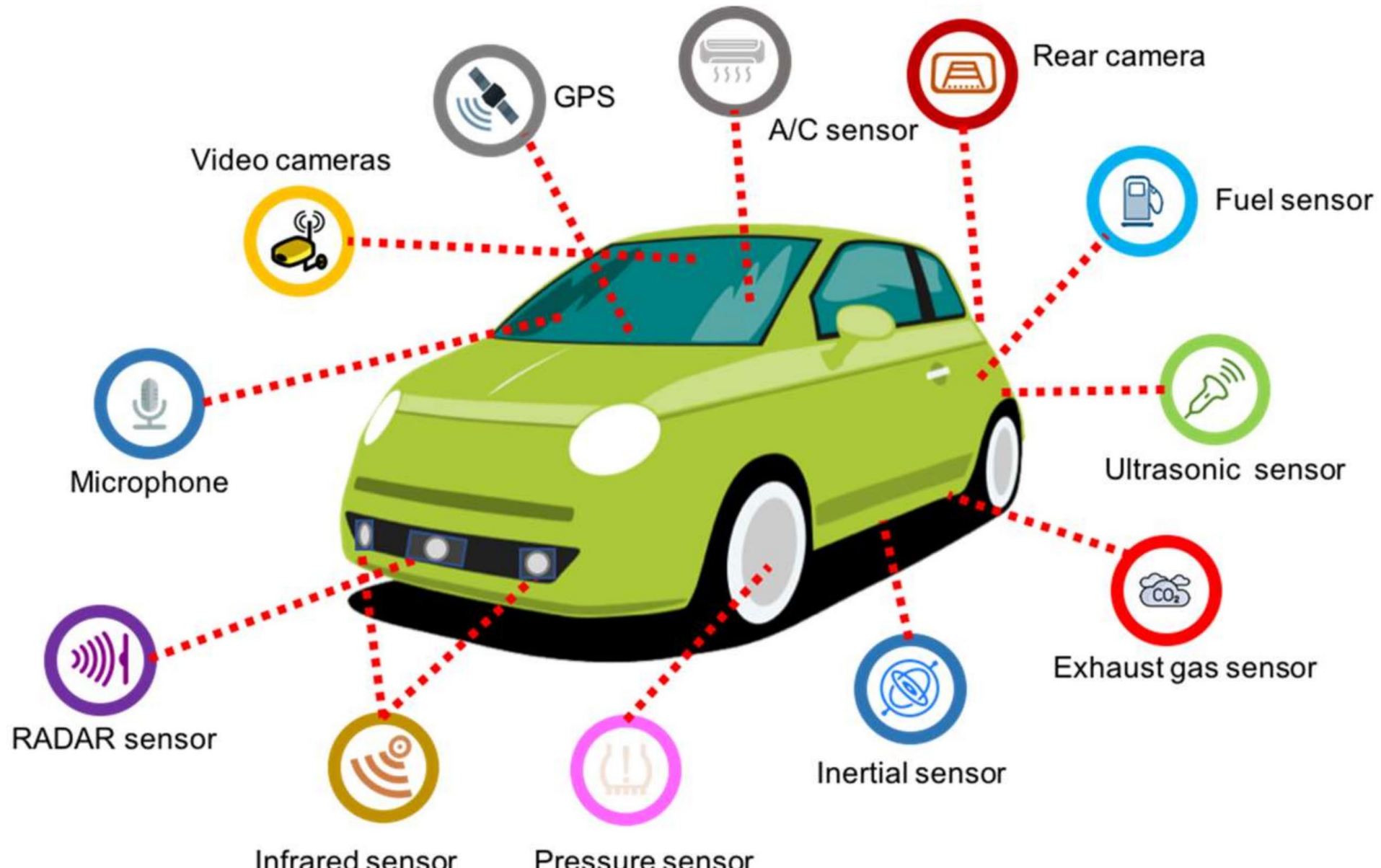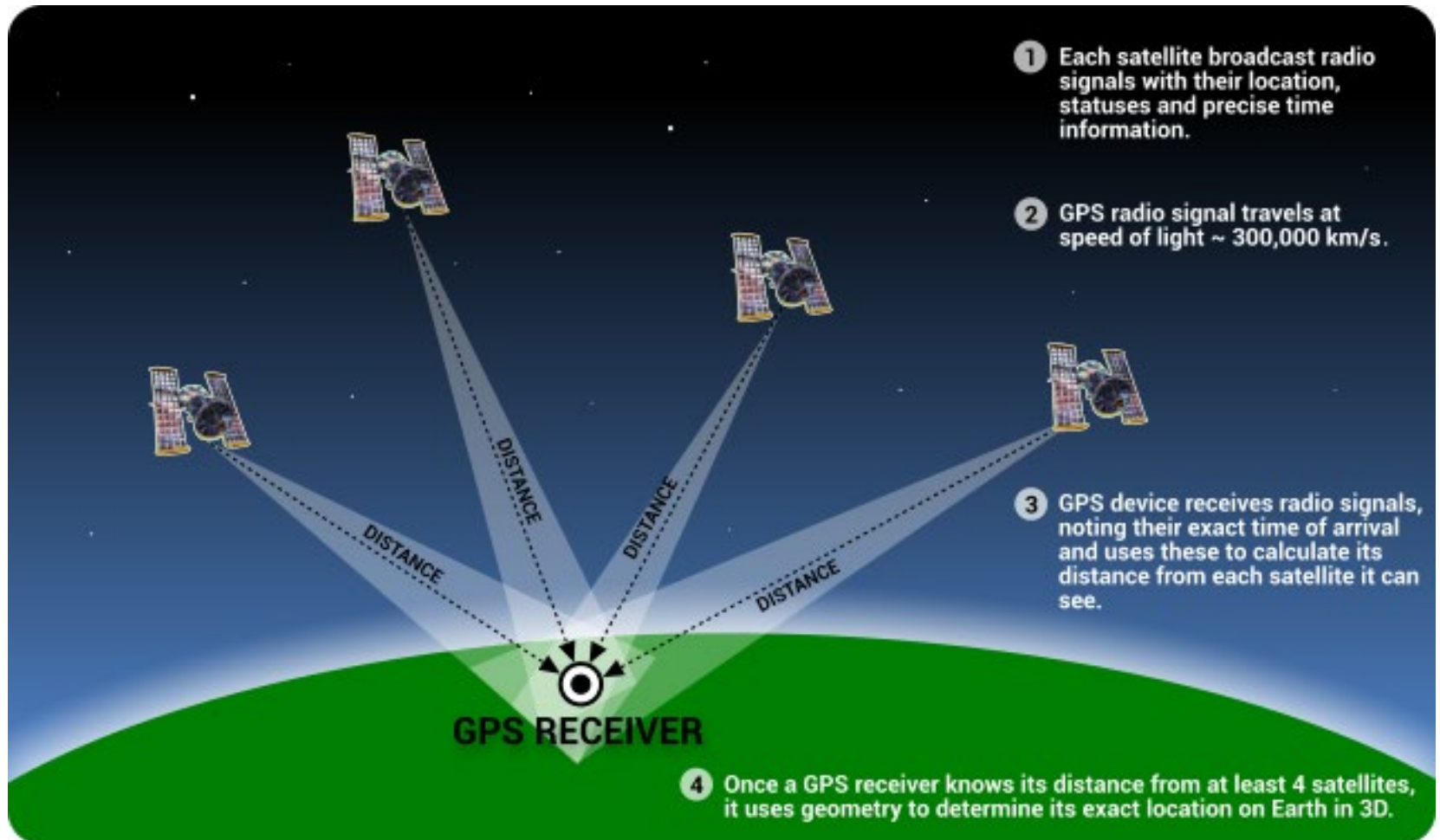
Map Making

Traditional

Modern

❑ Traditional map making is labor-intensive

❑ Modern map making is mostly the domain of big tech companies and may not be updated sufficiently frequently

❑ Can maps be inferred from data collected by vehicle sensors?

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Vehicle Sensors

Global Positioning System (GPS) Basics

1. Each satellite broadcast radio signals with their location, statuses and precise time information.

2. GPS radio signal travels at speed of light ~ 300,000 km/s.

3. GPS device receives radio signals, noting their exact time of arrival and uses these to calculate its distance from each satellite it can see.

4. Once a GPS receiver knows its distance from at least 4 satellites, it uses geometry to determine its exact location on Earth in 3D.

https://www.worthview.com/what-is-and-how-does-a-gps-work/

GPS provides latitude and longitude coordinates of the GPS receiver

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Map Inference

Map inference from GPS traces is the automatic generation of road locations and shapes from large amounts of opportunistically collected data from GPS sensors in multiple vehicles

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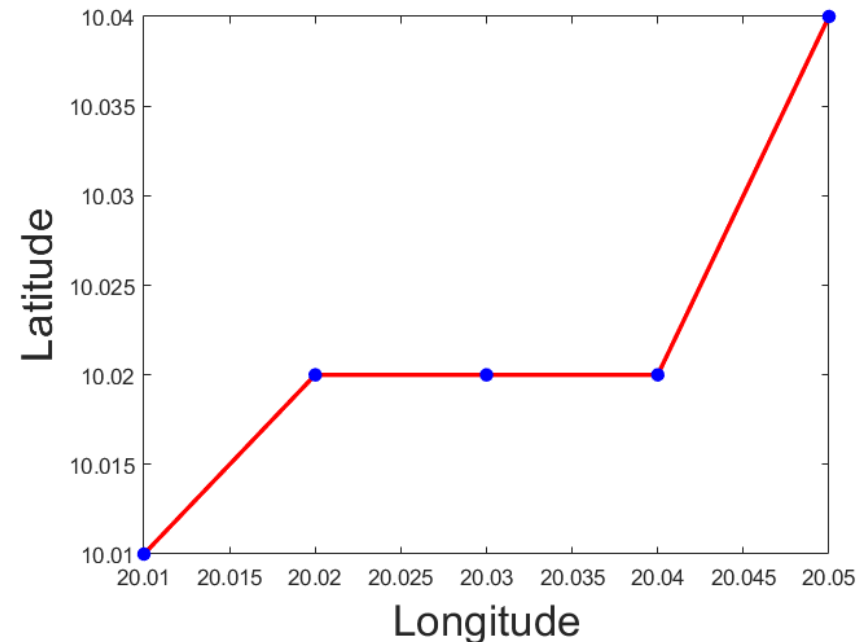
Challenges to Map Inference from GPS Traces

- ❑ **Undersampled** data
  - o Sensors may operate below Nyquist rate
  - o Requires multiple sensors to increase effective sampling rate
- ❑ **Non-uniformly** spaced data
  - o Mapping from time to spatial domain
  - o Asynchronous samples
- ❑ **GPS Location errors**

GPS data available in a region of Beijing Each black dot is a sample taken from a taxi's GPS device.

X. Liu, J. Biagioni, J. Eriksson, Y. Wang, G. Forman, and Y. Zhu, "Mining large-scale, sparse gps traces for map inference: comparison of approaches," in Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2012, pp. 669–677.

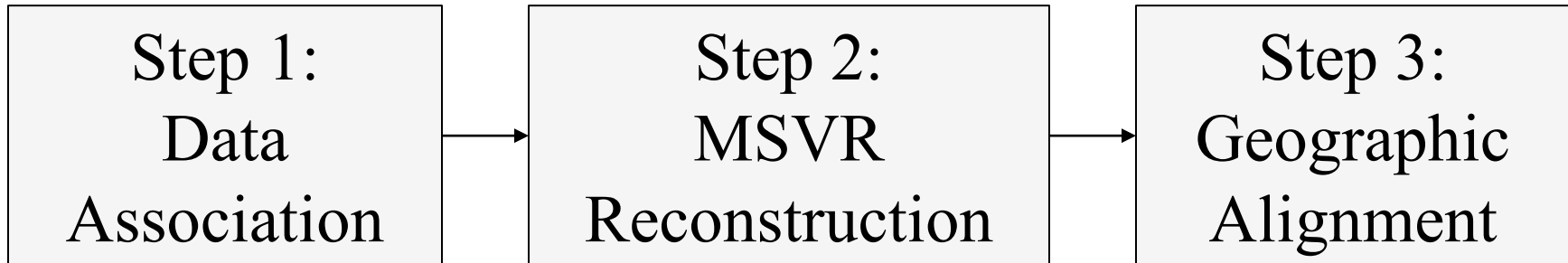Electrical & Computer ENGINEERING

Impact of Errors

GPS Traces
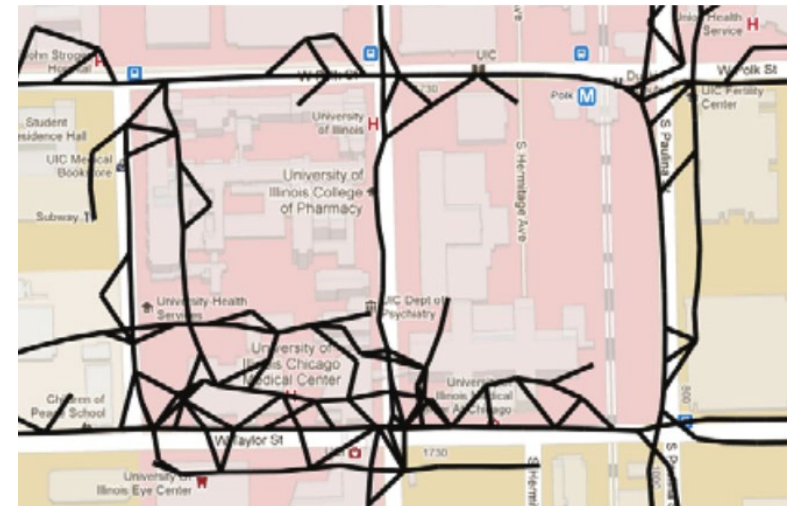
Map Inference Result

J. Biagioni and J. Eriksson, "Inferring road maps from global positioning system traces," Transportation Research Record: Journal of the Transportation Research Board, vol. 2291, no. 1, pp. 61–71, 2012.

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Multi-Source Variable-Rate (MSVR) Map Inference Method

| Step 1: Data Association	Step 2: MSVR Reconstruction	Step 3: Geographic Alignment

1. **Data Association**: Associating GPS datapoints to road segments

2. **MSVR Reconstruction**: Then we estimate the shapes of the road segments using these sets of GPS samples with the Multi-Source Variable Rate (MSVR) Signal Reconstruction method*

3. **Geographic Alignment**: Use domain knowledge to align road segments to better fit the shapes of the real road networks

*A. Fox, B. V. K.Vijaya Kumar, B. Fan, "Multi-source variable-rate sampled signal reconstructions in vehicular cps," *Proc. of IEEE INFOCOM*, 2016.
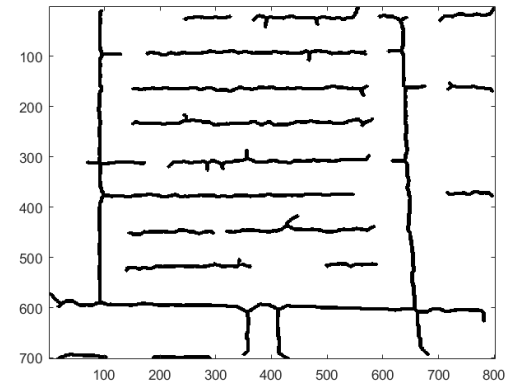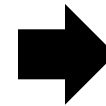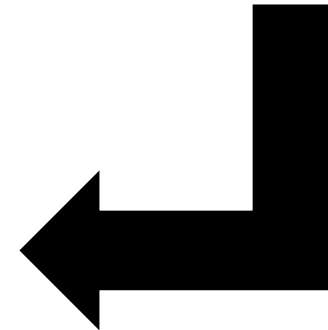
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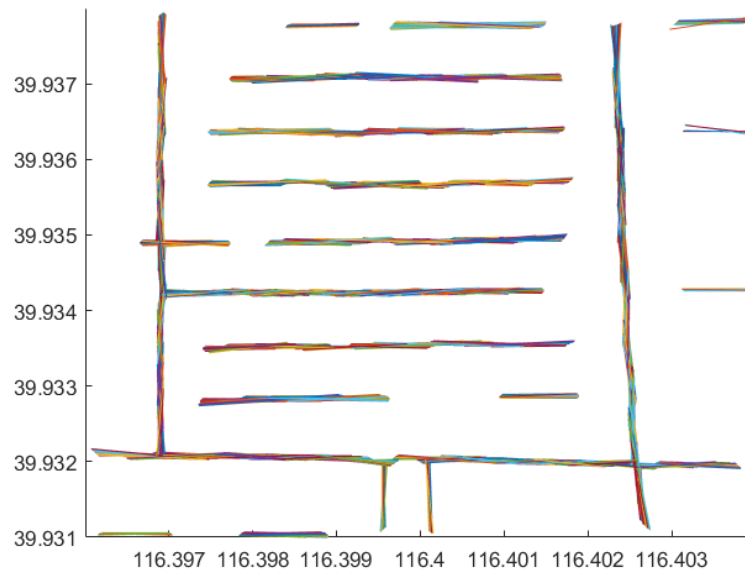ENGINEERING

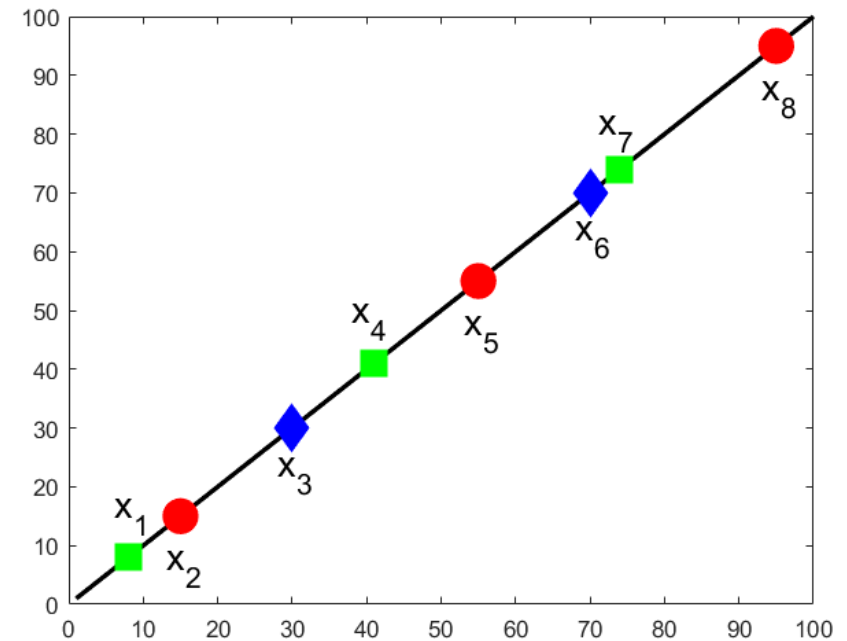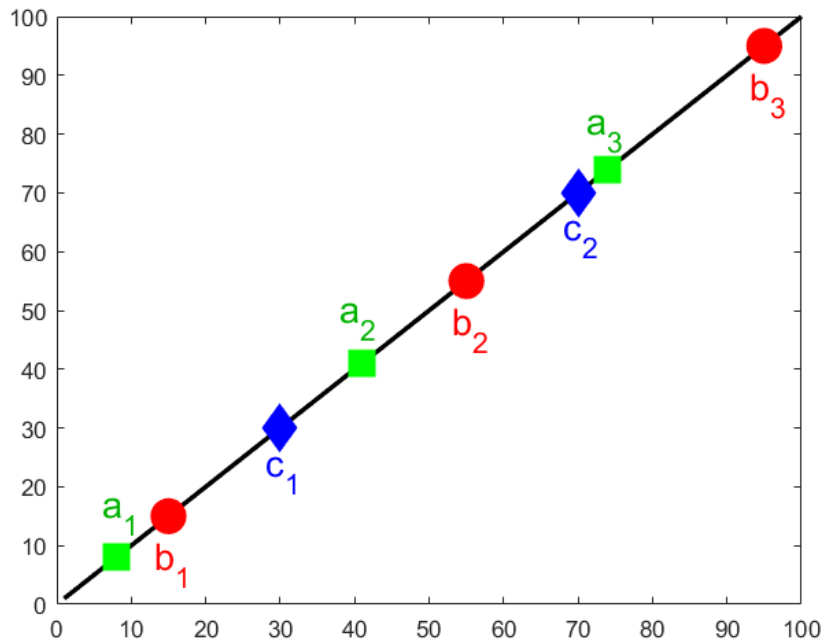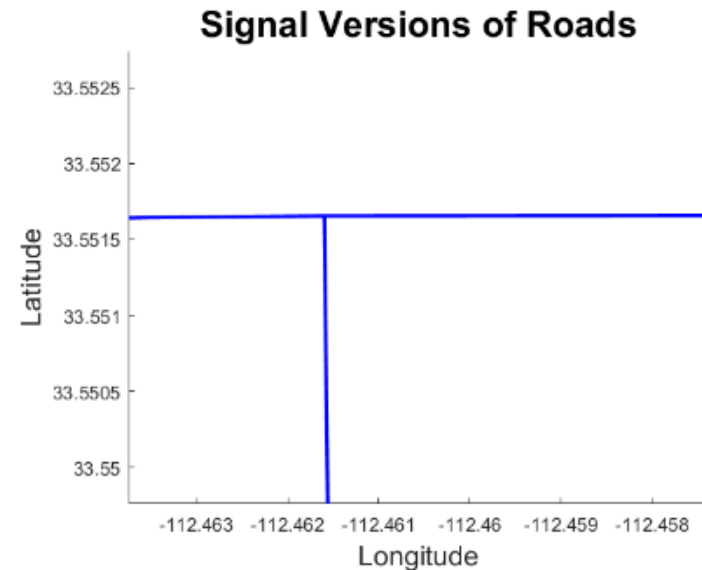# Data Association
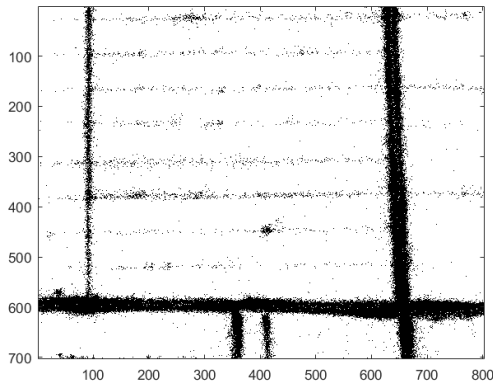
Original Image
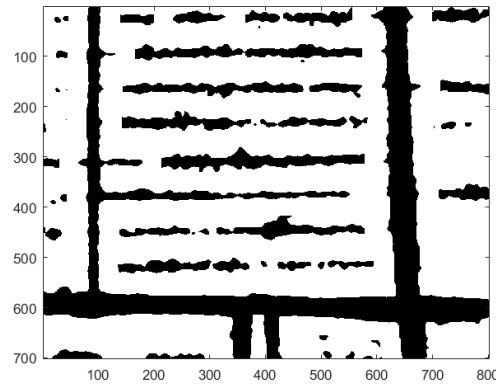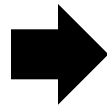
Blurred Image

Thinned then Thickened Image

Segmented Data

GPS Data Compilation

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MSVR Signal Reconstruction
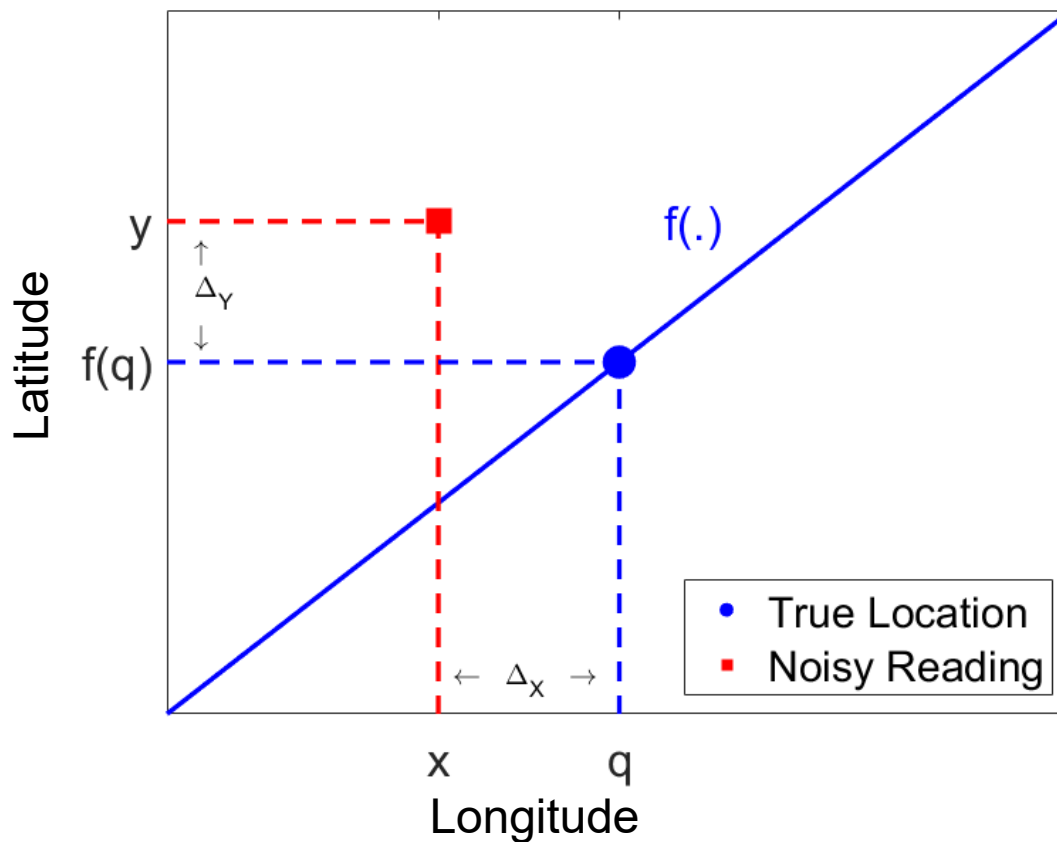

Signal Versions of Roads

- ❑ Represent a road as a signal or function f(.): Latitude as a function of longitude
- ❑ f(.) could be a straight line, an arc, a curve, etc.
- ❑ Estimate the parameters of f(.) from the crowd-sourced GPS samples in each segment

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Errors in Both Variables

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MSVR Signal Reconstruction

Error Vector

$$\min_{\theta,\Delta} \begin{bmatrix} f_\theta(q_1) - y_1 \\ \vdots \\ f_\theta(q_N) - y_N \\ q_1 - x_1 \\ \vdots \\ q_N - x_N \end{bmatrix}^{\mathrm{T}} \mathbf{C}^{-1} \begin{bmatrix} f_\theta(q_1) - y_1 \\ \vdots \\ f_\theta(q_N) - y_N \\ q_1 - x_1 \\ \vdots \\ q_N - x_N \end{bmatrix}$$

– $\mathbf{C}$ is the covariance matrix of the errors in Latitude and Longitude,

– θ are the parameters of the reconstructed signal $f_\theta(.)$

– q_n and $f_\theta(q_n)$ are the true Longitude and Latitude of sample n, and x_n and y_n are the reported Latitude and Longitude of sample n

– Δ are the errors between the reported coordinates and true coordinates

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$f_\theta(x)$ **Basis Functions**

Majority of road shapes are lines or gentle curves, which can be characterized by 3rd order piecewise smooth polynomials (splines)
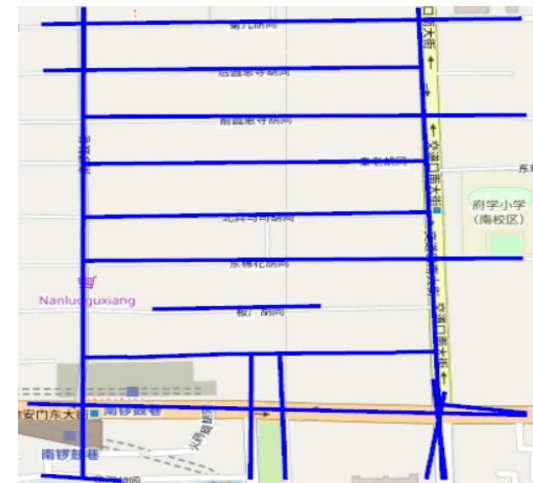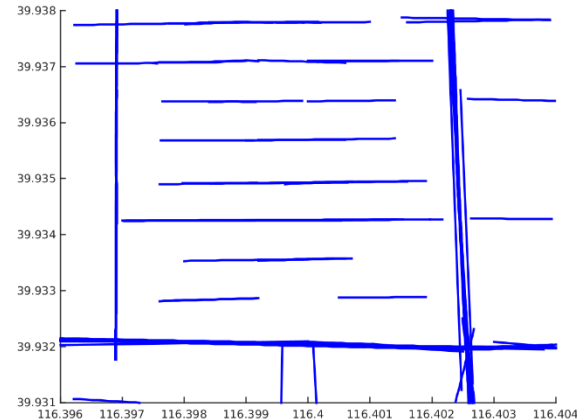
$$f_\theta(x) = \sum_{i=0}^{D} \beta_i x^i + \sum_{k=1}^{K} b_k (x - \xi_k)_+^D$$

$$(x - \xi)_+ = \begin{cases} 0, & x < \xi \\ x - \xi, & x > \xi \end{cases}$$
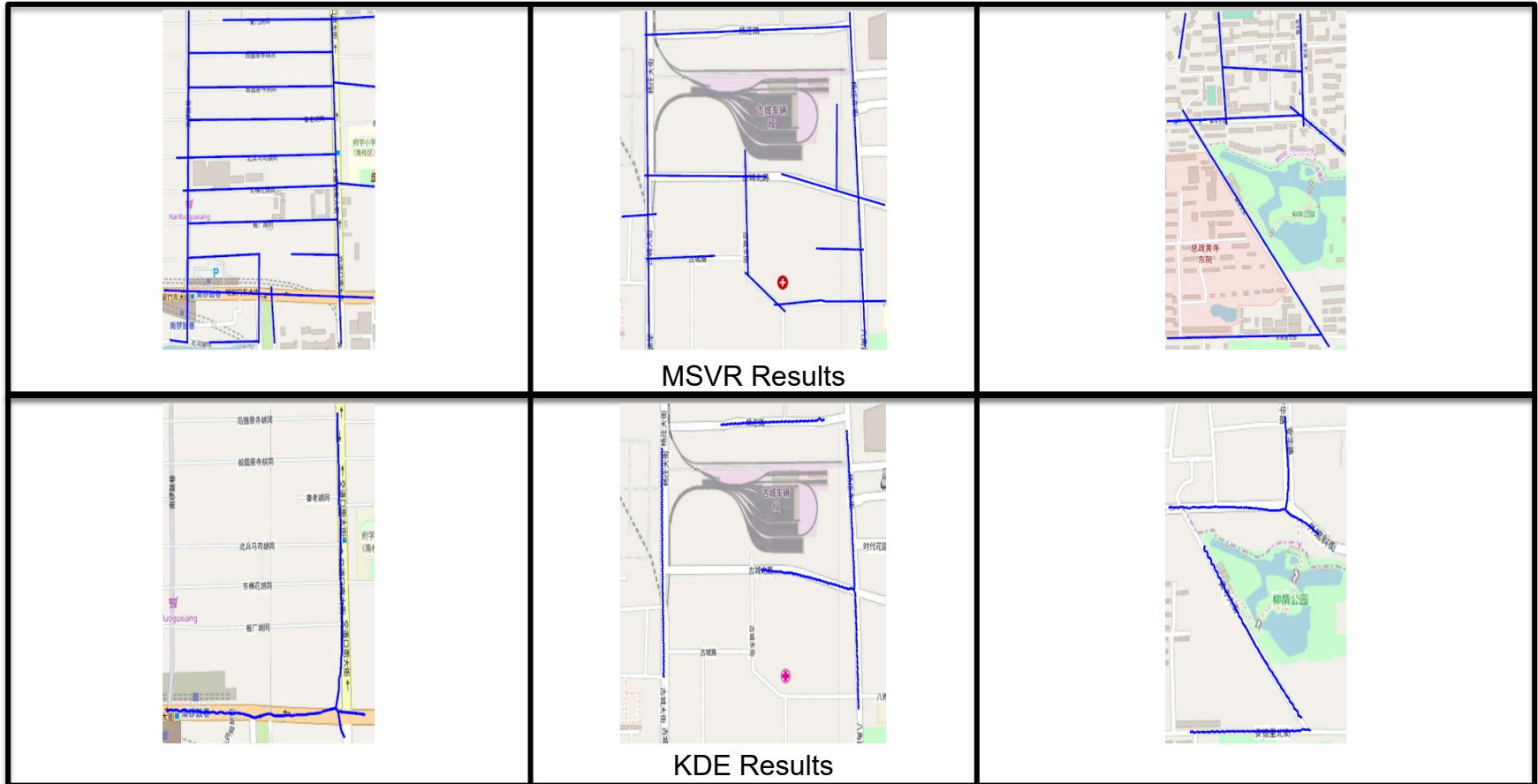
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Geographic Alignment

Once given the road segments output by the MSVR Reconstruction, we incorporate additional domain knowledge to align the geography of the road map.

- o Road Segment Pruning
- o Road Segment Merging

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Qualitative Results (Beijing)

MSVR Results

KDE Results

BJ1   BJ2   BJ3

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Qualitative Results (Shanghai)

MSVR Results

KDE Results

SH1

SH2

SH3

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Quantitative Results - F_{score}

	BJ1	BJ2	BJ3	BJ4	BJ5
MSVR	**0.8501**	**0.8010**	**0.7325**	**0.7994**	**0.7047**
KDE	0.4510	0.5581	0.6176	0.6569	0.4501

	BJ6	SH1	SH2	SH3
MSVR	**0.6371**	0.6320	**0.6296**	**0.7041**
KDE	0.3770	**0.7014**	0.4316	0.5399

$$Precision \text{ (Fraction of identified roads that are roads)} = \frac{TP}{TP + FP},$$

$$Recall \text{ (Fraction of real road that are correctly identified)} = \frac{TP}{TP + FN}$$

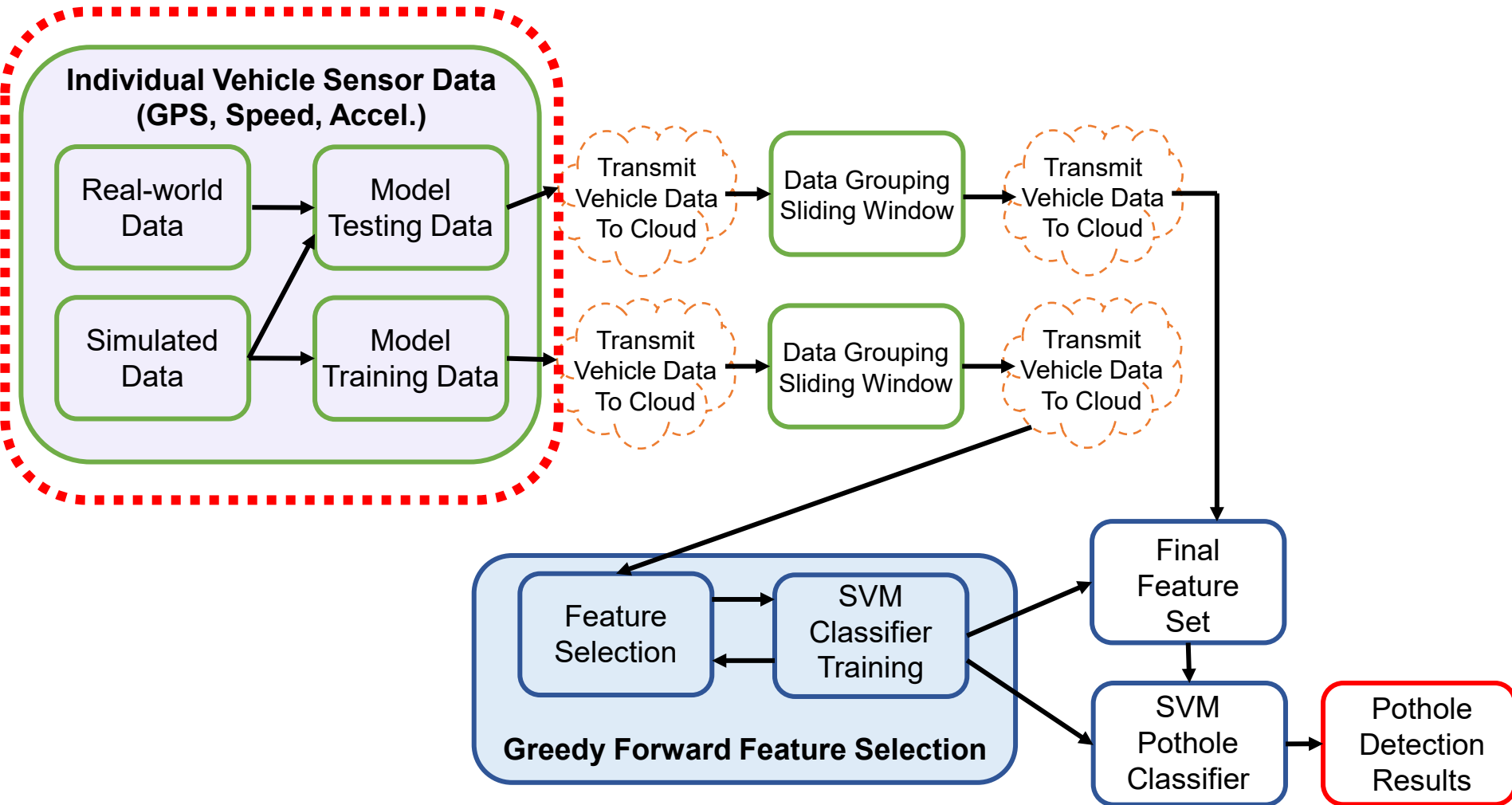$$F_{score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

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Road Pothole Detection from Crowd-sourced Vehicle Sensor Data

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Road Potholes

- Potholes damage vehicles and create dangerous driving conditions

  - Over **500,000** pothole-related insurance claims per year

  - **$6.4 billion** in repairs

- Detecting potholes and disseminating data is critical for pothole avoidance

- Use crowd-sourced vehicle sensor data (e.g., accelerometer signals) to detect road potholes

AAA Mid-Atlantic News Release
http://www.wusa9.com/story/news/nation/2014/02/24/potholes-damage-cost-us/5773501/

Detection Framework

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Training Data

- Require lots of data or vehicle(s) runs to capture full **variability** of the relevant data

- Pothole accelerometer output signal affected by sensor location, vehicle size, weight, dimensions, speed, quality of the suspension system, etc.

- Used simulated data (*CarSim*®) and real data to train algorithms


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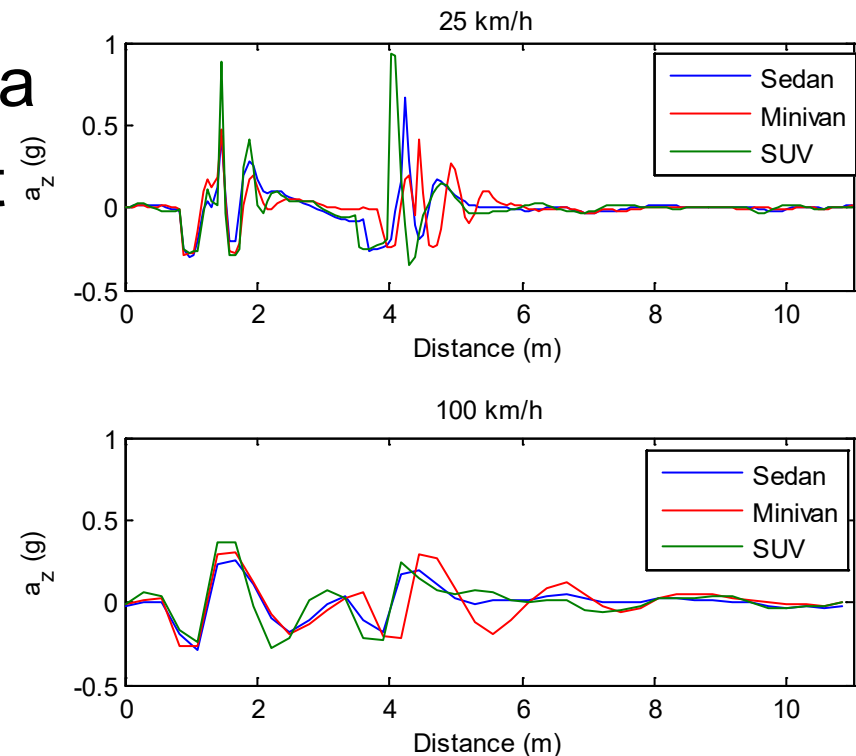
Feature Selection

- Candidate Features
  - $a_z, a_x, \frac{a_z}{v}, \frac{a_x}{v}, \frac{a_x}{a_z}, a_z v, a_x v, a_x a_z$
  - Max, Mean, Standard Deviation, Absolute Value

- Support Vector Machines
  - Two class regression classifier
  - Maximize margin between data sets
  - Radial basis kernel function

- Greedy Forward Feature Selection
  - Iteratively add best performing feature

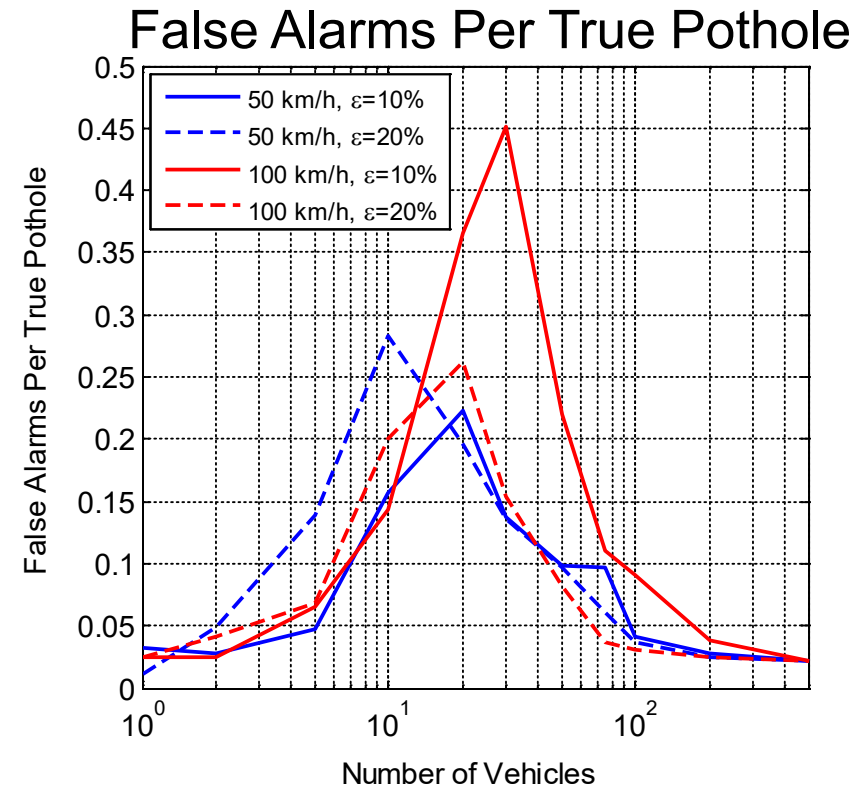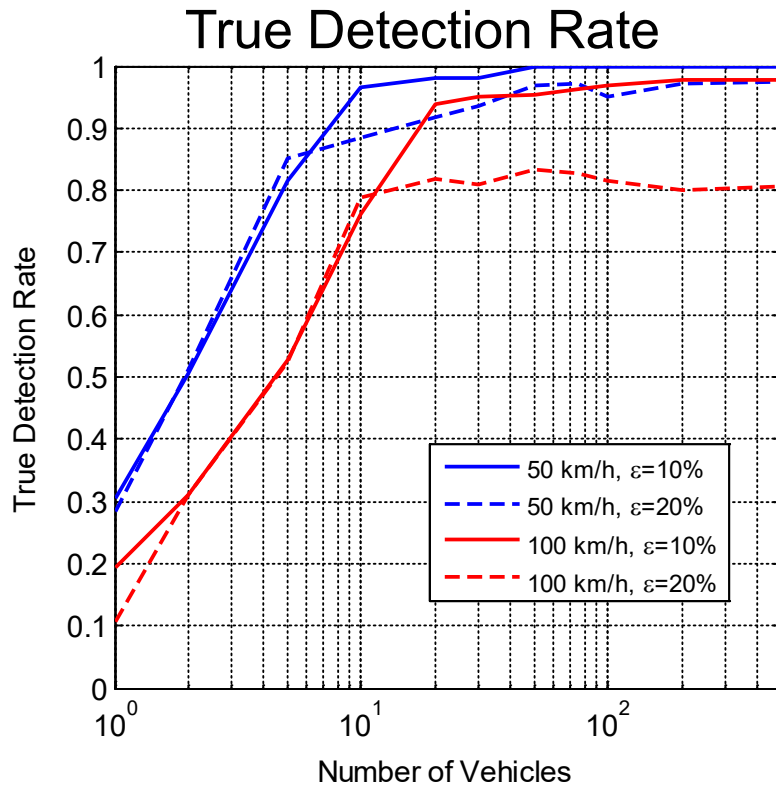Electrical & Computer
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27
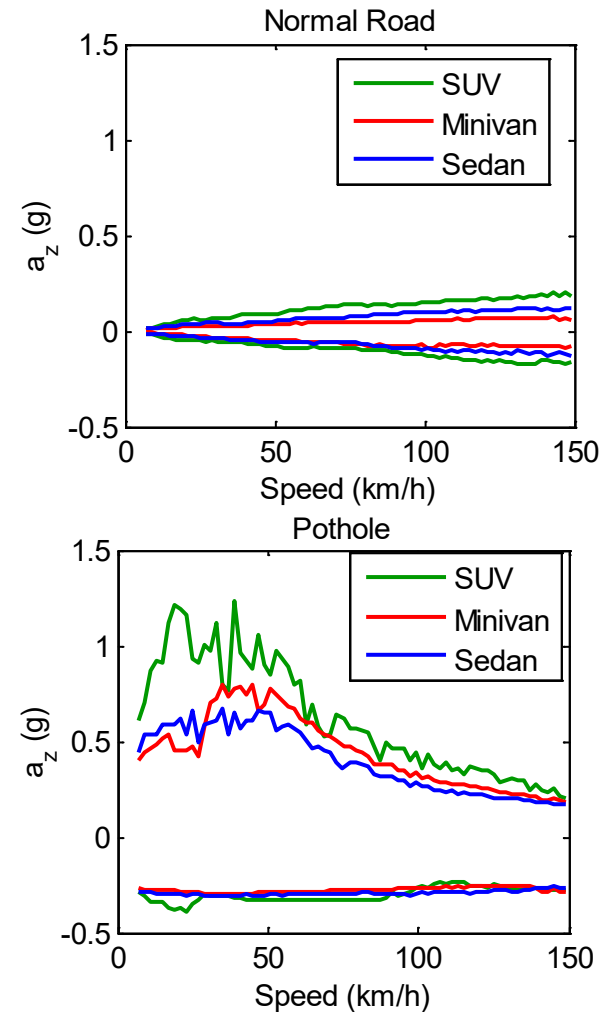
Binary Voting Detection
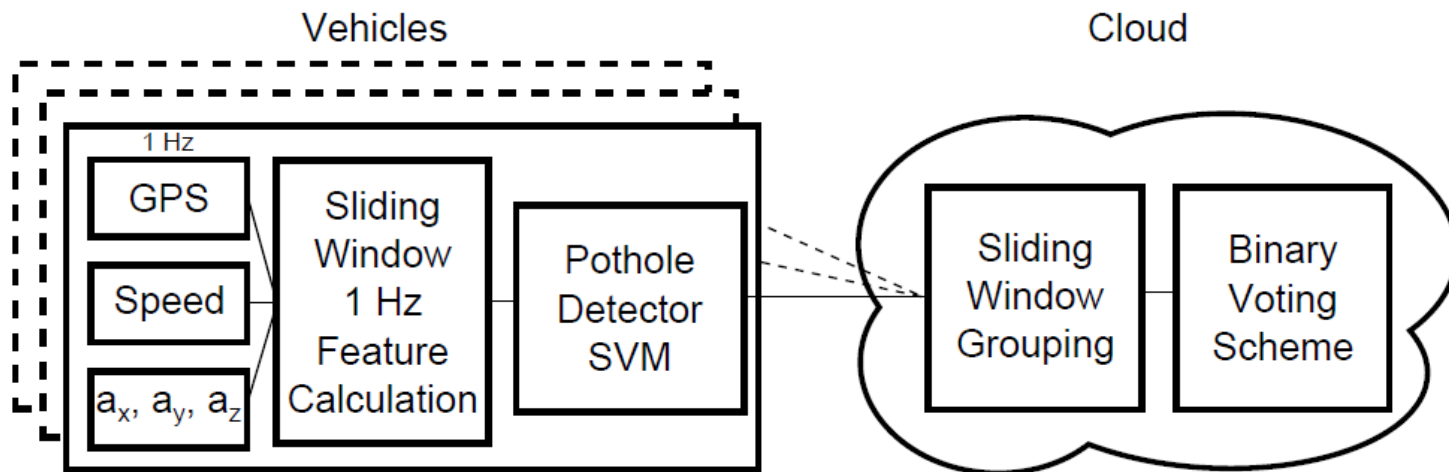
- SVM detector run on individual vehicles
- Single bit (plus location) sent to Cloud indicating if pothole is detected
- Greater than ϵ data points vote for pothole results in pothole decision

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Binary Voting Detection Results

- Increasing voting threshold decreases detection and false alarm rate
- Relies on weak detectors on individual vehicles
  - Voting threshold, ε, must be low
- 500 vehicles – 1.00 detection rate, 0.022 false alarms per true pothole

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Real-world Data Results

- **SVM classifiers trained using simulated data are applied to real-world data**

- 90.3% detection rate

- 0.25 false alarms per true pothole
  - 68 total false alarms
  - Need to reduce false alarm rate

- False Alarm categories
  - 9 – regions following large potholes
  - 14 – cracked roads
  - 30 – accelerating or decelerating from stop
    - Missed in simulation

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Conclusions

Increasing computing, communication and sensing capabilities offer opportunities for new transportation applications, e.g.,

- o Map inference
- o Pothole detection
- o Virtual traffic lights
- o Augmented vision for vehicles

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