Pavement Distress Data Collection Using Sensor-Mounted Connected Vehicles

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Outline

I. **Introduction**
   – Innovative road surface monitoring system with the use of sensor equipped vehicles

II. **Onboard Data Logging Algorithm**
   – Local algorithm: maximize the efficiency of local data logging

III. **Data Analysis at a Backend**
   – Machine Classifier: Neural Network
   – Data Integration: Trajectory Clustering

IV. **Conclusions**

V. **Current Research Activities**

Introduction

Motivation

Automated data collection vehicle for pavement management system

- Network-level pavement data are collected at highway speed
- Profiles of road surface: laser, acoustic, or infrared sensors
- Pavement distress: imaging technology (area scanning, line scanning , 3D laser imaging)

Source: http://www.roadware.com/products/survey_equipment/aran_9000/

Introduction

Motivation

Limitation of the current state-of-the-art practice

- High cost: The costs of imaging and sensor data range from **$24 to $85 per mile** [1]
- Data collection is in general conducted **periodically** due to its high cost.

Condition survey data collection and frequency [2]

Agency	Condition Data Collected	Frequency
Colorado DOT	Cracking, rut depth, and IRI	Annually
Florida DOT	Surface distress, faulting, rut depth, and IRI	Annually
Idaho DOT	Surface distress, rut depth, and IRI	Annually
Indiana DOT	Surface distress, rut depth, and IRI	Annually
Iowa DOT	Cracking, rut depth, faulting, joints spalling, and IRI	Every 2 years
Louisiana DOTD	Cracking, patching, faulting, rut depth, and IRI	Annually
New Mexico DOT	Surface distress and faulting	Annually
Oregon DOT	Surface distress, faulting, rut depth, and IRI	Annually
Pennsylvania DOT	Surface distress, faulting, rut depth, and IRI	Annually
Virginia DOT	Surface distress, rut depth, and IRI	Annually
Washington DOT	Surface distress, faulting, rut depth, and IRI	Annually

[1] McGhee, K. H. (2004). Automated pavement distress collection techniques, Vol. 334. Transportation Research Board.
[2] Pierce, L. M., McGovern, G., and Zimmerman, K. A. (2013). "Practical Guide for Quality Management of Pavement Condition Data Collection." Report No. FHWA-HIF-14-006, Federal Highway Administration, Washington, DC.

Introduction

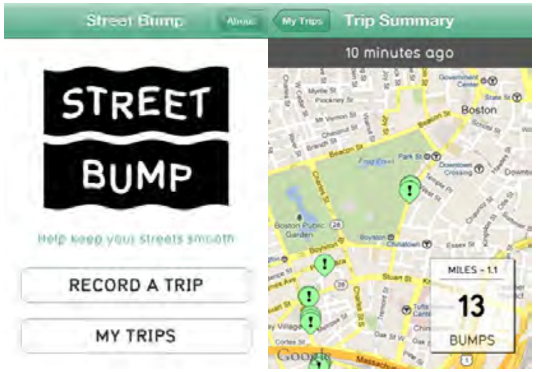
Motivation

Needs for more frequent and/or continuous data acquisition

- Most pavement distress (e.g., cracking and rutting) develop slowly. Therefore, the current data collection practice can be conducted periodically based on the aging of road surfaces
- There are street defects (e.g., pothole) which develop more quickly, which might need a more frequent and/or continuous data acquisition

Vibration-based road surface monitoring

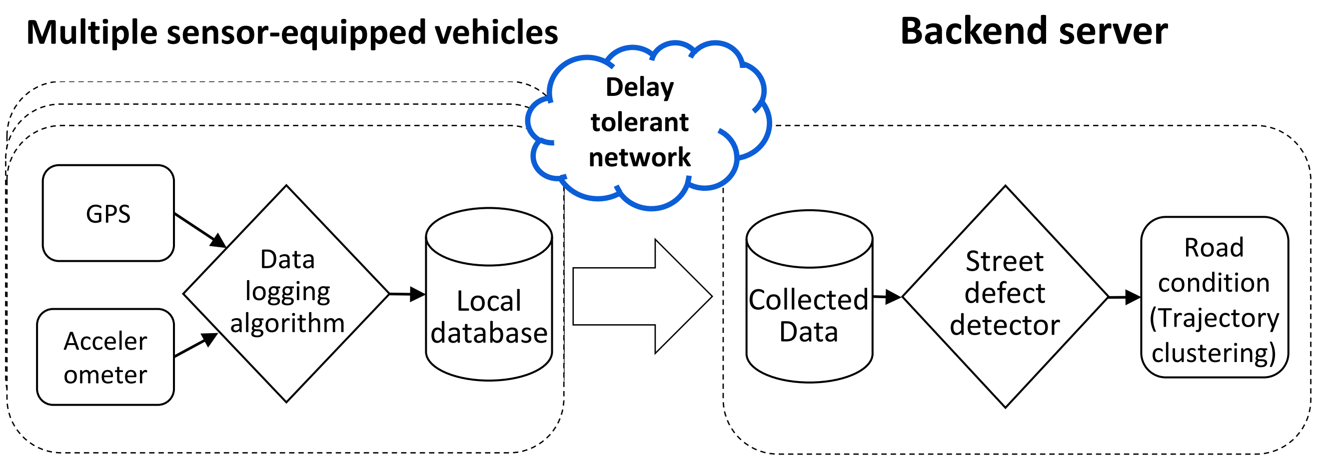
- Sensors (accelerometer and GPS) & Wireless networks
- Advantage: size of data -> less storage and computational expenses -> real-time process



Introduction

Road surface monitoring with sensor equipped vehicles

- **Architecture of the road surface monitoring system with sensor equipped vehicles**
  - The conditions of a large network of roads can be monitored continuously and simultaneously in daily life.



PHILIPS

Jang, J., Yang, Y., Smyth, A. W., Cavalcanti, D., and Kumar, R. (2016). "Framework of data Acquisition and integration for the detection of pavement distress via multiple vehicles." *Journal of Computing in Civil Engineering.* 31(2).

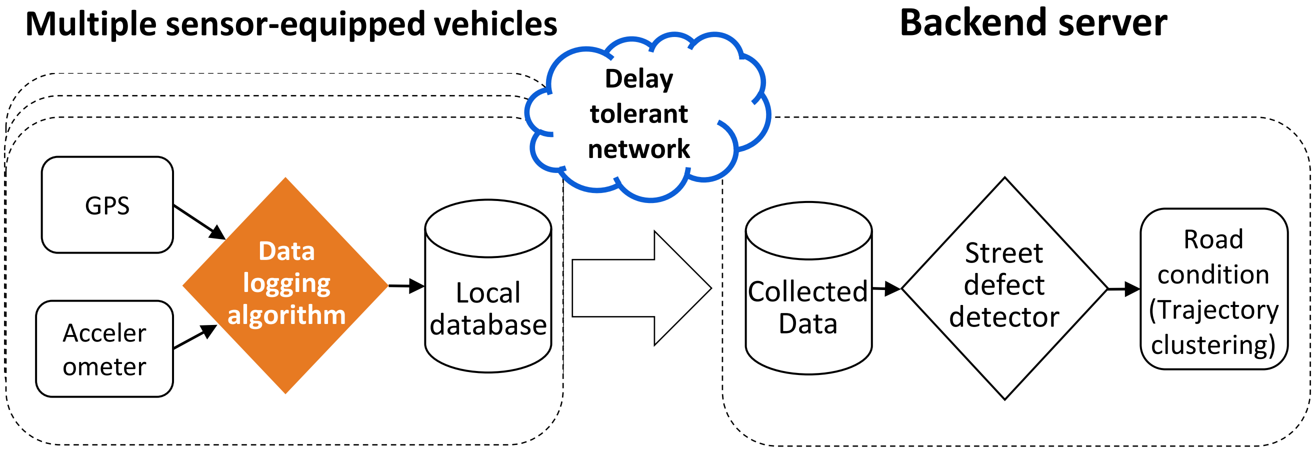
2. Onboard Data Logging Algorithm

Onboard Data Logging Algorithm

Data logging algorithm

Purpose

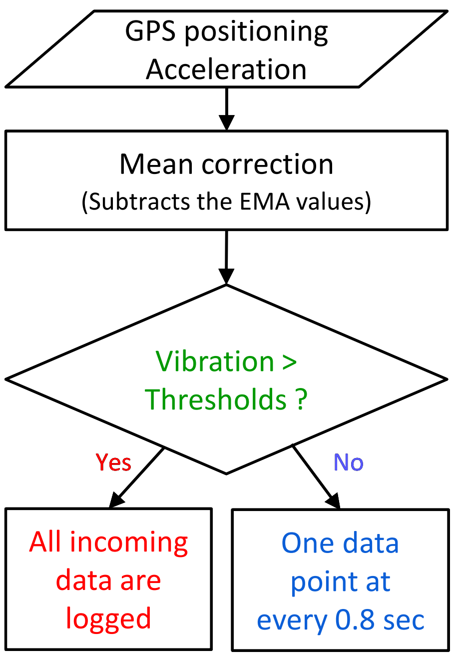
– Increase the efficiency of local data logging.
– Real-time processor
– Minimize the amount of cached data in each vehicle client.

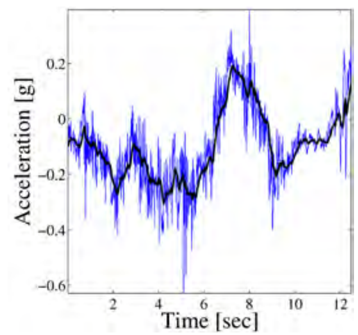


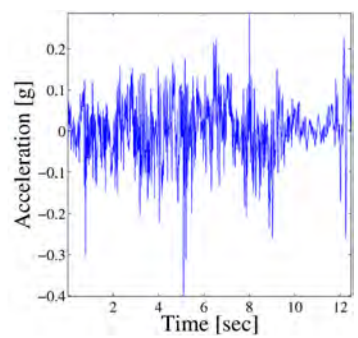
Onboard Data Logging Algorithm

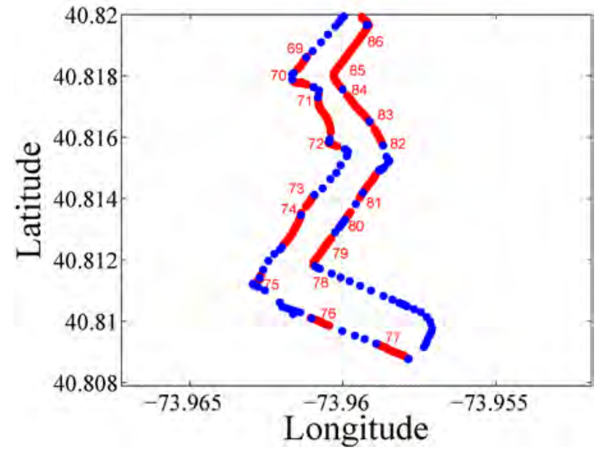
Data logging algorithm

Online local algorithm (Online algorithm)









- All incoming data
- One data point at every 0.8 sec

Data reduction

28,156 -> **7076** data point

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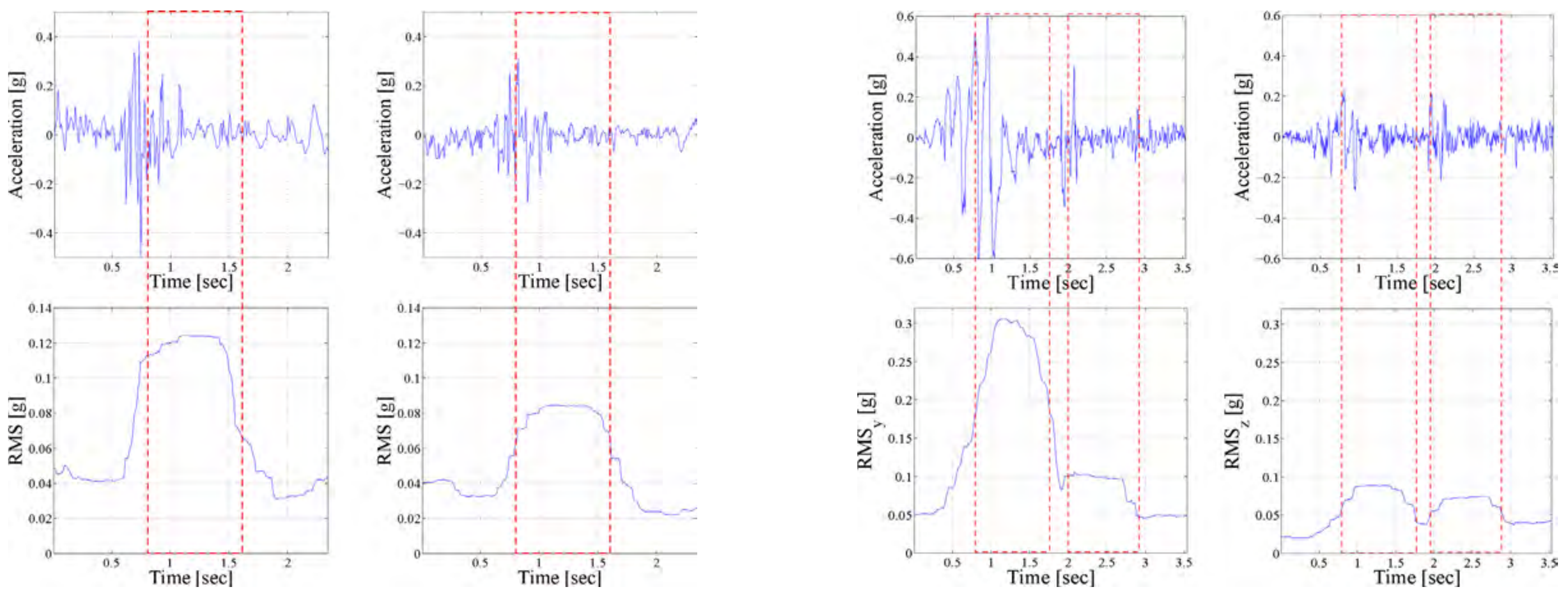
Onboard Data Logging Algorithm

Data logging algorithm

The thresholds are predetermined based on **a priori knowledge of actual road surface conditions.**

Triggering condition: $RMS_Y \geq 0.08$ g & $RMS_Z \geq 0.06$ g (Y: sideways and Z: vertical direction)



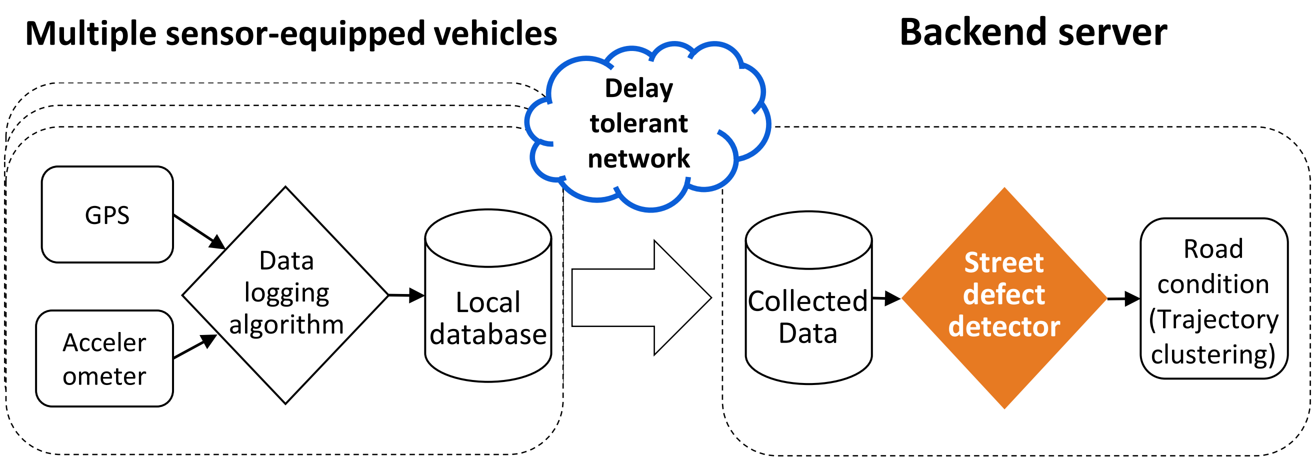
3. Data Analysis at the Backend

- **Machine Classifier: Neural Network**
- Data Integration: Trajectory Clustering

Classification of transmitted data

Street defect classification

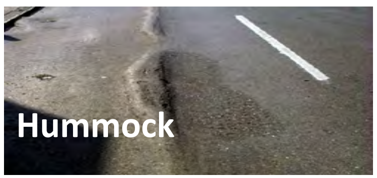
When logged data are transmitted from vehicle clients to the back-end server, Collected data are **classified into three different categories** based on the acceleration responses.

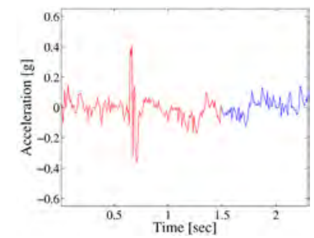


Classification of transmitted data

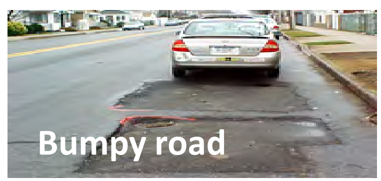
Three street defect categories

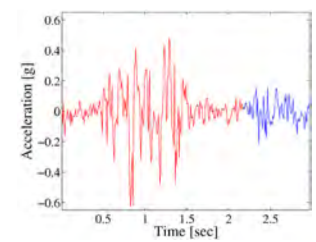
Impulse case



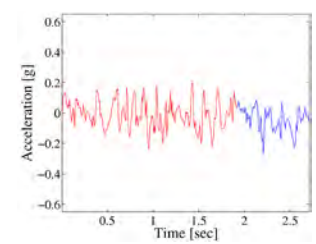


Rough case





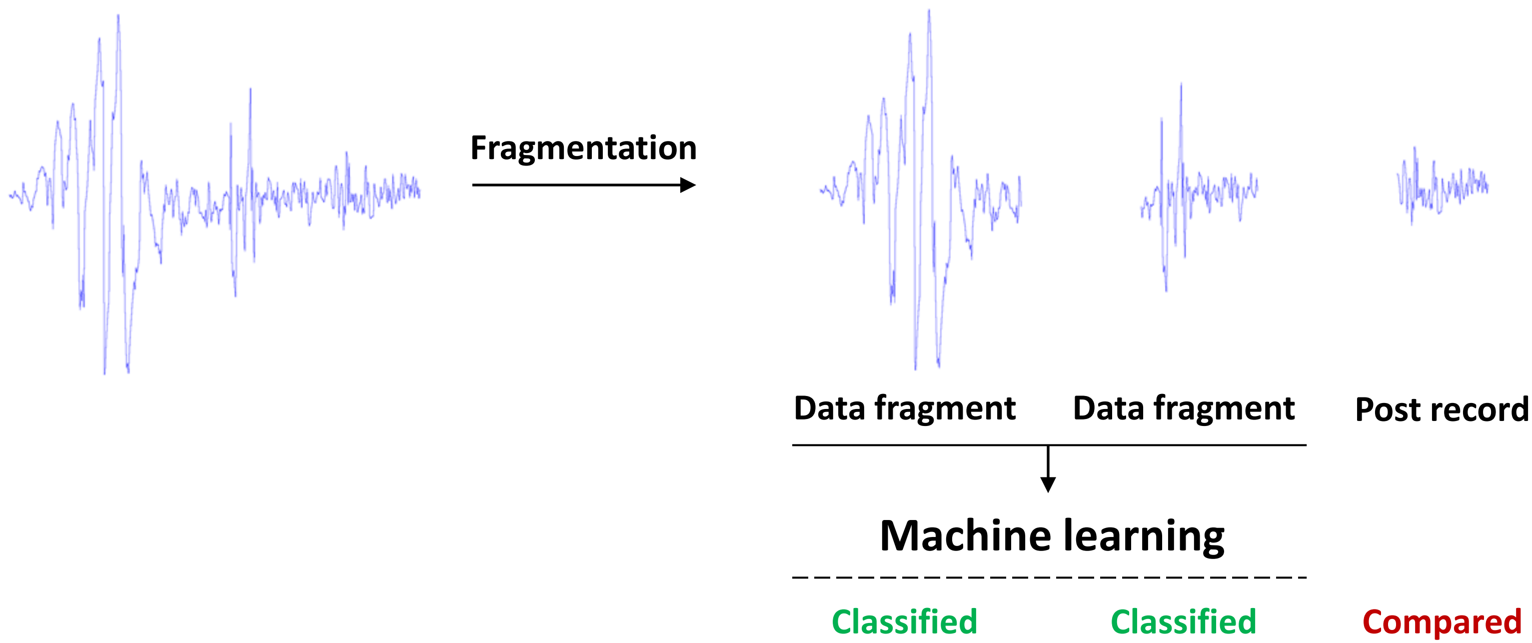
Smooth case



Classification of transmitted data

Segmentation of data

Consecutive street defects can be logged in **one data**. Therefore, the logged data are **divided** into smaller pieces (**data fragments**). The classification technique are applied to data fragments.

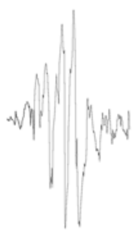


Classification of transmitted data

Supervised machine learning techniques

- **Input parameters (features)** for the supervised machine learning techniques

Data fragment



Acceleration responses in the Y and Z

GPS positioning data (Trajectory)

Feature extraction

- **Categorical inputs**
  - Type (CSUV, MSEDAN, BUS)
  - Location of sensor (TOP, SIDE)

- **Numeric inputs**
  - Speed of vehicle
  - Length of data
  - Max zero crossing
  - Max acceleration
  - Max jerk (1st time derivative of acceleration)
  - Max RMS values
  - Max acceleration in smooth part

Classification of transmitted data

Supervised machine learning techniques

Neural Network

- tansig transfer function
- 2 hidden layers
  - 1st layer = 10 nodes
  - 2nd layer = 7 nodes

Training of the classifier

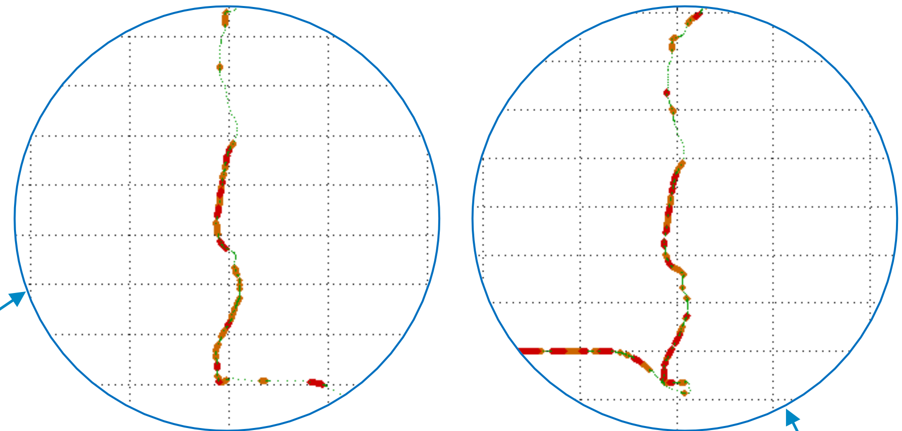
- **421 data fragments** are collected from the already-known actual street defects.
- A prior knowledge of the output categories and the input parameters is given for the training data set.
- **70%**: training and **30%**: validation

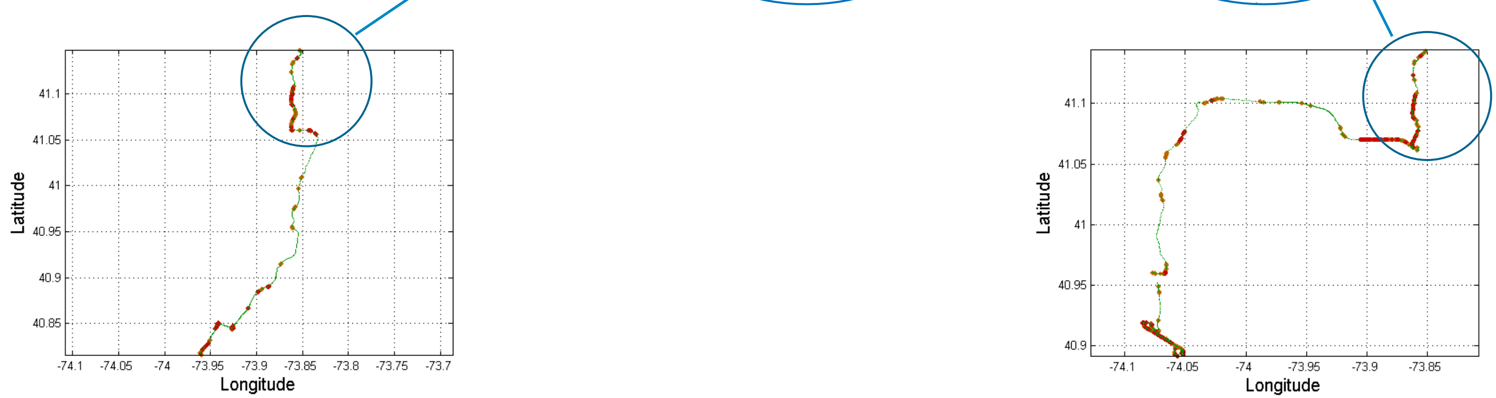
Output Class \ Target Class	impulse	rough	smooth
impulse	**35** 81.4%	**4** 9.0%	**4** 9.0%
rough	**3** 14.3%	**18** 85.7%	**0** 0.0%
smooth	**7** 11.3%	**1** 1.6%	**54** 87.1%

Classification of transmitted data

Supervised machine learning techniques

- **Red = Rough**
- **Oranges = Impulse**
- **Green = Smooth**





One-time measurement is not enough!

3. Data Analysis at the Backend

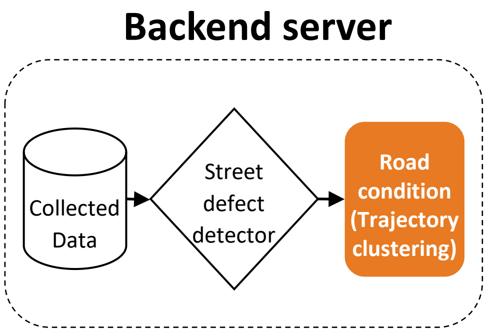
- Machine Classifier: Neural Network
- **Data Integration: Trajectory Clustering**

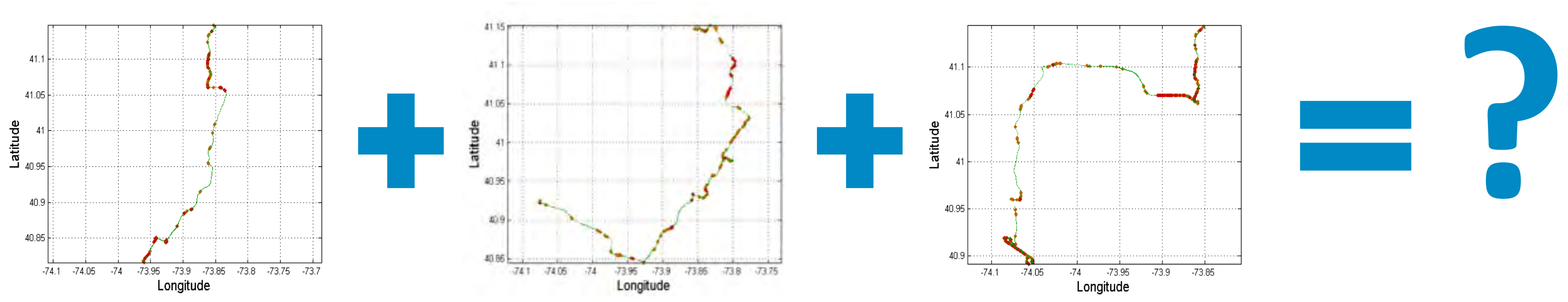
Integration of the classification results

Integration of the classification results

Purpose: Increase the accuracy of the road surface monitoring system by merging the classification results

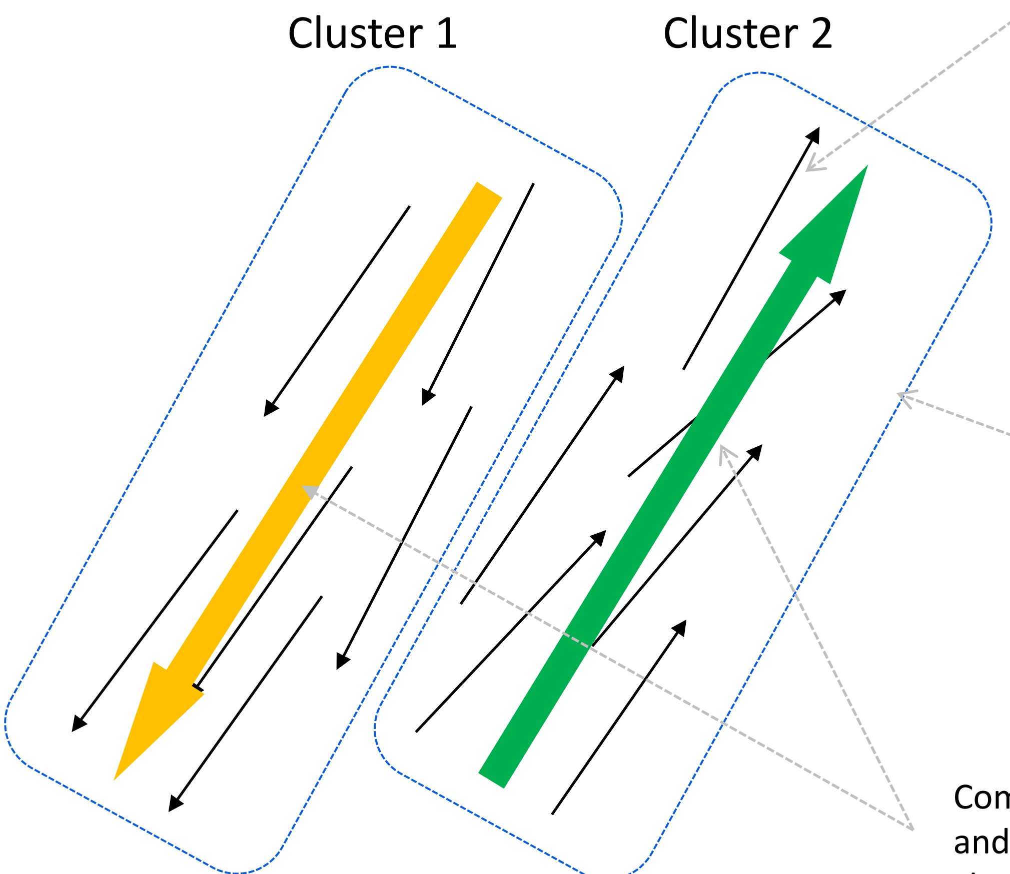
Method: **Trajectory clustering analysis**



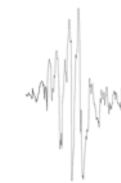


Integration of the classification results

Trajectory clustering analysis



Each trajectory has the starting and end points of a data fragment, associated with **classification result** and **travel distance**, etc



The trajectory clustering analysis is to group all trajectories into clusters based on their **locations** and **directions**

Compute a **representative trajectory** and **score for road conditions** for each cluster

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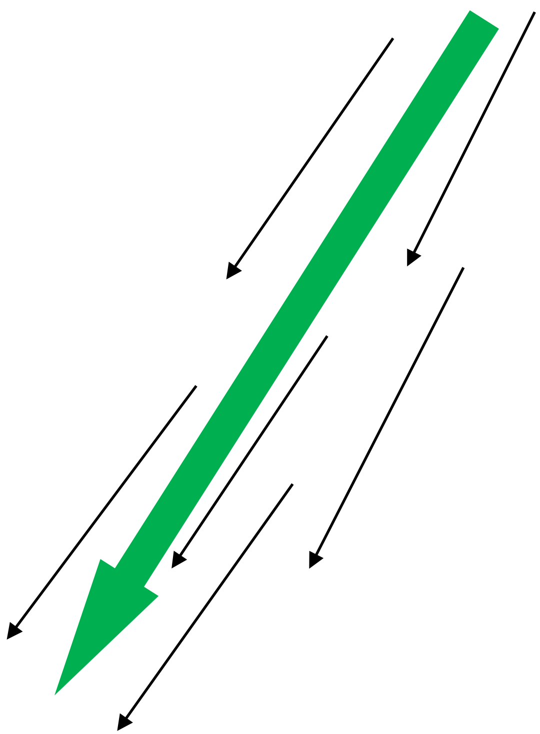
Integration of the classification results

Evaluation of road conditions



- $\boldsymbol{score_i}$ **is assigned to each trajectory** grouped into the same cluster based on the classification result.

- $score_i = \begin{cases} 1, if\ class\ is\ rough\ or\ impulse \\ 0, if\ class\ is\ smooth \end{cases}$

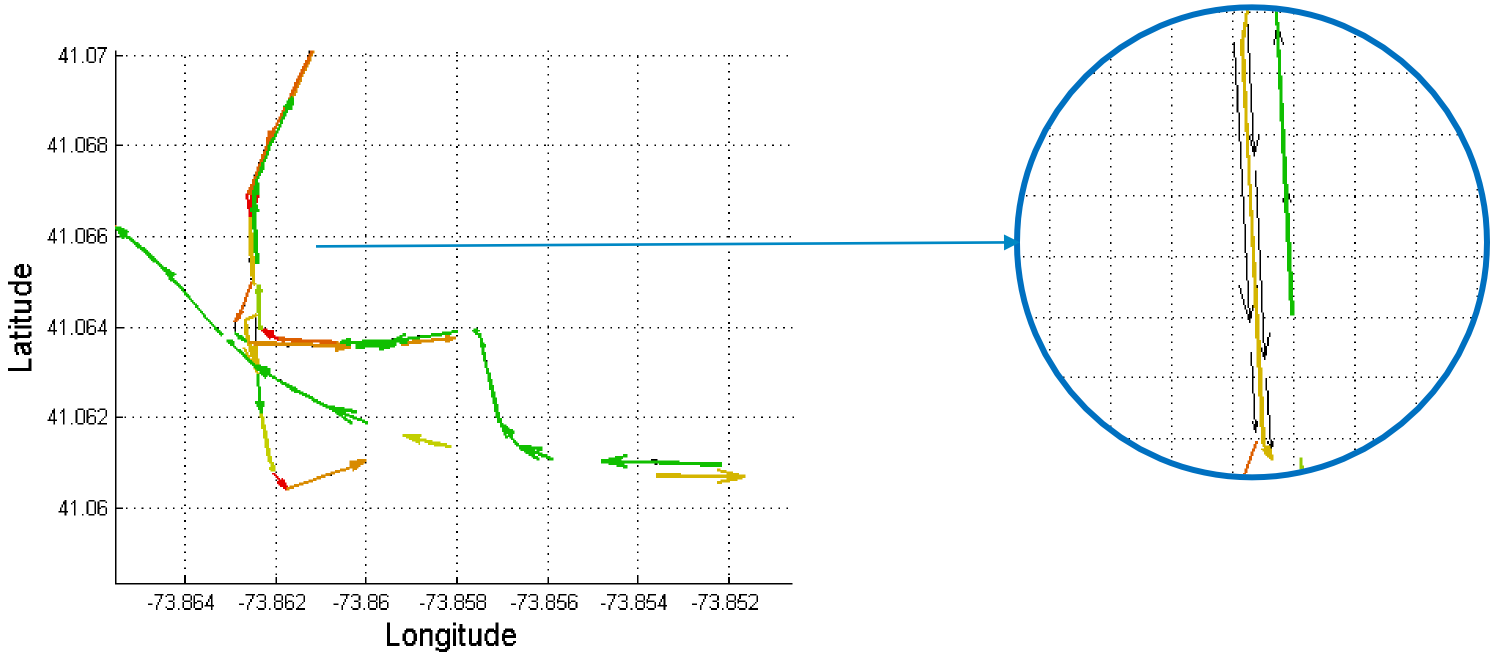
- **Representative trajectory** shows a **road condition level** calculated from trajectories and classification results.

- $Road\ condition = \sum_{i=1}^{n} \frac{score_i \times travel\ dist_i}{travel\ dist_i}$

Integration of the classification results

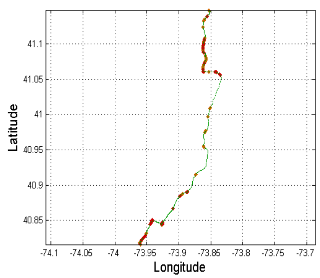
Evaluation of road conditions

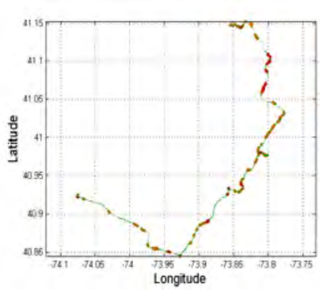
- **0 (Green) ≤ Road condition ≤ 1 (Red)**
- Color scale is divided into 10

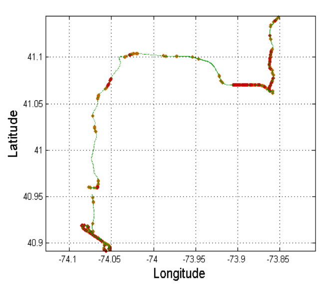


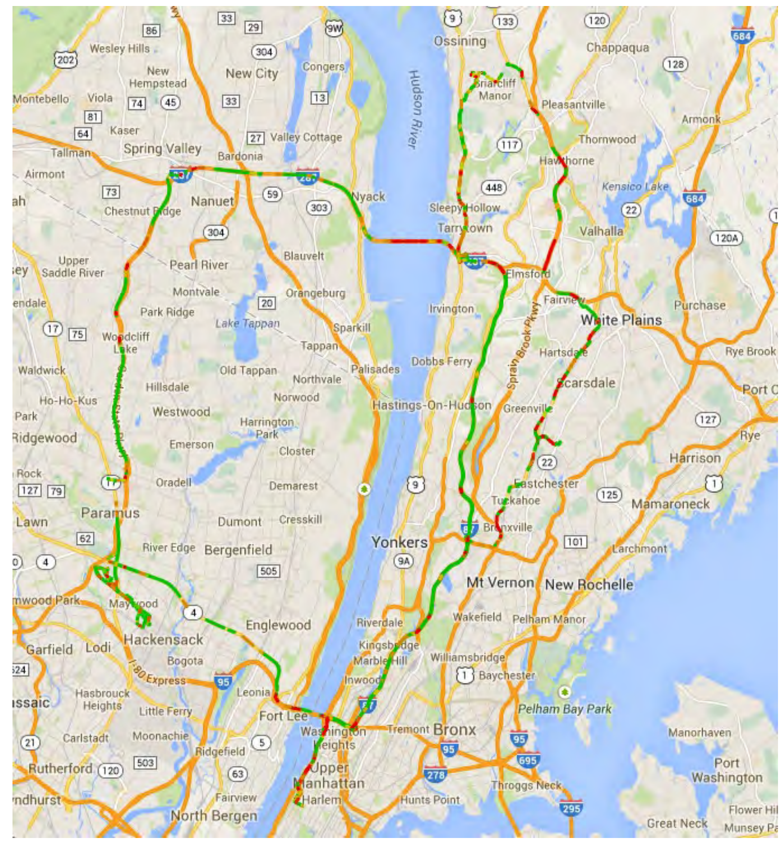
Integration of the classification results

Evaluation of road conditions









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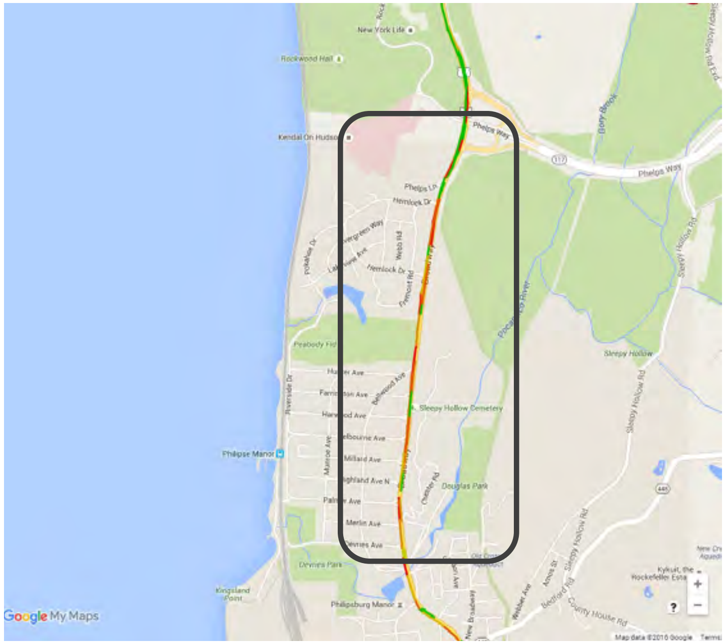
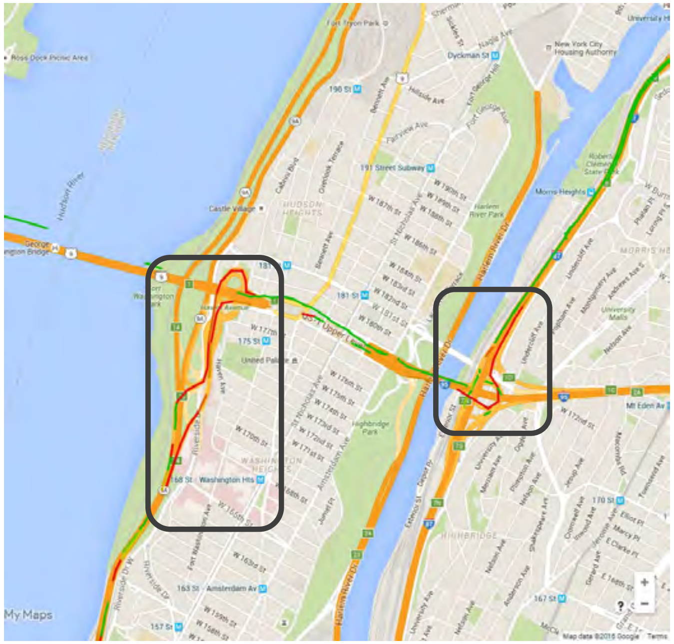
Integration of the classification results

Evaluation of road conditions

Resurfaced road networks





4. Conclusions

Conclusions

- **Conclusions**
  - Benefits
    - The conditions of a large network of roads can be monitored continuously and simultaneously in daily life.
  - Robust algorithm for the system
    - The local data logging algorithm embedded in the vehicle clients improves the efficiency of the use of local storage.
    - The trajectory clustering analysis helps road conditions evaluated by multiple sensor equipped vehicles.
- **Acknowledgment**

  - The research was funded by Philips Research North America (PRNA). The authors would like to acknowledge PRNA for permission to produce this work and for accesses to hardware.

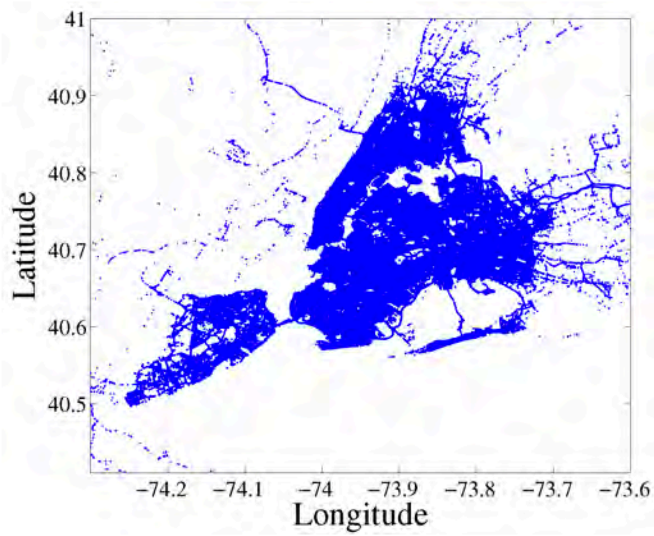
5. Current Research Activities

Current Research Activities

Big trajectory data analytics

- **NYC fleet vehicle**
  - Installed with EJ Ward CANceiver (OBD2) and GPS sensor
  - Fleet management purpose
  - Collected from thousands of vehicles
  - Vehicle speed and acceleration data

1,023,401 data point

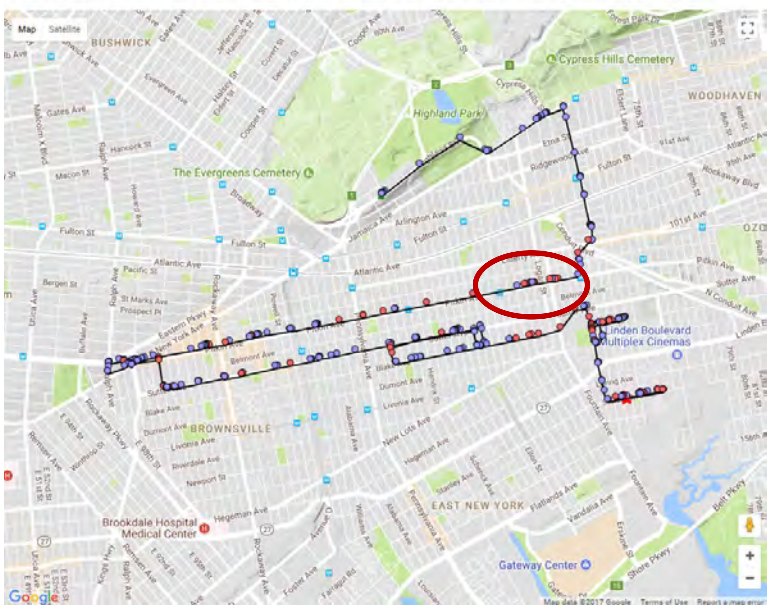


Current Research Activities

Big trajectory data analytics

- Hard acceleration and braking
  - Longitudinal acceleration > 0.18g

VID: 29312 (2007 TOYOTA PRIUS), Trip: 1, Travel time: 01-Jan-2015 06:23:12 - 01-Jan-2015 09:31:40 (3.14 h)



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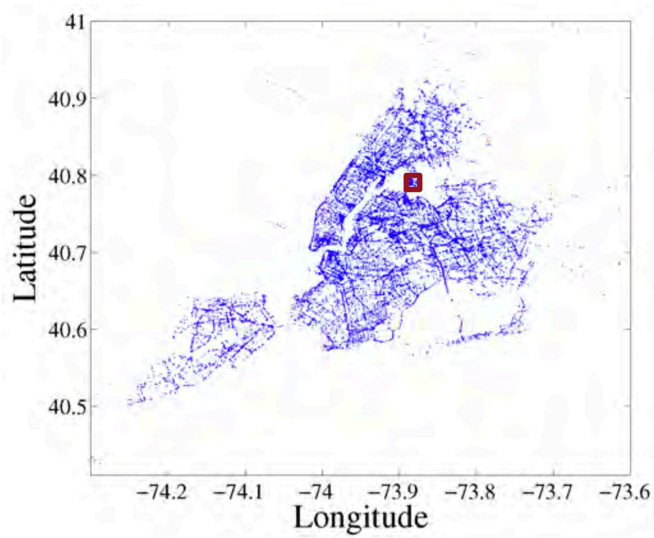
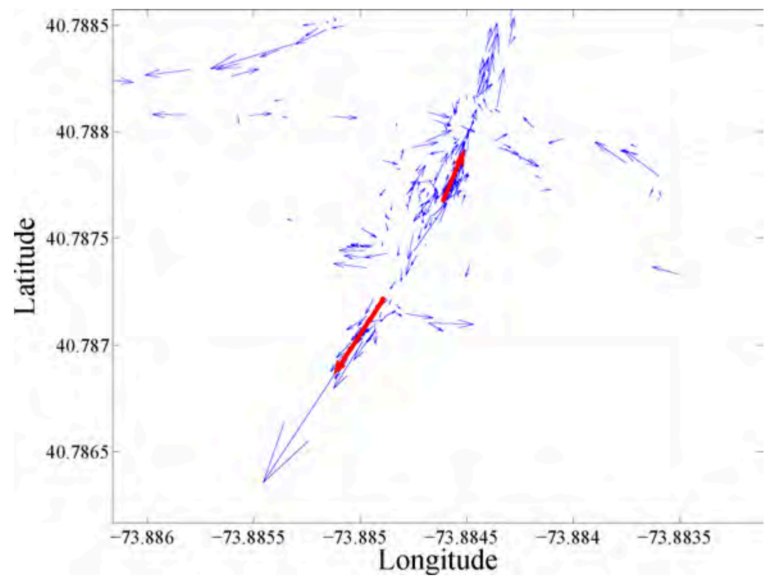
Current Research Activities

Big trajectory data analytics

- **Hotspots of hard accelerations and hard braking**

220,160 Hard accelertion events

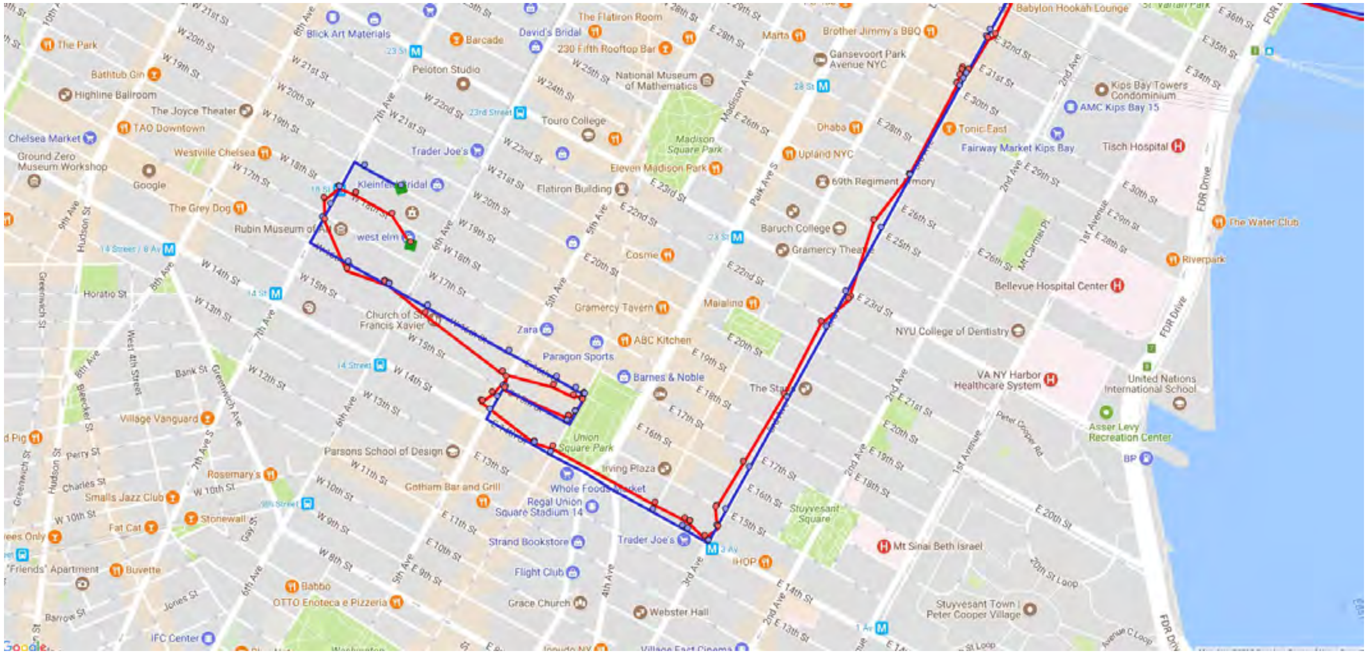




Current Research Activities

Map-matching

- **Map-matching example**
  - **Red**: original data points
  - **Blue:** matched data points



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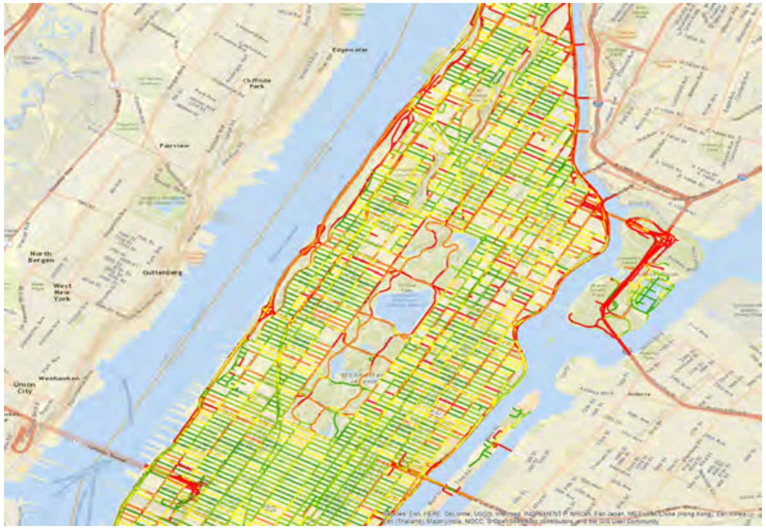
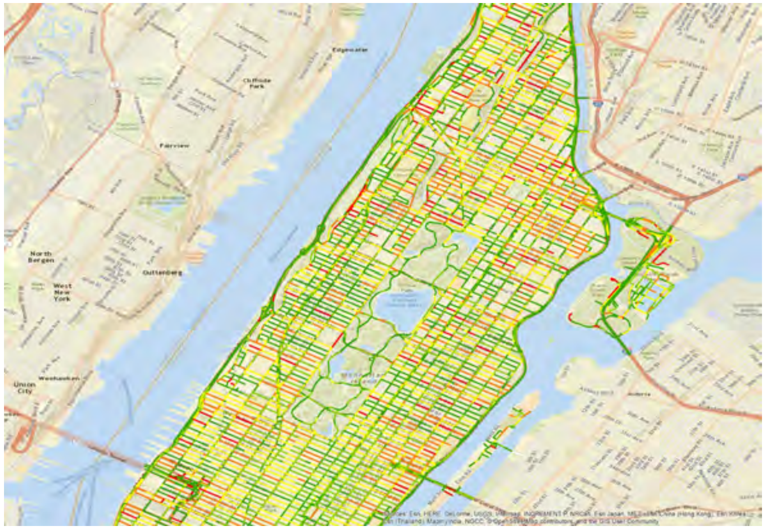
Current Research Activities

Map-matching

- **Driver Behavior Index**
  - Integrate vehicle speed data, hard acceleration, and hard braking with road segments (map data)
  - Results can indicate how drivers behave on roads





Thank you! & Question?