OLD DOMINION UNIVERSITY

IDEA FUSION

Sparse GPS Trajectory Data Compression and Recovery based on Compressed Sensing

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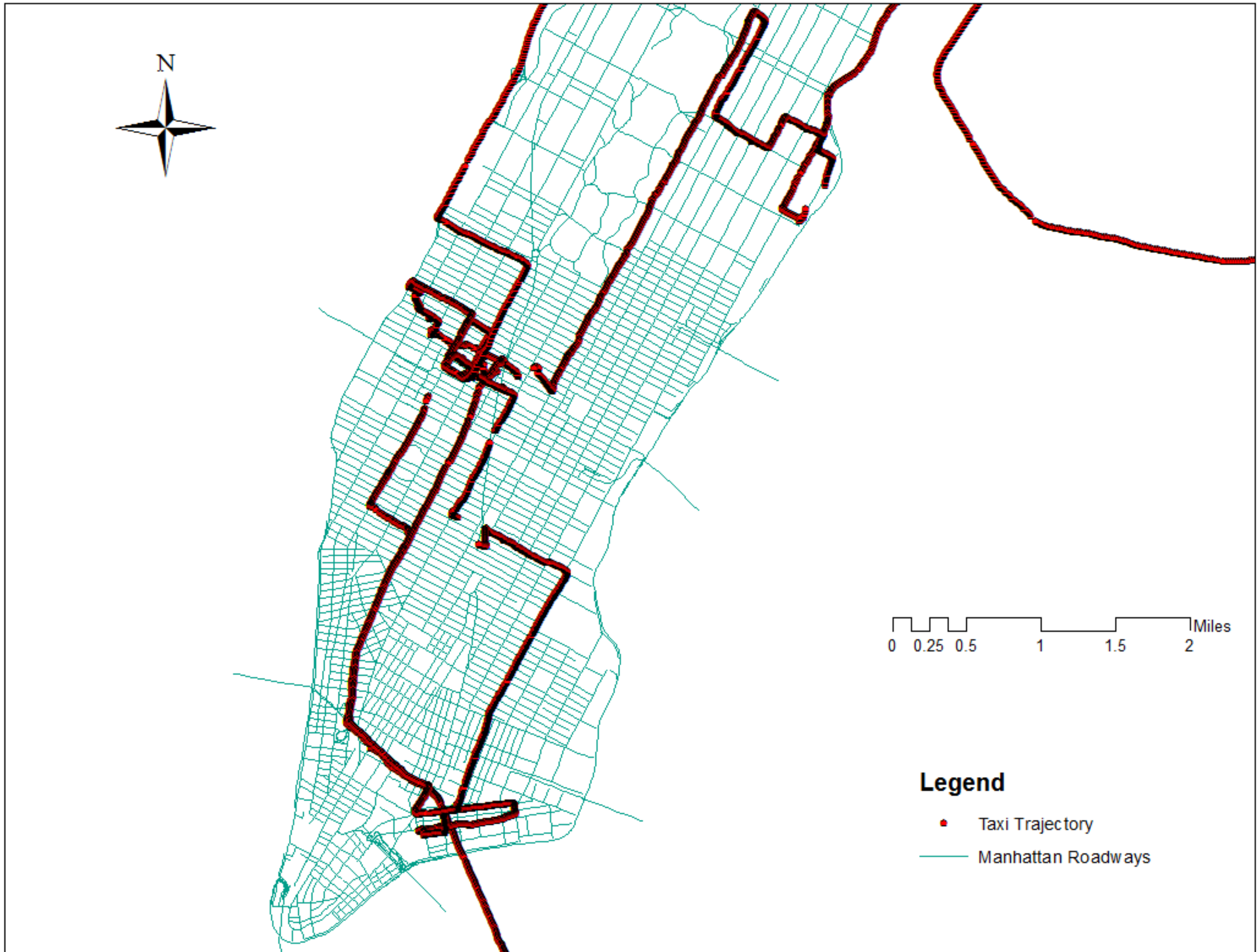
Motivations



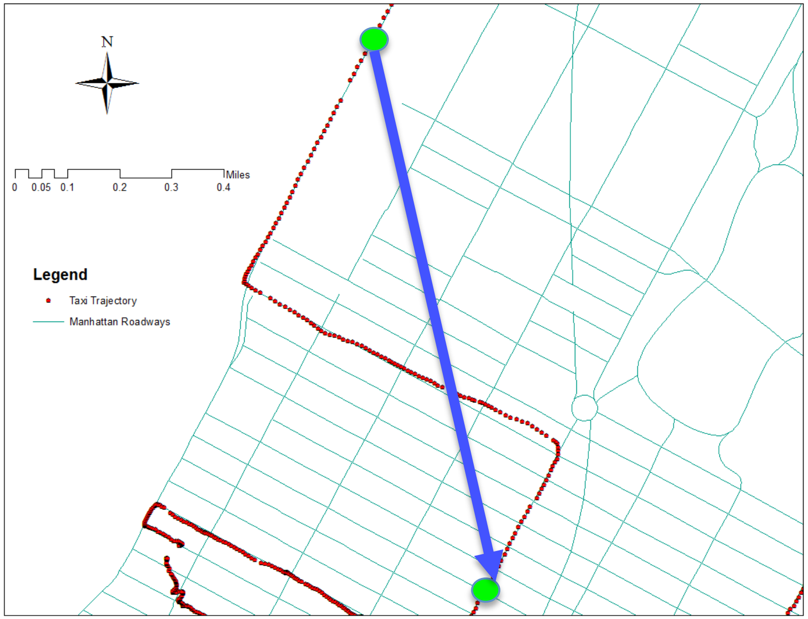
Massive GPS/ Smartphone trajectory data

Privacy concern

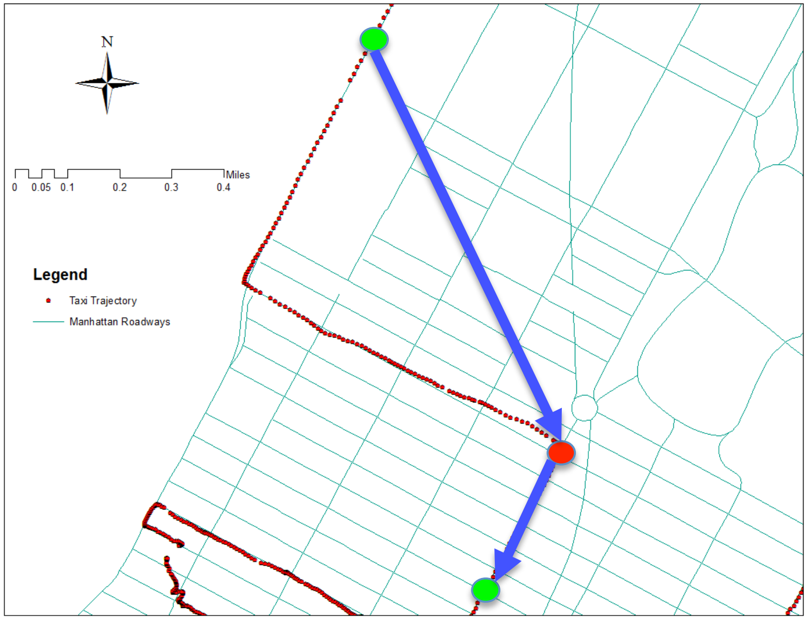
Data needs/ applications

Storage/processing issues

Challenges for Over-Compressed Data

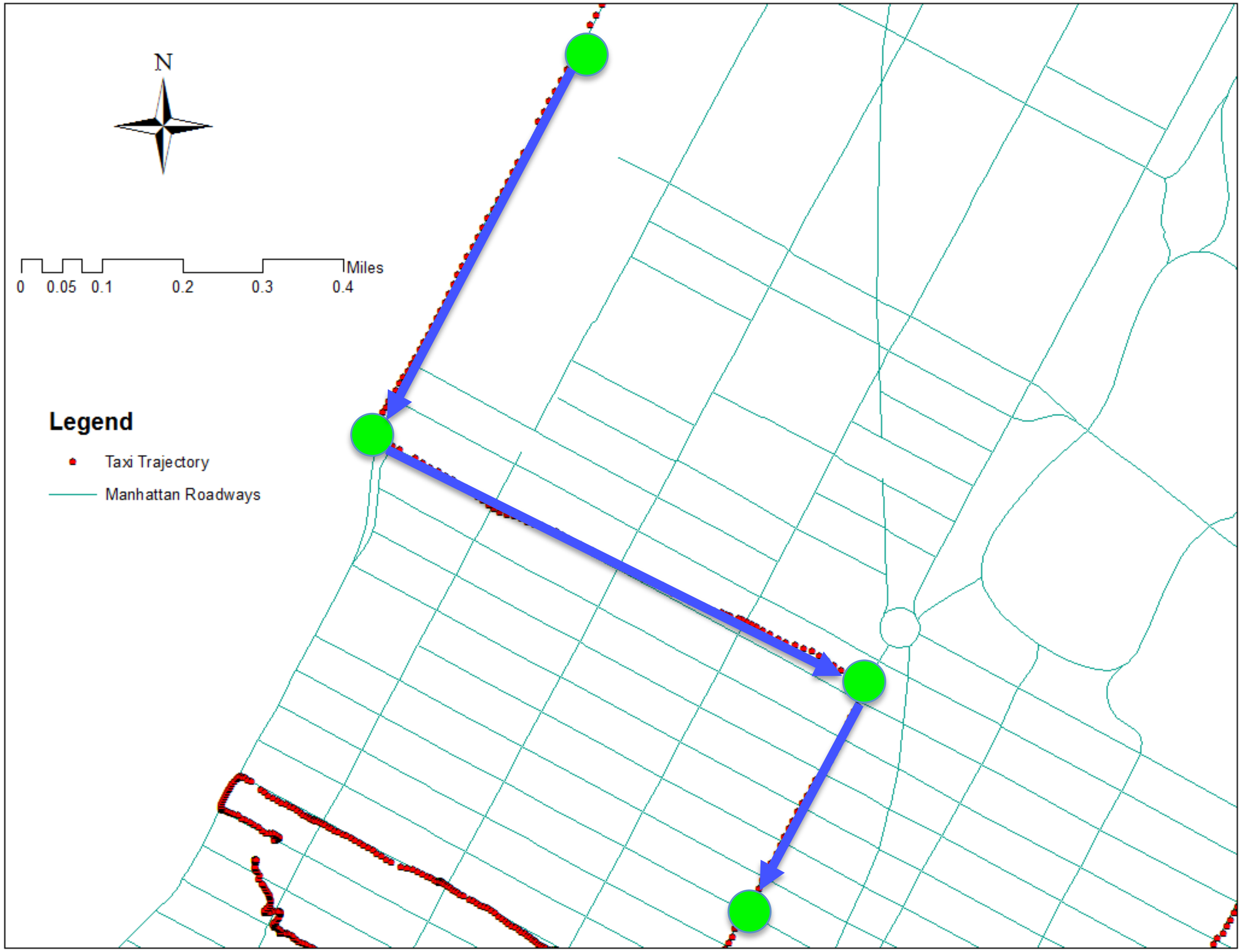


Only Origin and Destination are available. (i.e. current NYC Taxi trip data)



Origin, Destination and if given some points in between

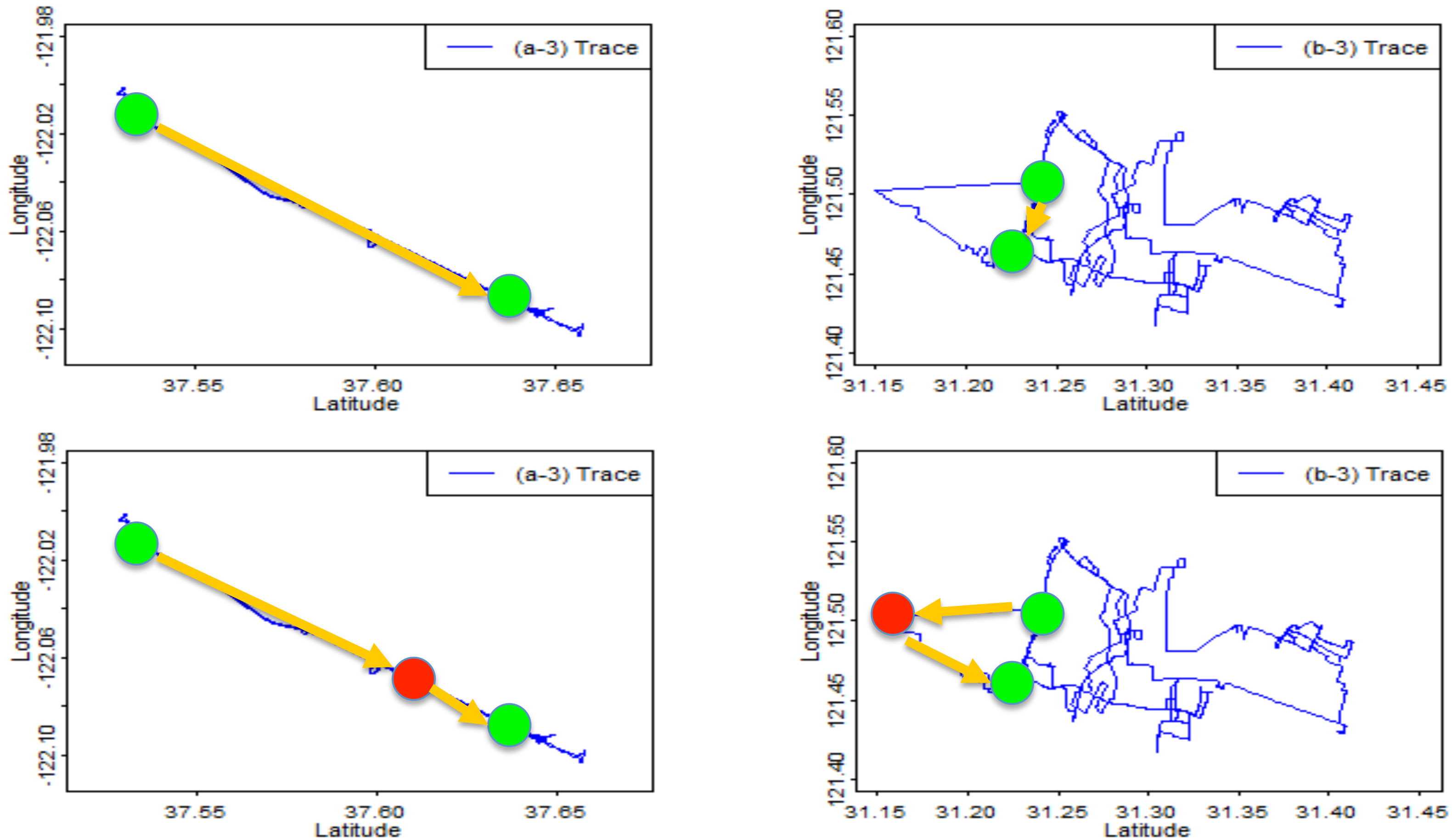
What if we provide more data points?



A better representation of the route?

What if we provide more data points?

- Different compressibility of the GPS trajectory may have different effects on different networks



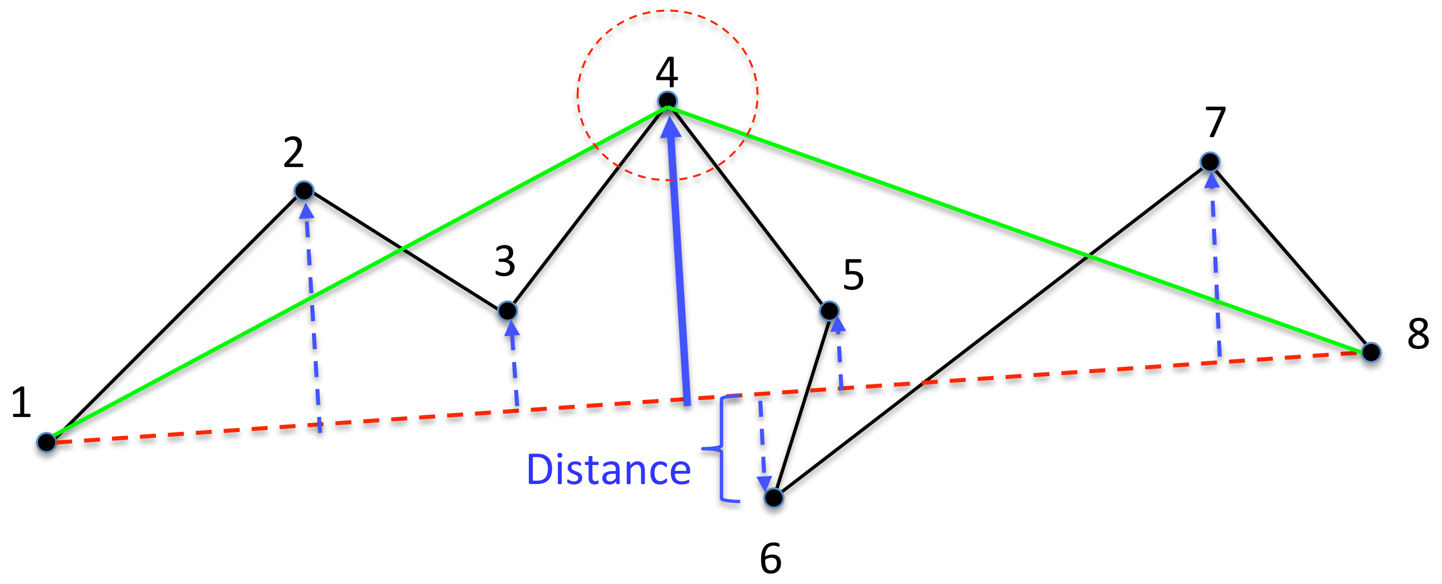
Existing Research / Practices

- Several classical methods using spatial and temporal dimensions to compress data
  - Uniform sampling
  - Douglas-Peucker algorithm
  - Bellman's algorithm
  - STTrace algorithm

- Other new methods using dimensions like sparsity and category
  - Greedy matching pursuit algorithm (GMP)
  - Compressed sensing (CS)
  - Coupled Hidden Markov Models

Methodology: Douglas-Peucker (DP) Algorithm

- DP - Using the spatial information

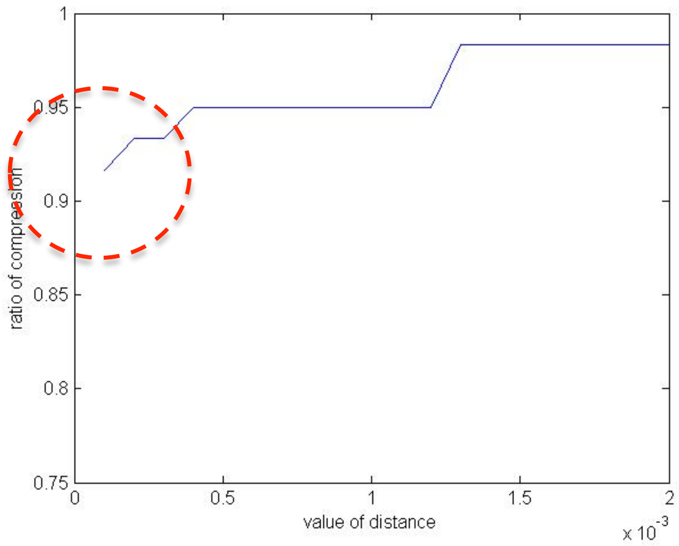


- Step 1: Link nodes 1 and 8
- Step 2: Identify node with maximum distance (Node 4)
- Step 3: Iteration

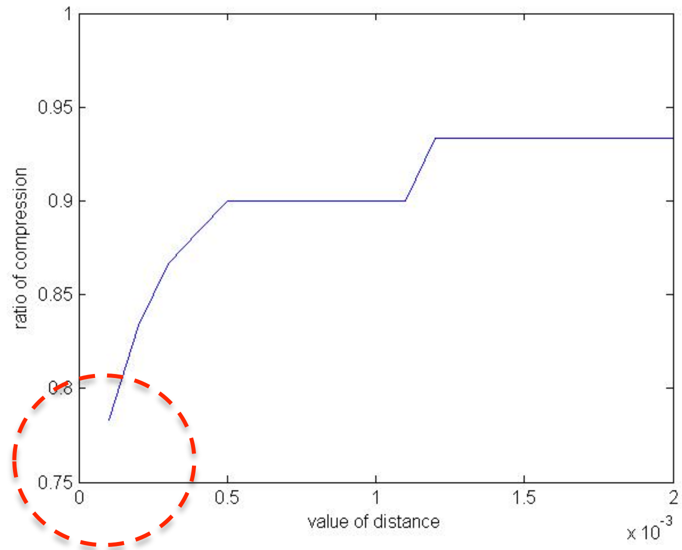
Issues of DP Algorithm

- Threshold of DP and the compression rate

Compression for highway data



Compression for local street data

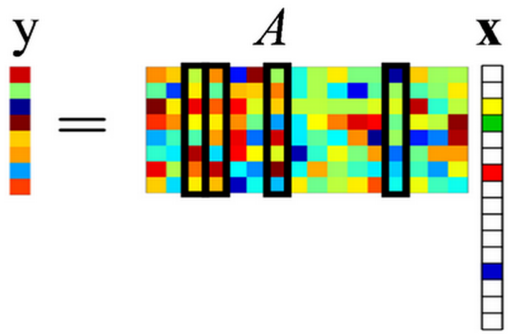


Some Issues:

- Need to sample all the data at the beginning
- Hard to deal with loop in the trajectory

Methodology: Compressed Sensing

- CS – using the sparsity information



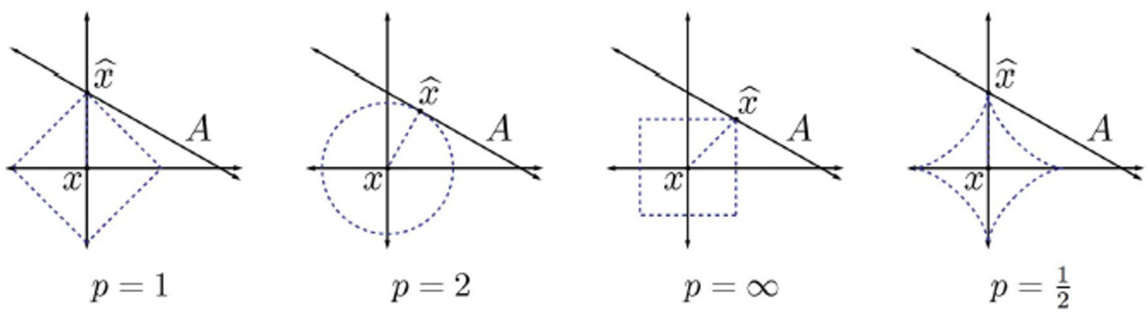
$$Ax = y$$

$$A = \begin{bmatrix} a_{11} & a_{12} & 1 & 1 & a_{15} \\ a_{21} & a_{22} & 1 & 1 & a_{25} \\ a_{31} & a_{32} & 1 & 1 & a_{35} \end{bmatrix},$$

$$x_1 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, x_2 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \quad y = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

The sparsity of the trajectory in the sparse basis is the key point sparse(A)>2k

The recovery of the 2-norm of x is a convex problem



Methodology: Compressed Sensing

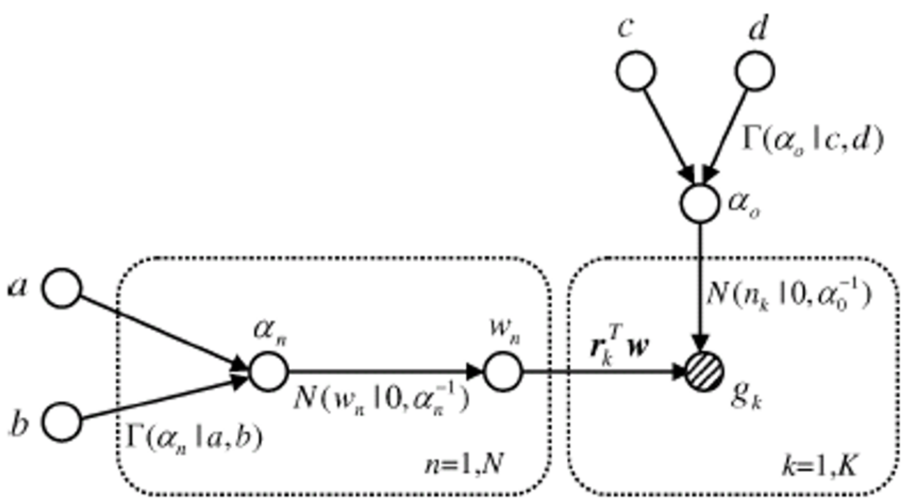
- $y = Ax = sample\_matrix \times basis\_matrix \times x$

$= sample\_matrix \times Tr$

y: $sampled\ data\ (m \times 1)$ $sample\_matrix$: $\mathrm{m} \times n$

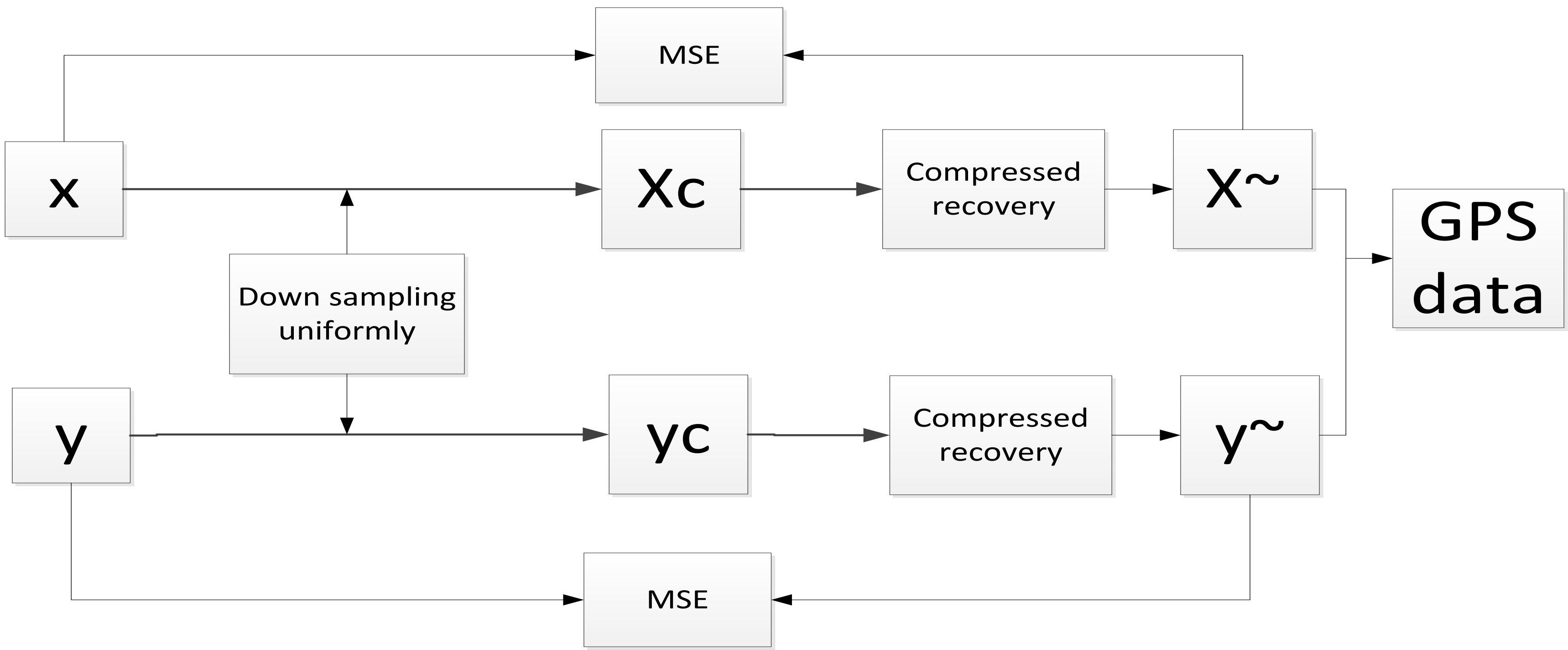
x: $n \times 1$ $basis\_matrix$: $n \times n$ Tr: $raw\ data\ (n \times 1)$

- Choose suitable $sample\_matrix$ and $basis\_matrix$ to get a sparse representation x of y
- The mode (BCS)



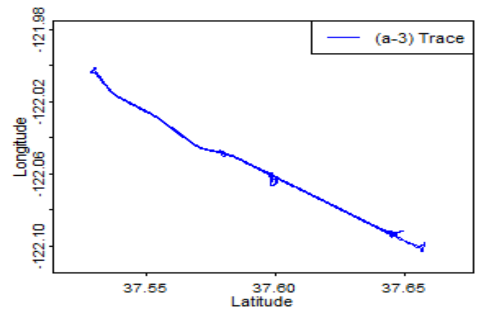
Methodology: Compressed Sensing (CS)

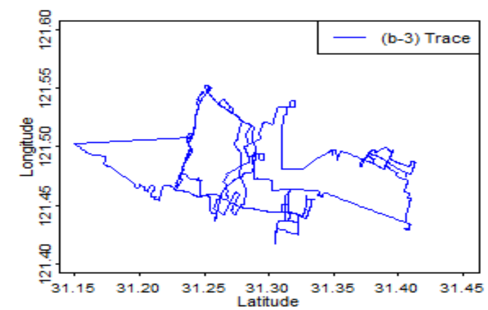
- Framework of CS in GPS data compression



Simulation Results

- Test Scenarios





- Data and Parameters

Parameter	Description	Value
τ_1	The interval of trajectory observation (highway)	3s
τ_2	The interval of trajectory observation (local street)	10s
N	The length of the processed sequence	60
n	The number of Monte Carlo simulations	100
б	The dB value of Gaussian noise	15

- Performance measure

$$\mathrm{Error}(x, y, x^{\sim}, y^{\sim}) = \frac{\left\|(x^{\sim}, y^{\sim}) - (x, y)\right\|_2}{\left\|(x, y)\right\|_2}$$

Simulation Results

- Performance of DP vs. CS with compression rate = 0.5

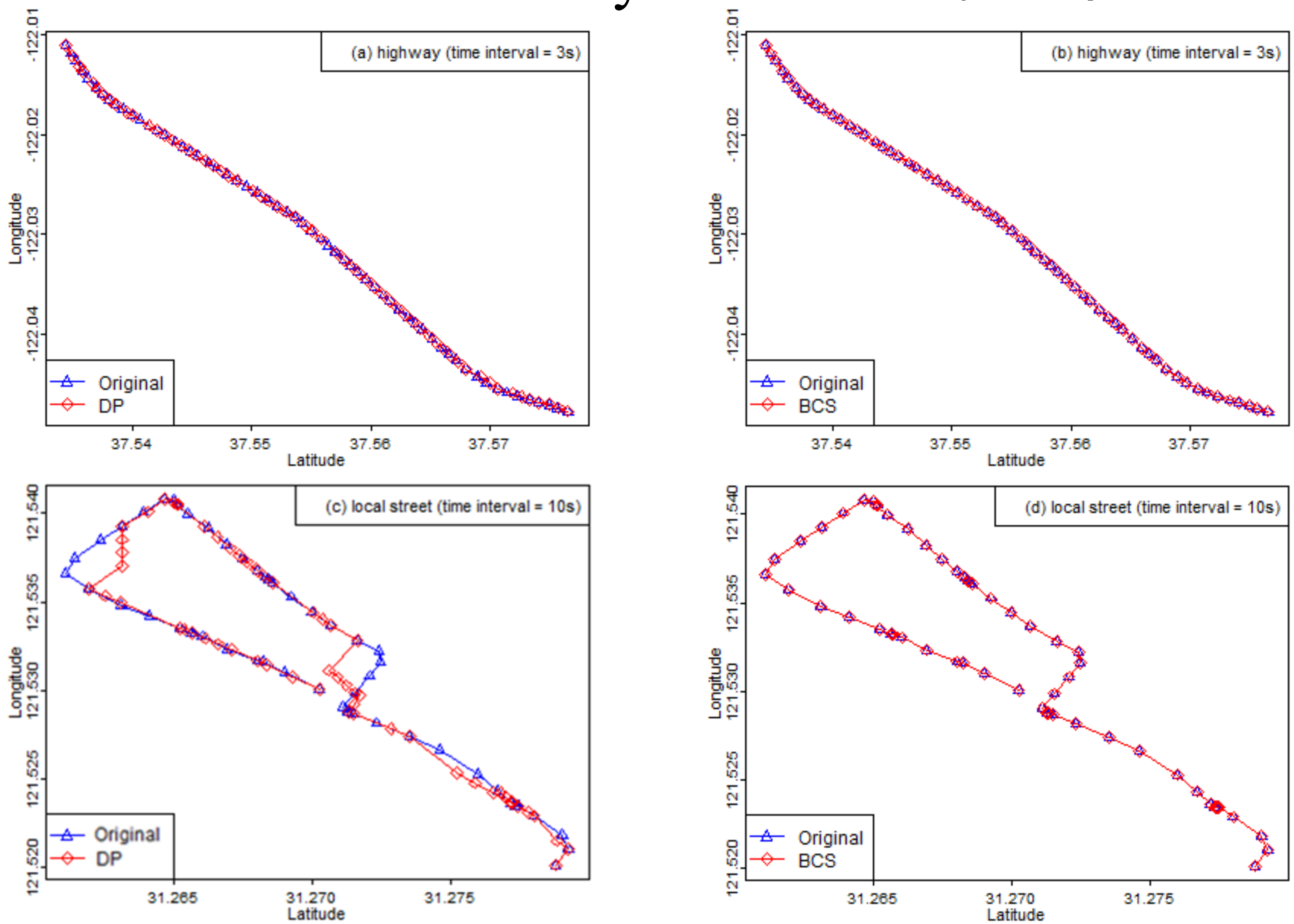
Data	Algorithm	Error
Vehicle 1 (highway)	DP	$2.7*10^{-6}$
Vehicle 1 (highway)	BCS	$3.4*10^{-11}$
Vehicle 2 (local street)	DP	0.1291
Vehicle 2 (local street)	BCS	$9.1*10^{-10}$
Vehicle 3 (highway)	DP	$3.9*10^{-6}$
Vehicle 3 (highway)	BCS	$1.1*10^{-11}$
Vehicle 4 (local street)	DP	0.1825
Vehicle 4 (local street)	BCS	$7.7*10^{-10}$
Vehicle 5 (highway)	DP	$3.3*10^{-6}$
Vehicle 5 (highway)	BCS	$1.06*10^{-11}$
Vehicle 6 (local street)	DP	0.2132
Vehicle 6 (local street)	BCS	$4.3*10^{-10}$

- Performance with Gaussian noise of 15dB in highway

Compression rate	Scenario	DP Error	BCS Error
0.5	highway	0.1040	0.0697
0.2	highway	0.1192	0.1041

Simulation Results

- Trace and recovered trace by DP & BCS (compression = 0.5)



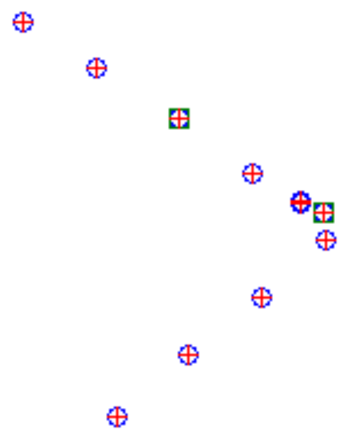
Discussion

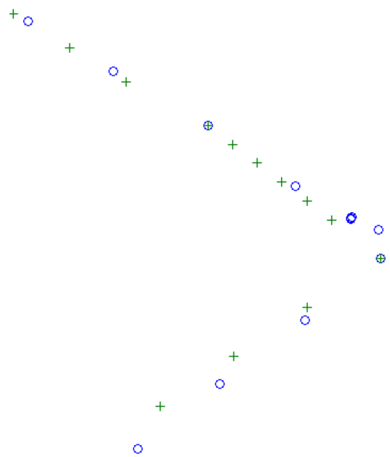
- Loss/Distortion of information (acceleration, speed, travel time, etc.)

Labels:
Circle: original points
Plus: recovered points

10 real points on local street

CS Approach

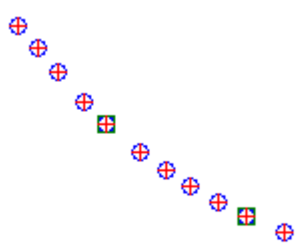


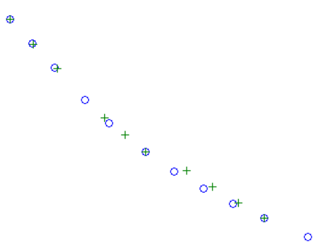


DP Approach

10 real points on highway

CS Approach





DP Approach

Concluding Remarks

- Raw GPS data can be represented relatively well by using appropriate compression techniques
- The proposed BCS approach can achieve relatively higher compression rate but maintain a better performance
- Despite the complexity, BCS approach does not require to store all raw data before sampling
- Compression means information loss/distortion (Consider trade off between compression rate and information change)

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Thank You Very Much!

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