AutoWitness: Locating and Tracking Stolen Property While Tolerating GPS and Radio Outages

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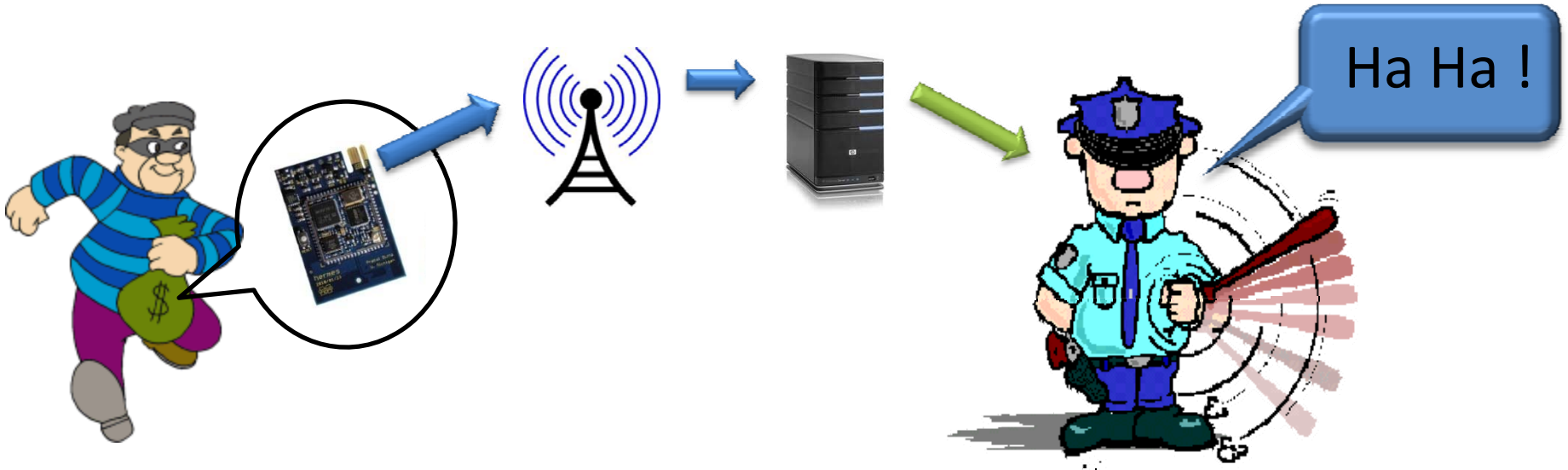
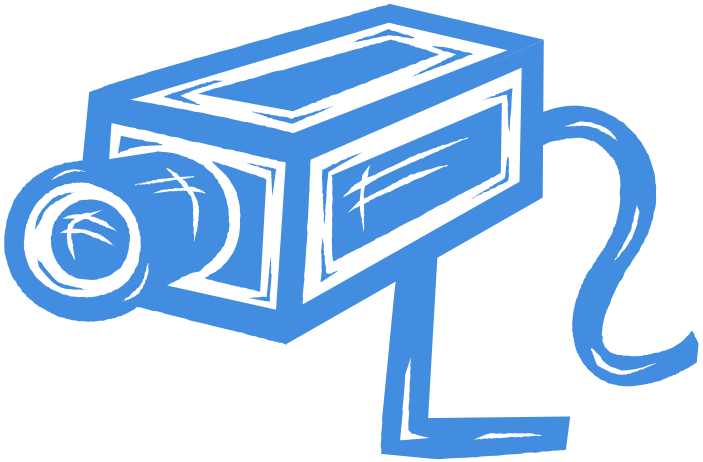
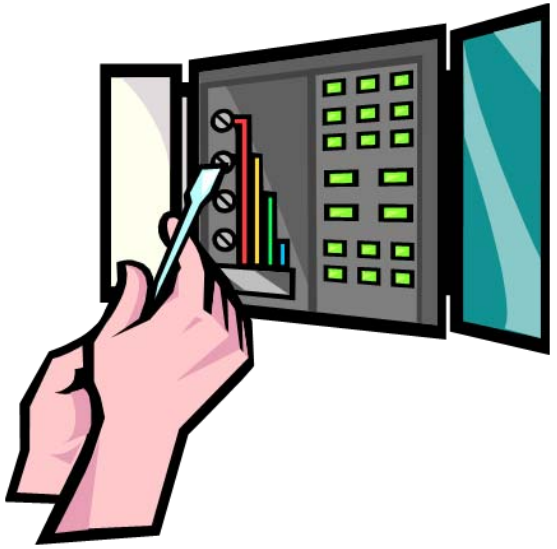


In United States:
Over 2 million reported burglaries in 2009
~ An average $ 2000 loss per incident

Existing Theft Detection Systems





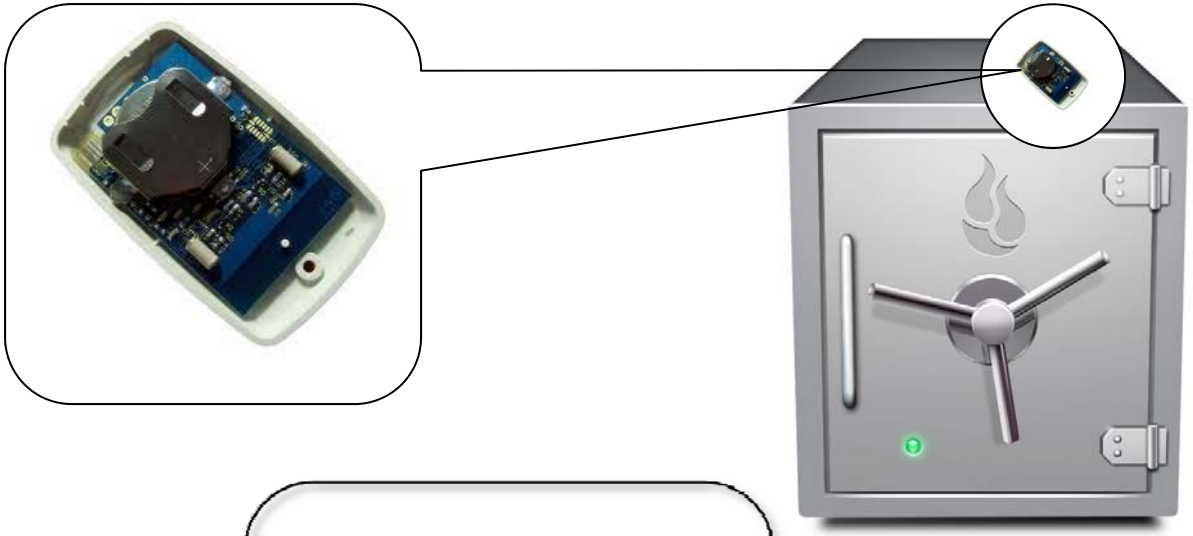
- Either deter or detect burglary incidents

Existing Tracking Systems

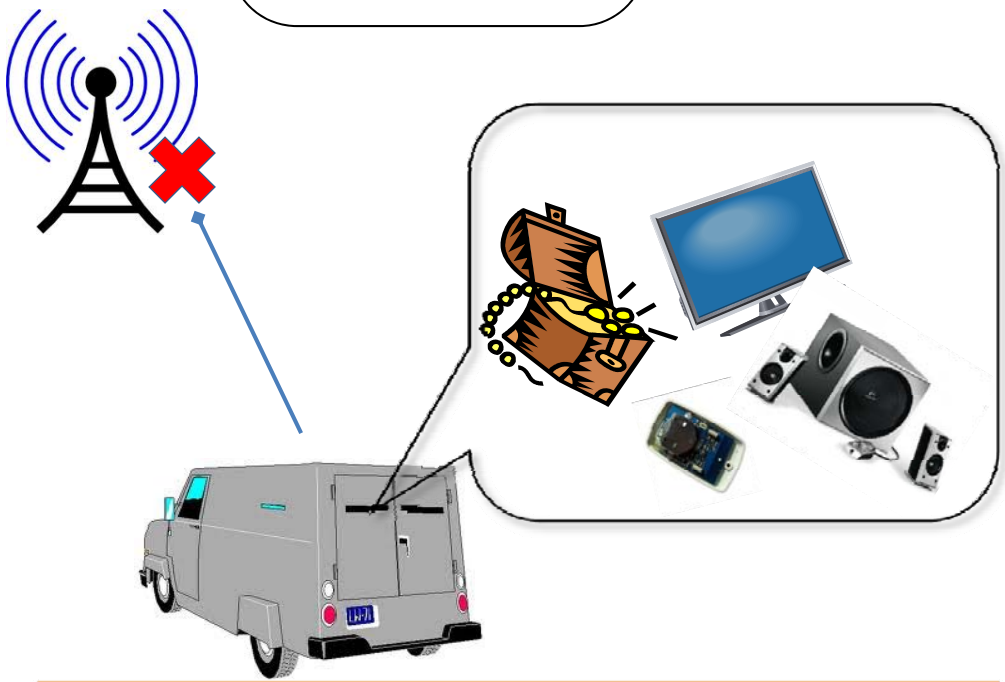
LIVEVIEWGPS
TRACKING YOU CAN TRUST

- Radio Outages
- Unsuitable for smaller assets

We need a system that is…



Stealthy



Immune to Radio Outages

Long Life

1 year

2 years

Our **"AutoWitness"** system

Detects Burglary Autonomously

- Using Vehicular Movement as an identifier of theft

Tracks Asset, Pinpoints Final Location

- Using a HMM based model to track burglars using only inertial estimates.

AutoWitness

Tag Node

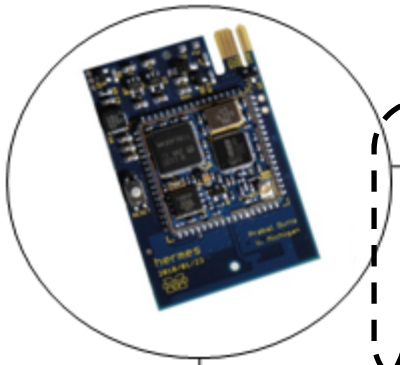
Embedded in expensive items

Server

Used for Map Matching

AutoWitness Server

Tag Node inside the Stolen Item in Burglar's Car



Distance and Turn Estimates

Cell Tower

Position and Travelled Path of Burglar's Car

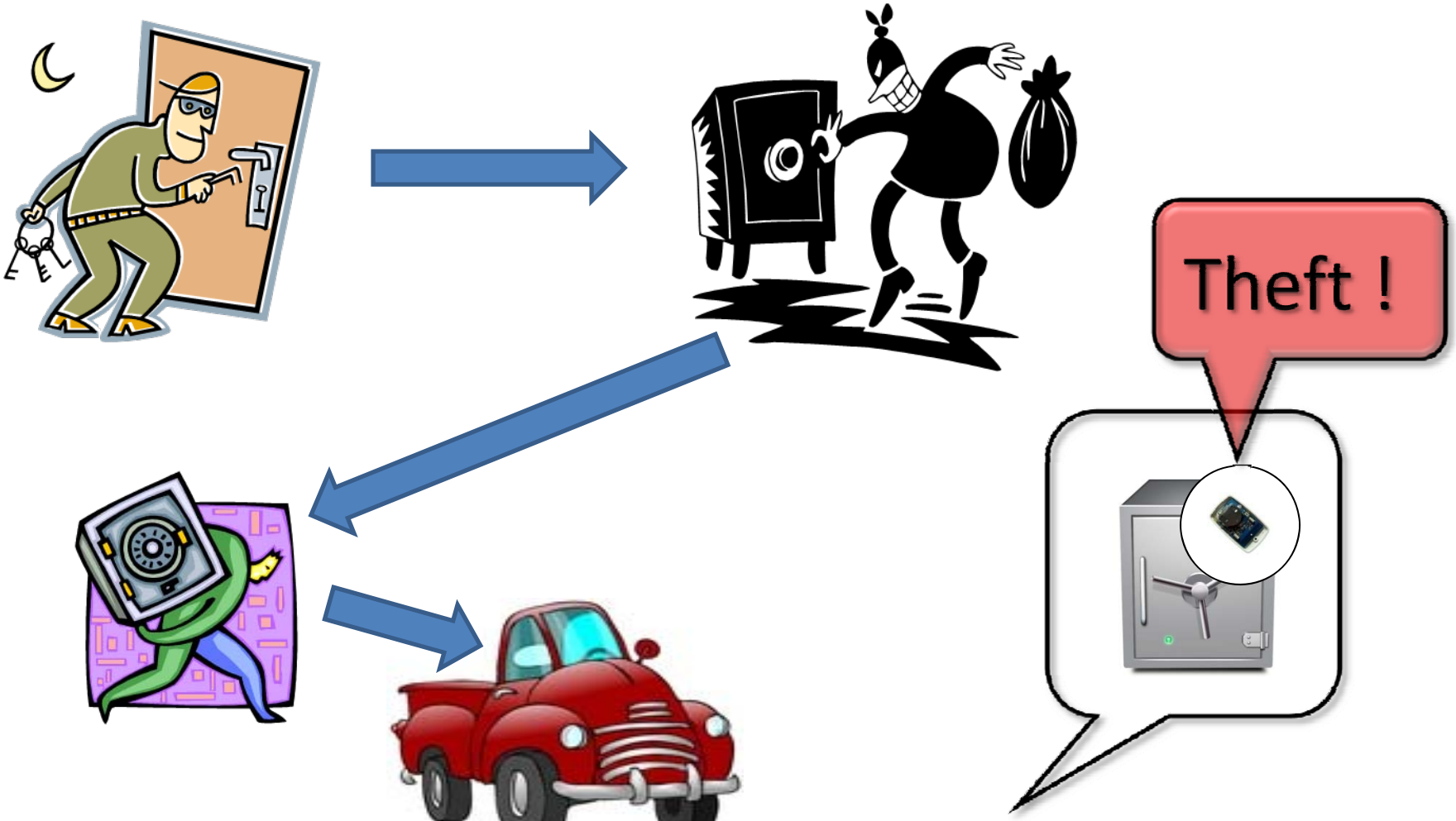
Burglar's Car

Police Car

How does AutoWitness work ?

Autonomous Detection of Burglary by the Tag Node

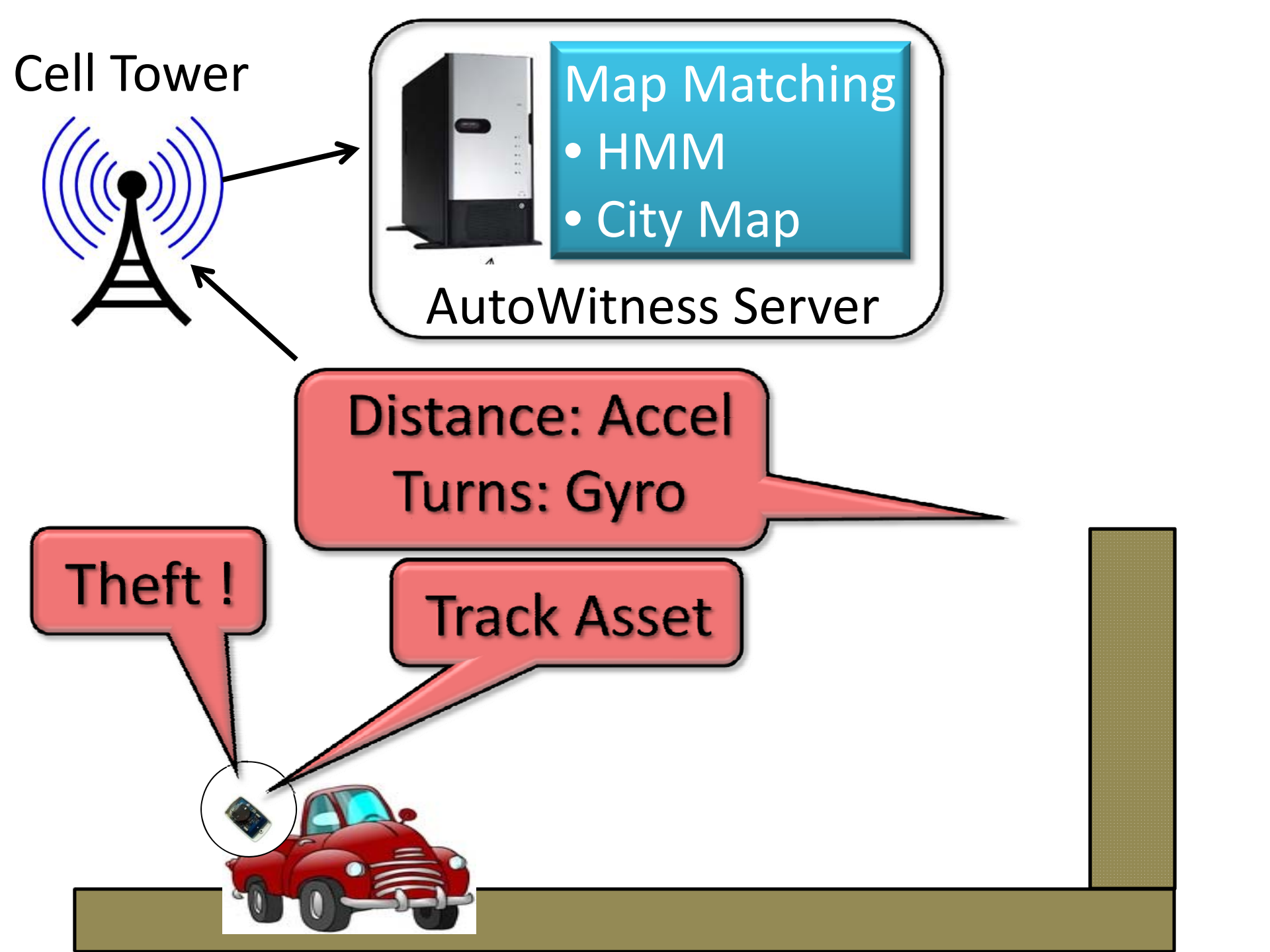
Vehicular Movement Indicates Theft



How does AutoWitness work ?

Autonomous Detection of Burglary by the Tag Node

Detection of Theft initiates tracking of assets

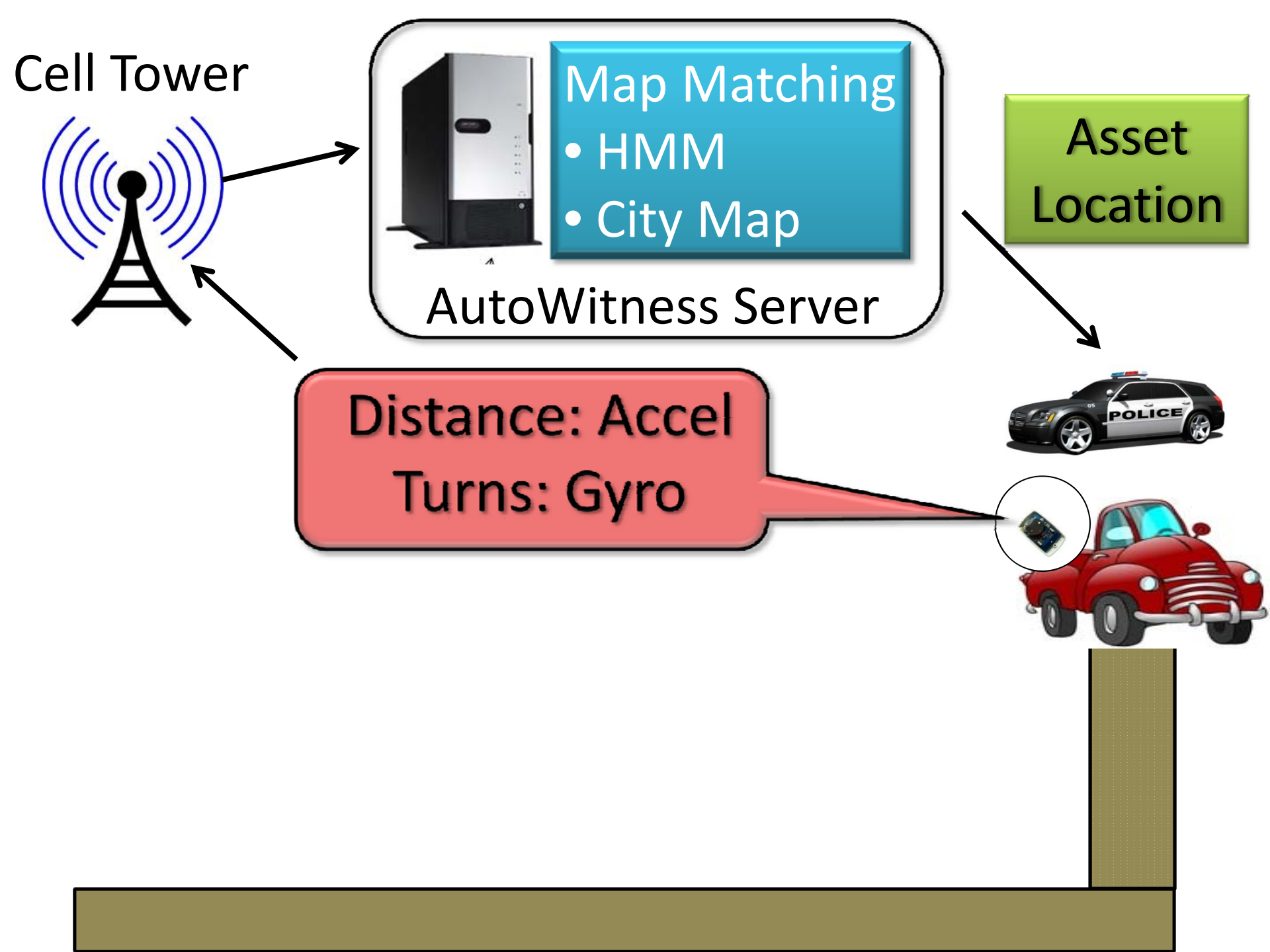

Cell Tower
Map Matching
• HMM
• City Map
AutoWitness Server
Distance: Accel
Turns: Gyro
Theft !
Track Asset

How does AutoWitness work?

Autonomous Detection of Burglary by the Tag Node

Detection of Theft initiates tracking of assets

Track is provided to law enforcement officials when cell tower is available completing the process of asset recovery


Cell Tower
Map Matching
• HMM
• City Map
AutoWitness Server
Asset Location
Distance: Accel
Turns: Gyro
POLICE

Thank you AutoWitness !

- Classifies Theft by Detecting Vehicular Signature
- Produce inertial estimates using accelerometers and gyroscopes
- Computes track of burglar using a HMM
- Informs the Police

Key System Challenges: AutoWitness

Real Life Deployment presents several system challenges

Challenges
- Tag Node
- Server

Key System Challenges: Tag Node

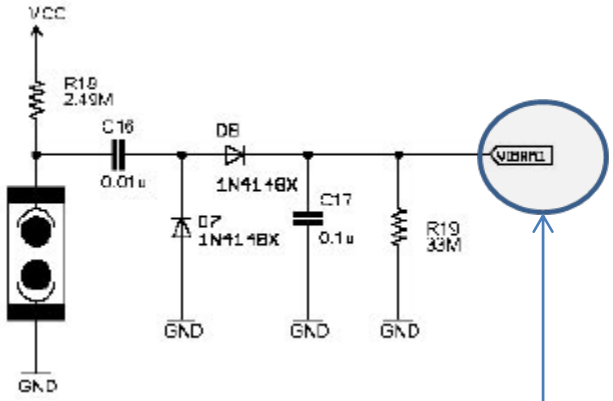
Producing Accurate Inertial Estimates

Choosing appropriate Hardware

Re-orientating Tag Node

Developing Theft Classifier

Choice of Hardware for Tag Node



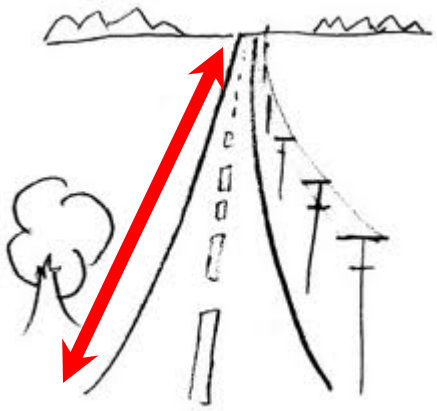
Wake Up Circuit

Vibration Dosimeter

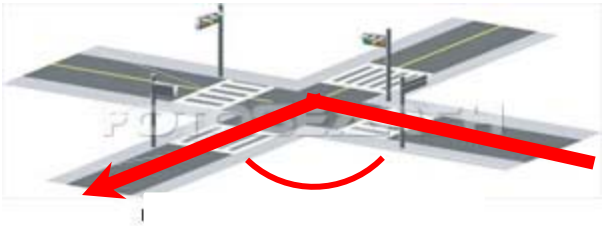
- Filters out insignificant vibrations and prolongs tag node lifetime

Choice of Hardware for Tag Node

Distance = d



Angle = Θ



- 3 axis accelerometer
- 3 axis Gyroscope

Choice of Hardware for Tag Node

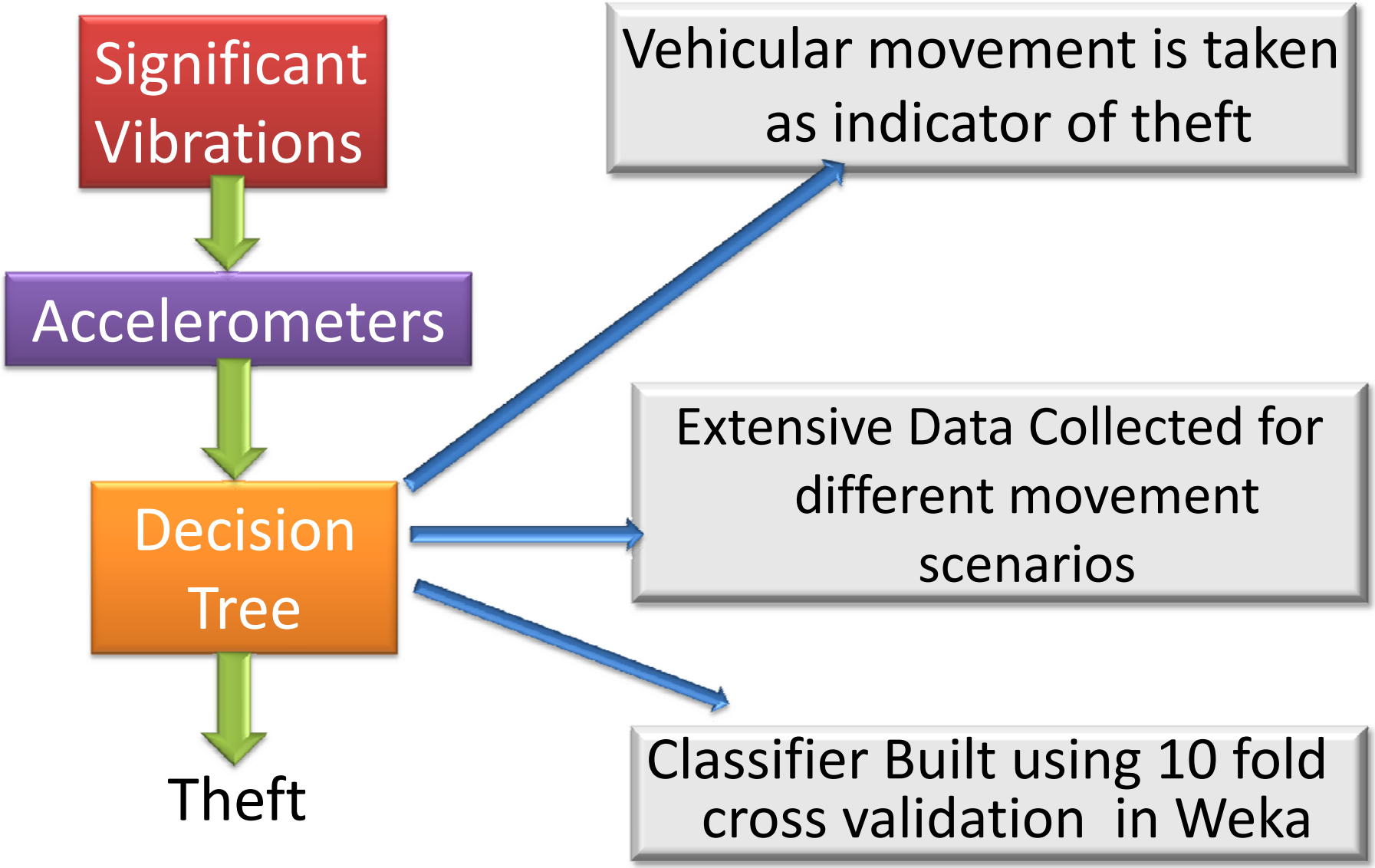
Cell Tower

AutoWitness Server

- A GSM \ GPRS modem

All integrated in a Epic Core Platform

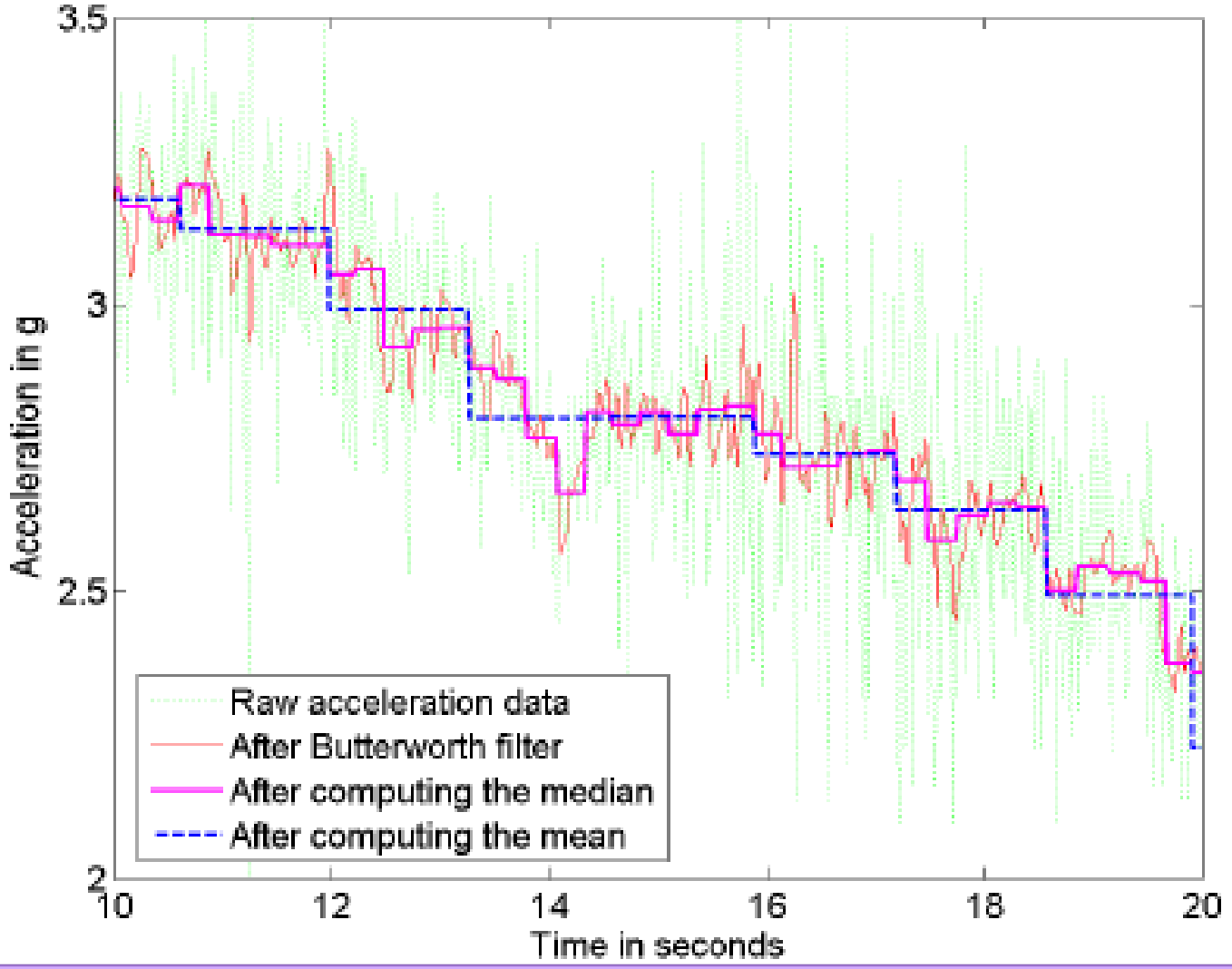
Light Weight detection of burglary on Tag Node



Producing Accurate Inertial Estimates

- Distance Computation using inertial sensors
- Remove noise
- Re-orient Tag Node
- Correct for Radial Acceleration
- Correct for drift

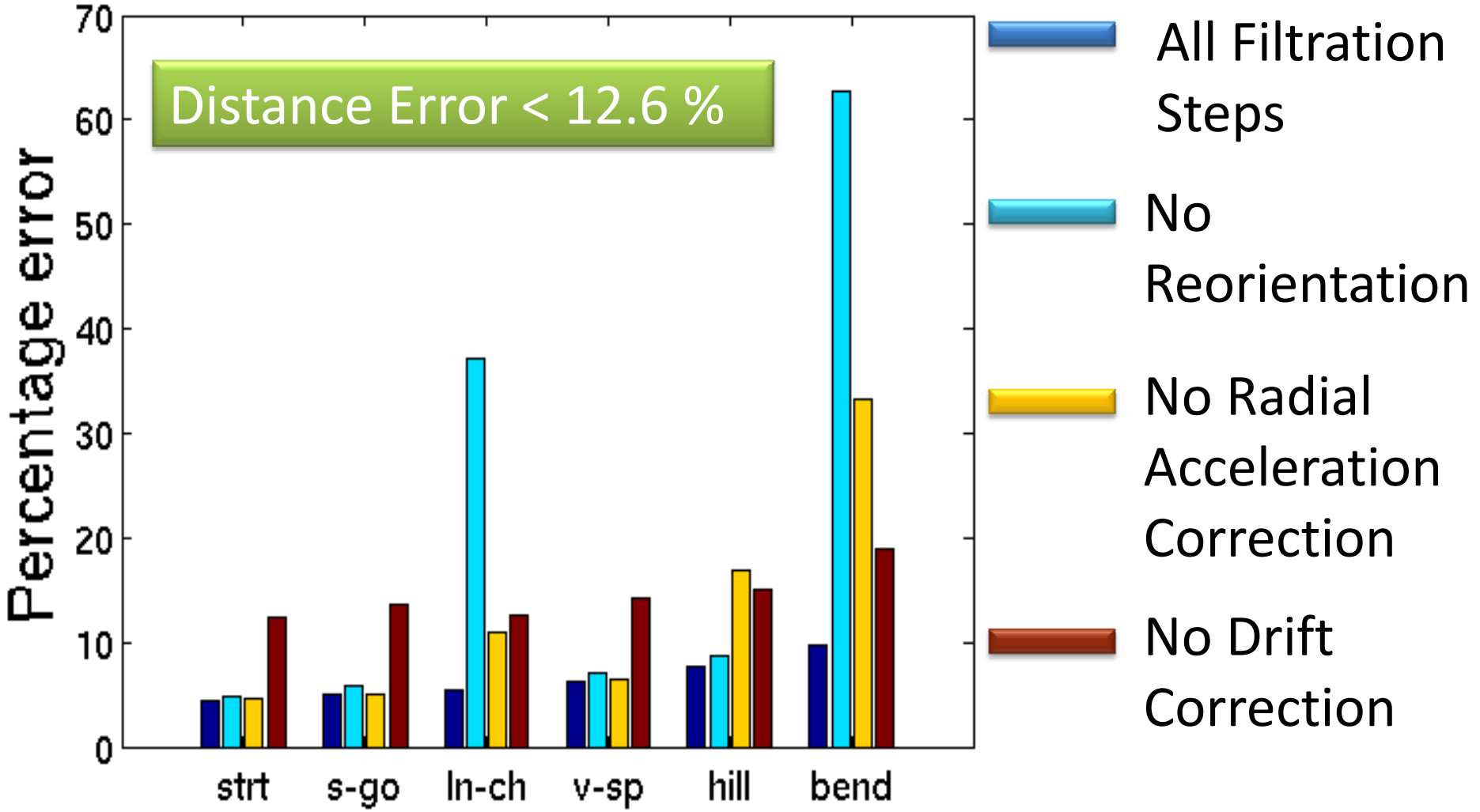
Distance Computation



- Remove Noise
- Subtract Mean between stops to correct drift
- Double Integrate

Also remove component radial acceleration for curves

Distance Computation



Key System Challenges: Server Side

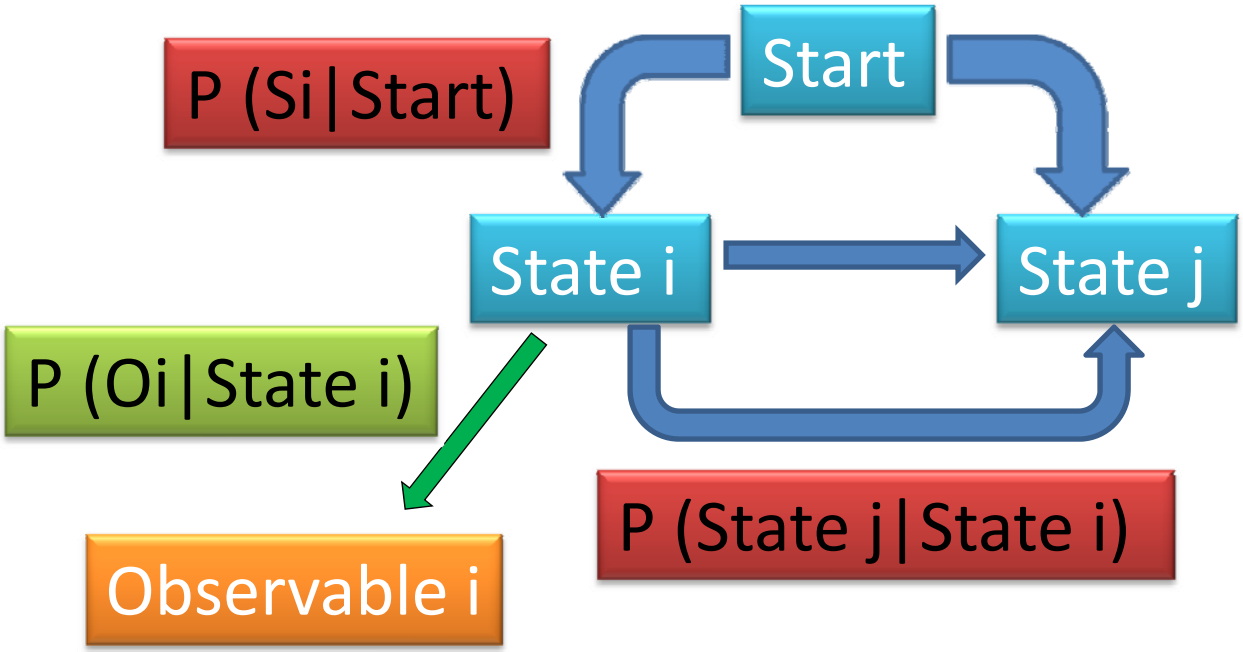
Using only Inertial Estimates

Pinpoint the asset's final location

Reconstruct the path driven by burglar

Reconstruct Path driven by Burglar

Hidden Markov Model



Existing Systems using HMM for map matching require GPS coordinates as inputs

Start Probabilities

Start states emerge from Intersections within uncertainty range

No of Intersections = 4

Start Probability = 1/4

Transition Probabilities (TPs)

We want to assign TPs

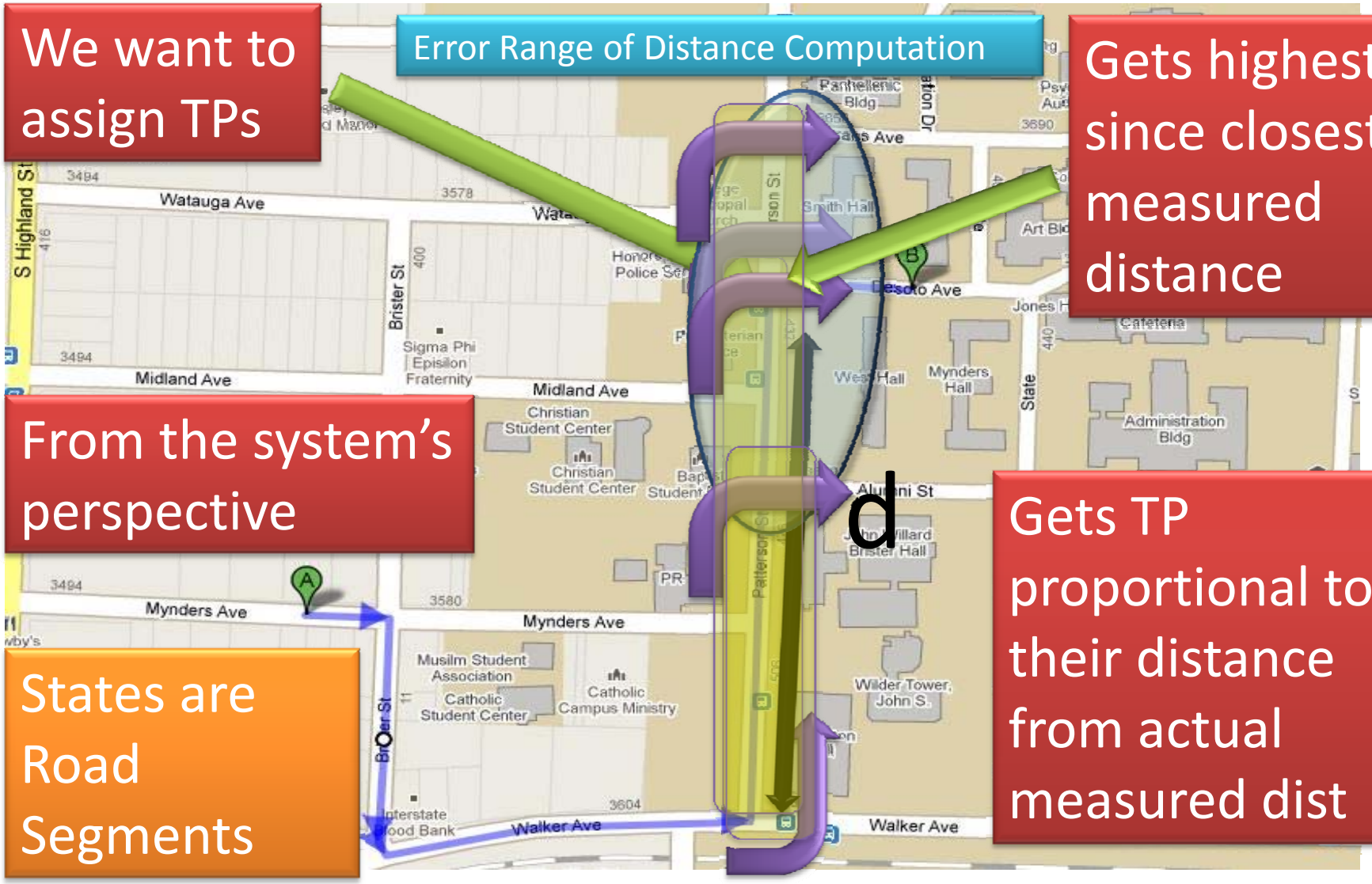
Error Range of Distance Computation

Gets highest TP since closest to measured distance

From the system's perspective

Gets TP proportional to their distance from actual measured dist

States are Road Segments



Observables

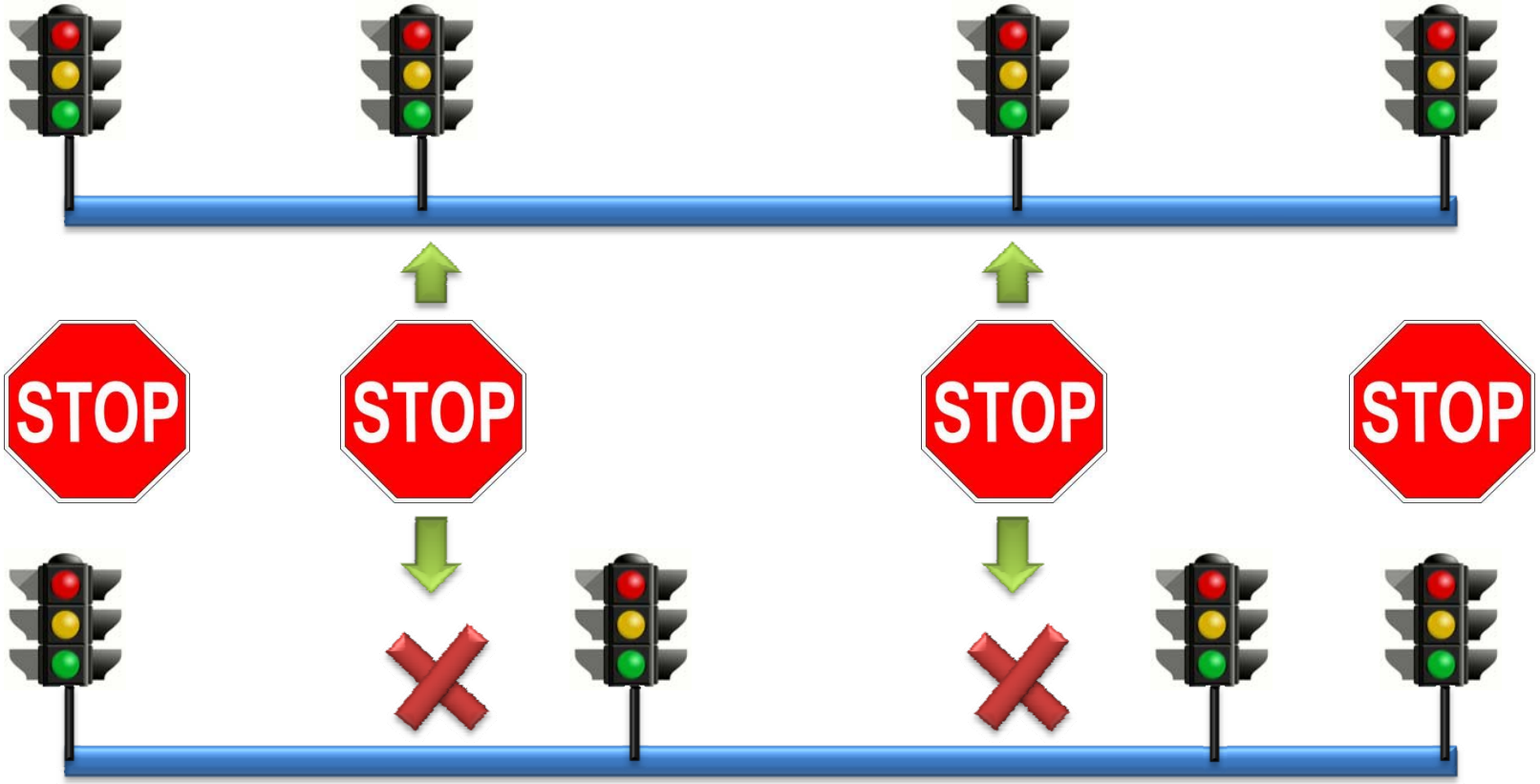
Speed of the Car ?

Curvatures of Roads ?

Sequence of distances between every pair of turns and/or stops experienced by the burglar's car

Road Segment A

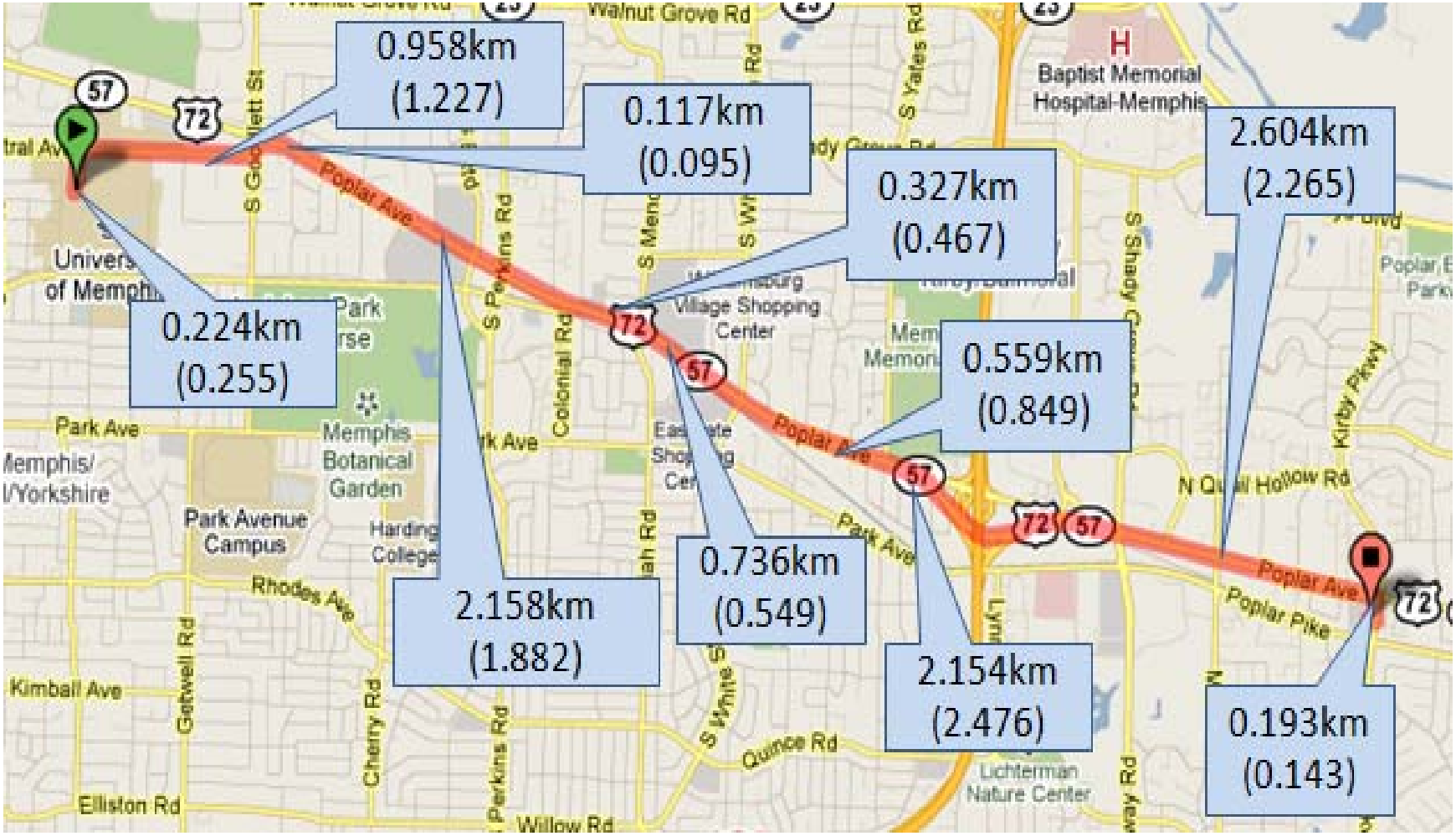
Let’s say there are two road segments of identical length



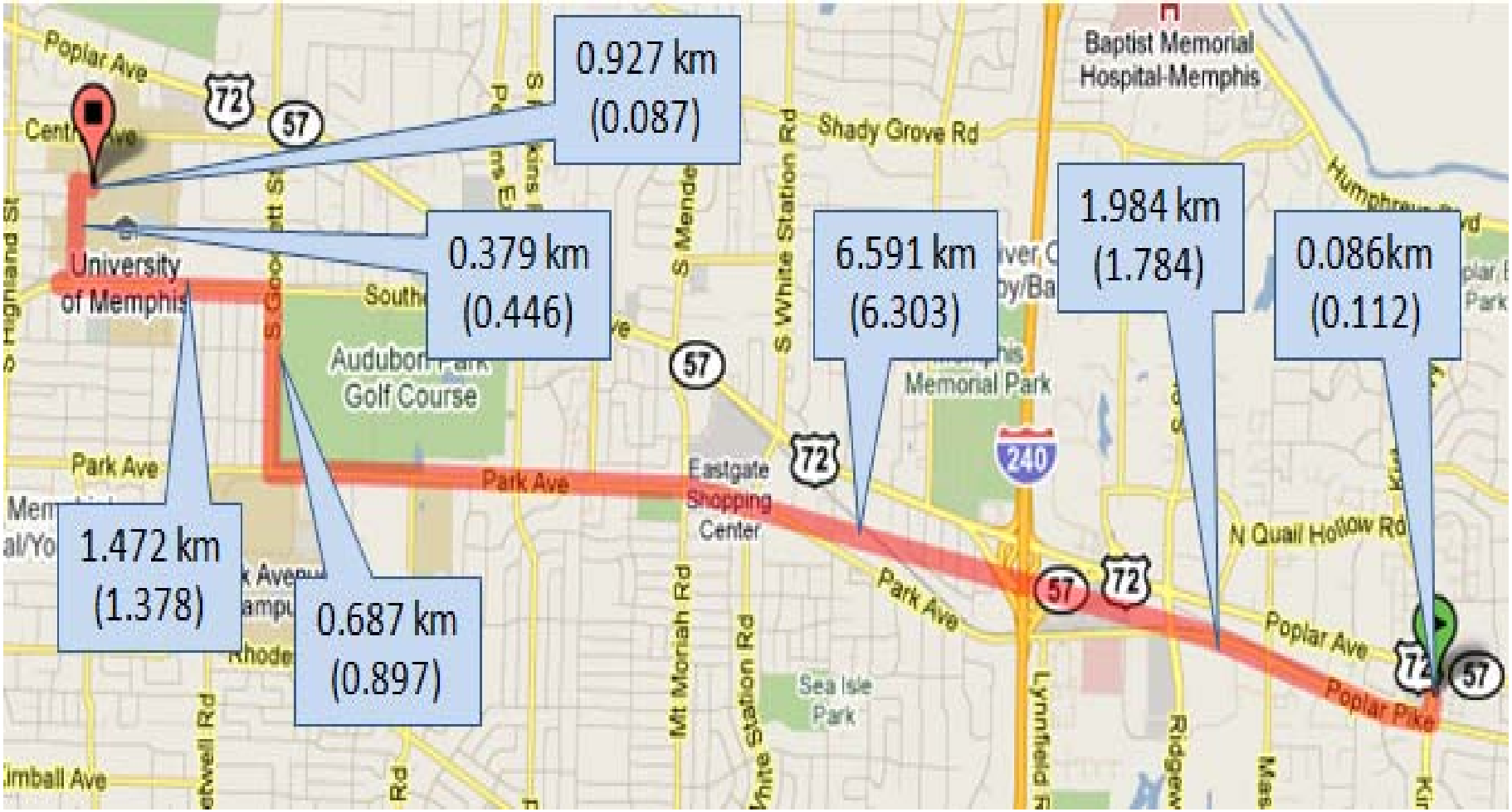
Road Segment B

Discrimination using location of traffic lights on roads

Real Life Test



Real Life Test-Return Path

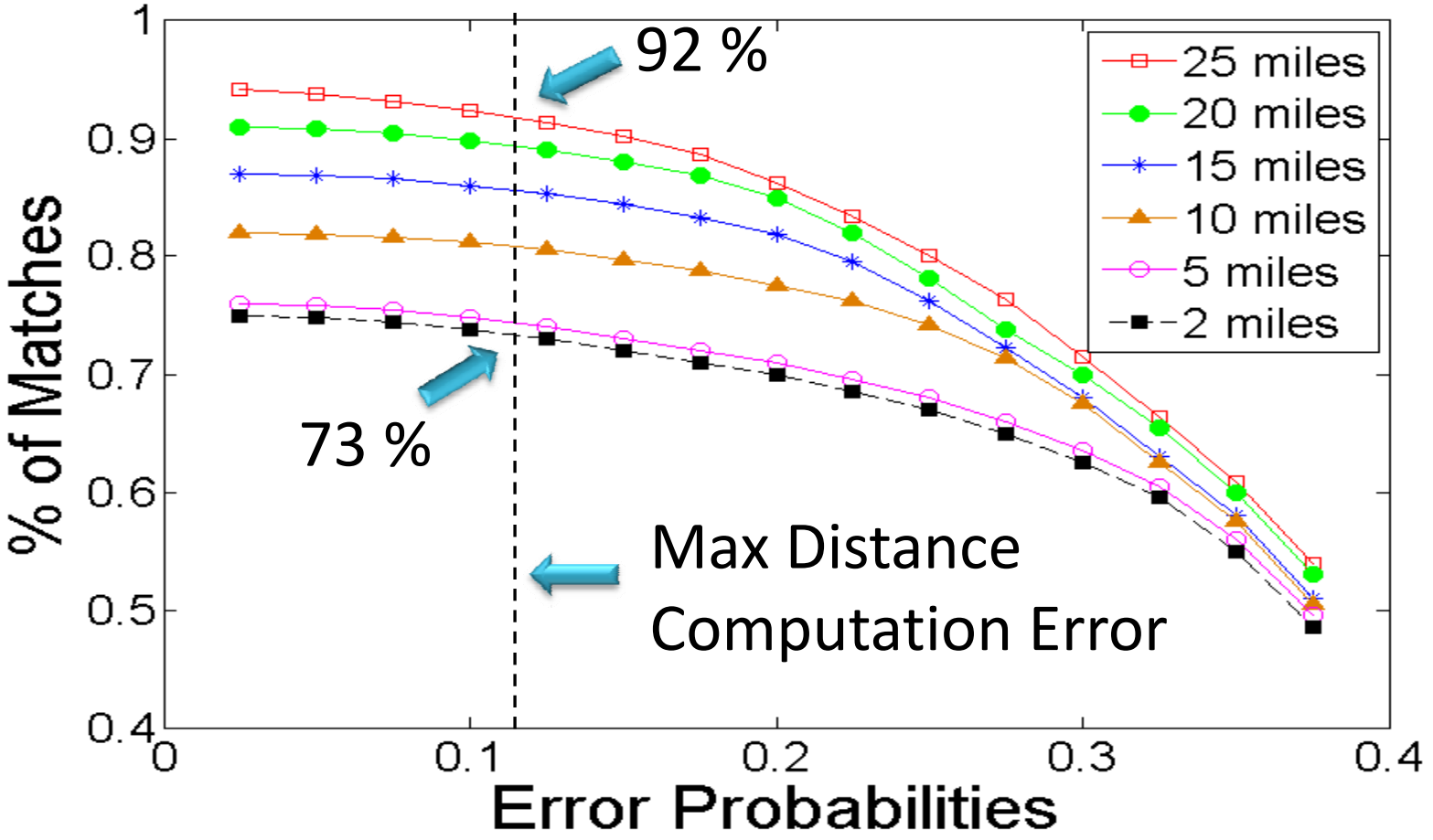


Evaluations at Scale

Set up for the evaluations:

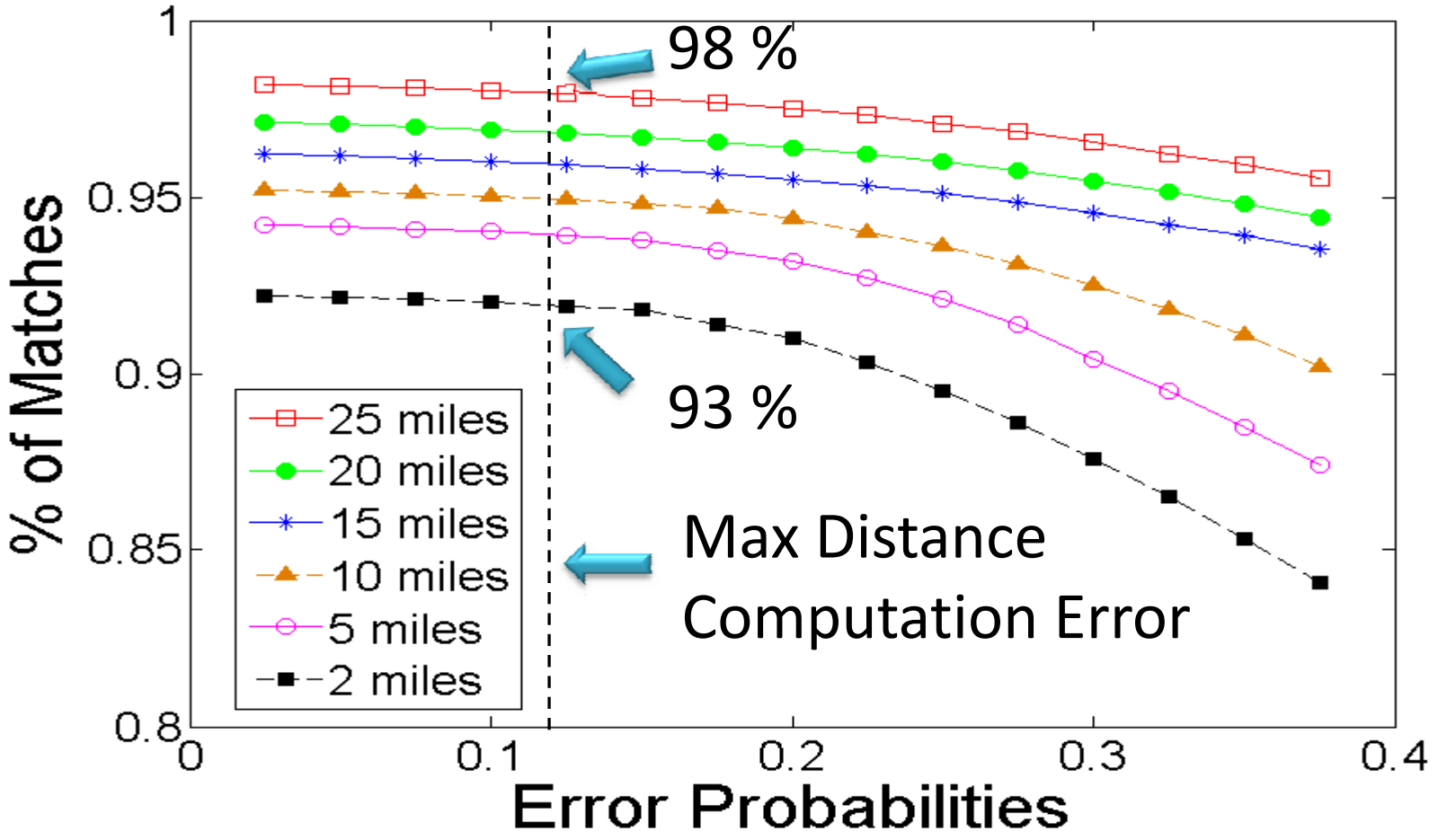
- We used Openstreetmap.org GIS data base
- Chose 100 different locations through out the city as our starting locations
- Fort each stating location chose 10 different directions for a fixed travelled distance
- Created synthetic paths from the database marking a set of intersections as STOP

Evaluations of Map Matching



Stopping Sequence, Localization at Destination

Evaluations of Map Matching



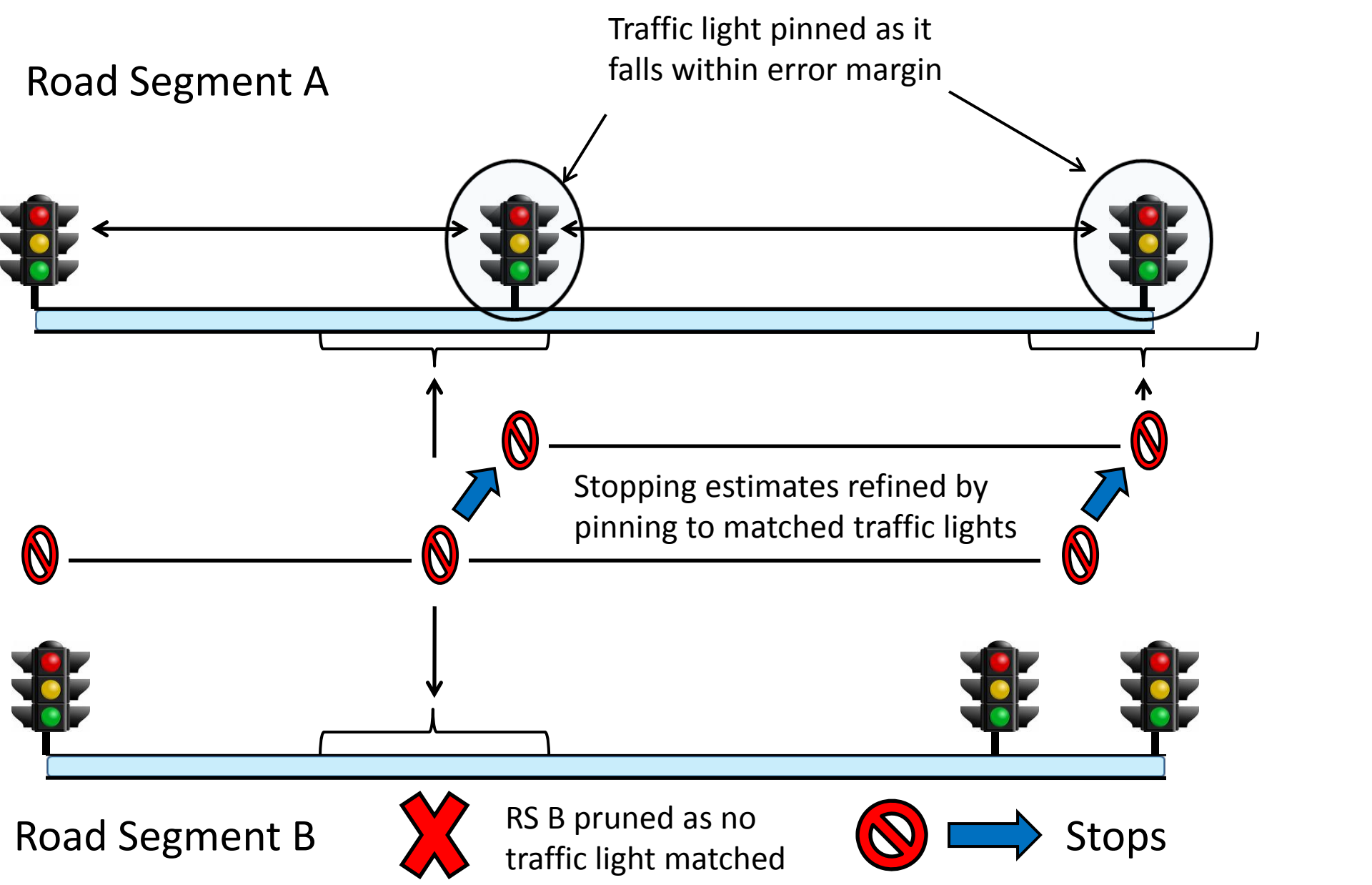
Stopping Sequence, Localization at each Turn

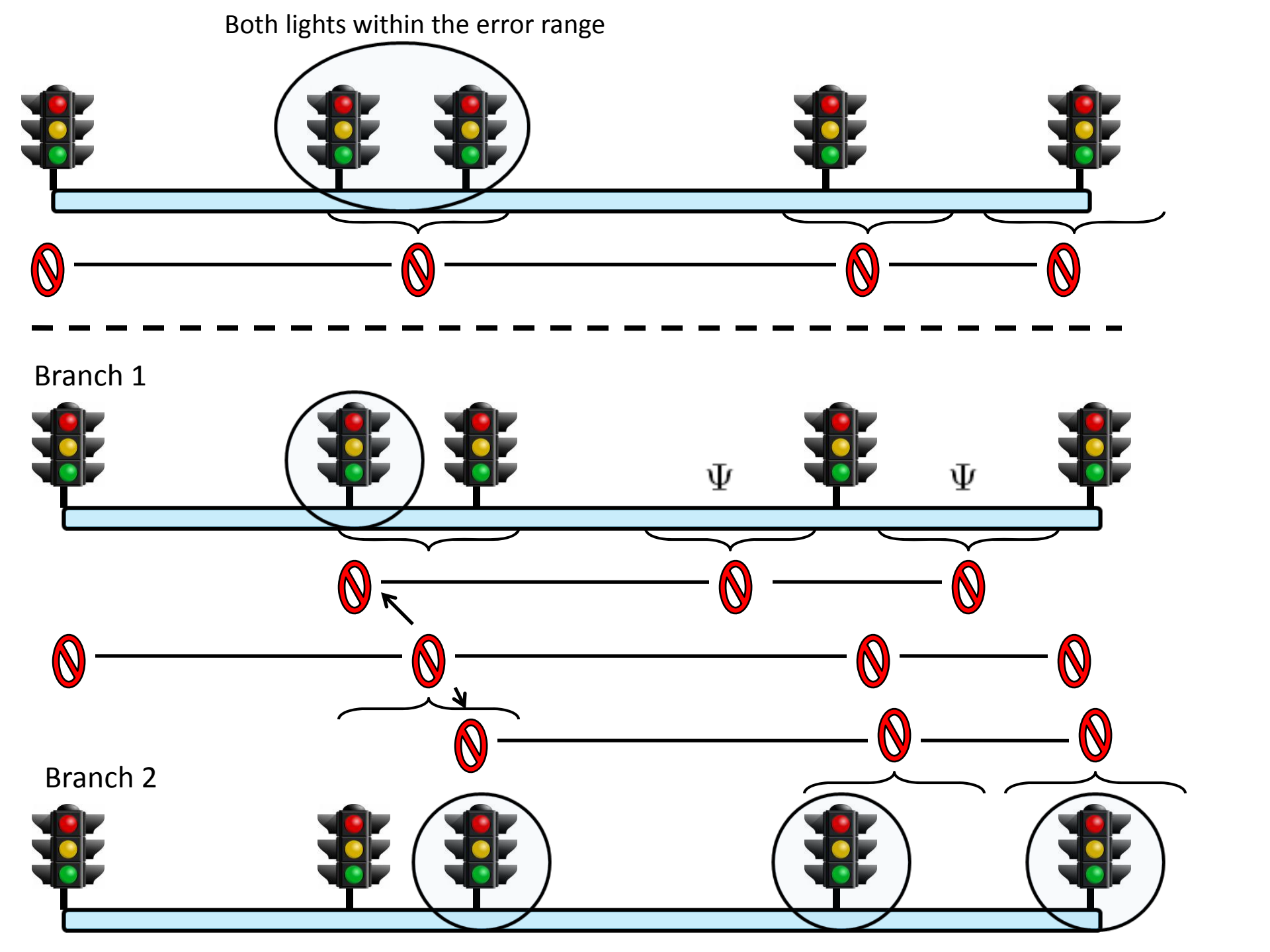
Conclusions

- Achieves over 90% accuracy in identifying the path driven by the burglar using inertial estimates
- Immune to Radio Outages
- Life Time prolonged due to filtration by Vibration Dosimeter

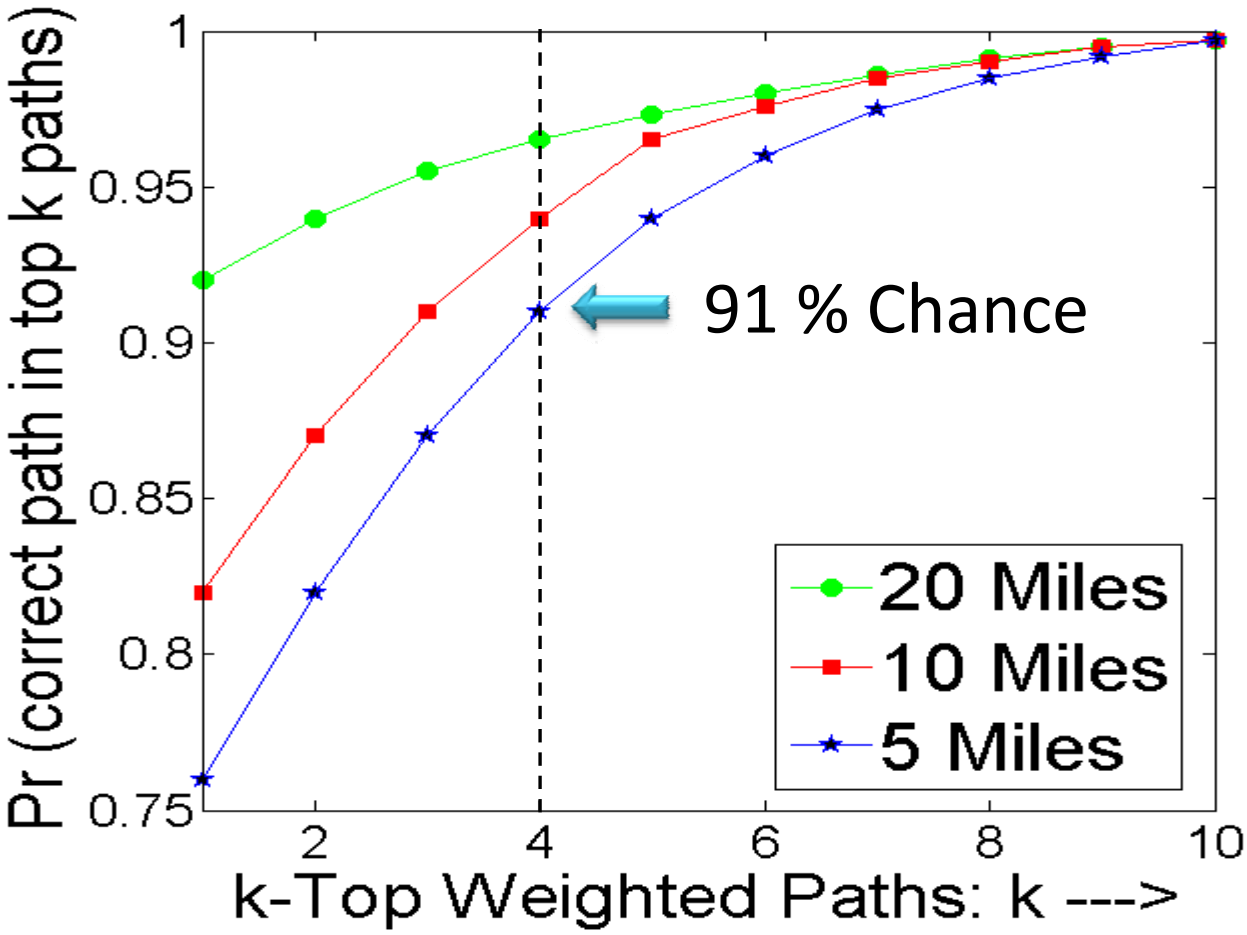
Future Work

- Locate apartment or house of the burglar


Road Segment A
Traffic light pinned as it falls within error margin
Stopping estimates refined by pinning to matched traffic lights
Road Segment B
RS B pruned as no traffic light matched
Stops


Both lights within the error range
Branch 1
Ψ
Ψ
Branch 2

Evaluations of Map Matching



Cumulative Prob. of correct path in K top weighted paths