Smart Broward County Transportation: Using Big Data Analytics and Artificial Intelligence

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Talk Outline

• Smart Societies
• Impact of Technology on Smart Societies
• Broward County Metropolitan Transportation Plan
• Research and Development at University of Florida (with potential applications to Broward County)
  o Analyzing Traffic Signals
  o Video Analysis
  o Incident Detection
  o Smart Intersections
  o Smart Networks
  o Vehicle and Commodity Classification
• Conclusions
• Serving the mobility needs of underserved communities by providing reliable and affordable transportation alternatives
• Break down digital barriers and improve transparency for all residents using innovative technology-based solutions
• Manage traffic congestion and improve safety by using big data and related technologies
• Use data driven approaches for decision making, planning, evaluation and measurement
• Support efficient movement of goods, services and people by using practices that are environmentally sustainable
• Stimulate economic prosperity by improving access to jobs using expanded mobility access to major job centers
• Enhance tourist and visitor experience by providing easy to access information about mobility alternatives

Source: 2045 Métropolitan Transportation Plan (MTP)
Connected & autonomous vehicles are becoming prevalent.

**Convergence**
Expected in 2025

**Autonomous Vehicles**
Source: Peter Runcie, CSIRO peter.runcie@data61.csiro.au

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**Connected Vehicles**
Source: http://gelookahead.economist.com/infograph/car-os/
Communication is going through a revolution
Technology convergence will revolutionize transportation, dramatically improving safety and mobility while reducing costs and environmental impacts.

- Connected Vehicles
- Vehicle Automation
- Internet of Things
- Machine Learning
- Big Data
- Mobility on Demand

**Benefits**

- Order of magnitude safety improvements
- Reduced congestion
- Reduced emissions and use of fossil fuels
- Improved access to jobs and services
- Reduced transportation costs for gov’t and users
- Improved accessibility and mobility

Source: USDOT Smart City Challenge Presentation
Impact of tech applications on improving mobility

- **Real-time public transit information**: Real-time information about departure and arrival times.

- **Predictive maintenance of transportation infrastructure**: Sensor-based monitoring of infrastructure (such as rails, roads, and bridges) so that predictive maintenance can be performed to reduce disruptions.

- **Intelligent traffic signals**: Improvement of overall traffic flow through dynamic optimization of traffic lights. Give priority to transit and emergency vehicles, public buses, or both.

- **Smart parking**: Dynamic guidance and variable pricing based on location and availability.

- **Real-time road navigation**: Real-time navigation tools based on traffic and incidents.

Source: Mckinsey Global Institute, Smart Cities Report
Smarter Transportation Research at UFL

Smarter intersections will be equipped with cameras (including infrared) and/or lidar to collect data

1. Better Pedestrian and Bicyclists Safety by examining the conflict points of the vehicle/pedestrian trajectories (near-misses)
2. Better Demand Profiles by understanding real-traffic behavior for more effective signal timing and understanding relationships between existing (loop detector) and new technologies (video).
3. Better SPaT messaging by understanding traffic behavior on the intersections.

Smarter Streets by use of transit buses with forward facing cameras to continuously collect video data from streets (and intersections).

1. Better Pedestrian Safety by detection of jaywalking/“mid-block crossing” behaviors that are prevalent in university campuses.
3. Better Lane and Street Sign Design by tracking indicator lights, lane-changing maneuvers undertaken in front of the bus.

Funded by National Science Foundation under their Smart Cities Program and Florida Department of Transportation
Smarter Transportation Research at UFL

**Smarter Network** by sensing data from multiple intersections will enable

2. Better Signal Retiming for different corridors by time of day and day of the week to reflect the changes in network demand.
3. Better System-wide Network Utilization by utilizing a global view of the entire network and historical traffic patterns based, and potential disruptions.

**Smarter Interactions with Connected and Autonomous Vehicles** by analyzing data collected from CAVs will lead to

1. Improved Safety by effectively managing CAVs.
2. Better Understanding of CAV Behavior and Interaction with Traditional Vehicles.
3. Better Signal Timing and Trajectory Optimization for CAVS.

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Trapezium/I-Street project in Gainesville

Trapezium after SPaT project

Data Sharing and ATSPM
Upgraded Linux based ‘ATC’ Controllers. ATSPM Data sharing to University of Florida and third party (TTS, TrafOps, Live Traffic Data, Connected Signals)

DSRC Radios
Siemens DSRC Radios with MAP and SPaT Broadcast

Added value option
Emergency Vehicle Pre-emption and vehicle OBUs
Trapezium/I-Street project in Gainesville (Additions)

Trapezium after SPaT project

Multiple FishEye Cameras
Full intersection view, streaming cameras with full count, presence and queue detectors

Multiple Lidars
For ground level ground truth verification and ped and bike application

Several In-bus video
For Dynamic/Vehicle Perspective to supplement Static/Infrastructure.
Edge (Fog) and Cloud Computing

- Flexible infrastructure
- Adapt to changing requirements
- Anywhere, Anytime Availability
- Less Hardware, More Storage

Diagram:
- Intelligent Device
- Cloud
- Many Devices
- Many Users
- WAN
- LAN Occasionally
Overall Architecture

Incident Detection (Controller Logs, Crash Reports, Here.com)
- Gainesville, Jan 2019 Onwards
- Orlando, Aug 2018 Onwards

Bluetoad
- Gainesville, Jan 2019 Onwards

Crash Data
- Jan 2018 onwards

Video Data
- 2 feeds in Gainesville, Dec 2018 onwards. Option to add more.

Here.com (Probe car) Data
- Gainesville, Jan 2019 onwards

Map, Weather and Transit
Prototyping stage
(Option to add Historical records for Here, Bluetoad, and crash data)

Funded by FDOT

Controller logs
- Gainesville, Jan 2019 Onwards
- Orlando, Aug 2018 Onwards

Future

Network Optimization (Controller Logs, Signal Timings, Here.com)
Integrated and Intelligent Data Store

Open data environment containing data from multiple sources

- Monitoring
  - Loop Detectors
  - Video Data
  - PCD data
  - Infrastructure Data
- Evaluation
  - Travel Times
  - Pedestrian Counts
  - Usage of Cross Walks
- Predictive Modeling
  - Incident Detection
  - Response Speed
  - Crash Prediction

- Optimization
  - Signal Optimization
  - Corridor Optimization
  - Network Optimization
- Analysis
  - Geographical Analysis
  - Socio Economic Analysis
- Planning and Investments
  - Evaluate ROI
  - Before and After Studies
Real-time Multiple Object Detection

Funded by Florida Department of Transportation

Mini Map Trajectory Demo
- **White**: car
- **Green**: bike/motorbike
- **Yellow**: pedestrian
Real-time Visualization

Single phase visualization

Multiple phase visualization
Anomalous Trajectory Detection

Anomalous Track

Video
Ranking & Classifying Signalized Intersections

- Controller logs from Gainesville:
- Extract-Transform-Load: Downloaded the data, cleaned and reformatted it.
- Identified Relevant MOE, Computed MOE cycle by cycle.
  - Platooning ratio:
    - The ratio of the number of vehicles arriving
    - during the green time/phase to the proportion
    - of the green interval of the total cycle.
  - Arrivals on Green vs Arrivals on Red: Percentage AOG varies from .25 to .45
  - Split Status: Gap out/Max out/Force off
- Rank Signals based on MOE: Best or worse performing intersections.
- Identify Signal behavior based on high resolution plot.
- Automatic Classification of signals based on behavior.

<table>
<thead>
<tr>
<th>Arrival type</th>
<th>Range of platoon ratio ($R_p$)</th>
<th>Default value ($R_p$)</th>
<th>Progression quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\leq 0.50$</td>
<td>0.333</td>
<td>Very poor</td>
</tr>
<tr>
<td>2</td>
<td>$&gt; 0.50 - 0.85$</td>
<td>0.667</td>
<td>Unfavorable</td>
</tr>
<tr>
<td>3</td>
<td>$&gt; 0.85 - 1.15$</td>
<td>1.000</td>
<td>Random arrivals</td>
</tr>
<tr>
<td>4</td>
<td>$&gt; 1.15 - 1.50$</td>
<td>1.333</td>
<td>Favorable</td>
</tr>
<tr>
<td>5</td>
<td>$&gt; 1.5 - 2.00$</td>
<td>1.667</td>
<td>Highly favorable</td>
</tr>
<tr>
<td>6</td>
<td>$&gt; 2$</td>
<td>2.000</td>
<td>Exceptional</td>
</tr>
</tbody>
</table>
Smart Intersections

- Video Processing
- Lidar Processing
- Infrared Nighttime Video Processing

Fusion Algorithms

Loop Controller Data

Trajectory Database and Visualization

Anomaly Detection
Near Misses
Incident Detection
Signal Timing

Funded by NSF and FDOT
Smart Streets: Artificial Intelligence based Real-time Incident Detection

Challenge
• Detect Traffic Interruptions ASAP (ideally within 100 seconds)
• Simple Volume Based Approaches (e.g. 80% reduction in volume) create too many false alarms (e.g. 10 false alarms for every correct detection)

Opportunity
• Newly installed loop detectors allow for arrivals/departures at a deci-second intervals, but generate 20 GB per day for 1000 signals
• Use Bigdata Artificial Intelligence and Machine Learning for detecting all traffic interruptions (80% reduction for 5+ minutes)

AI based Solutions (Consensus of three experts)
• Volume Reduction Expert: Predicts traffic volume using last 10 minutes and previous weeks data for the same time window to detect potential reduction
• Gap Analysis Expert: Learns gap distribution from current and past history to and determine if current gap is abnormal
• Platoon Analysis Expert: Learn platoon size distribution from recent history and determine if traffic after a small amount of gap is much smaller
• Tested on 90 day historical data collected from 150 “advance” detectors on 25 intersections
• Close to zero missed traffic interruptions
• Average Wait time 110 secs (2-3 false alarms for every 10 correct detections)
Smart Streets: Artificial Intelligence based Real-time Incident Detection

Incident on Detector ID 206511 at 2018-08-24 10:38:37

Example of a case where volume dip happened but the gap/platoon analysis showed that there is no need for an alarm

Note: Not all traffic interruptions are crashes or reported

Funded by FDOT
Smart Network (of Arterials)

- Historical Analysis
  - Day of the week and hour of day patterns of traffic

- Real-time Analysis
  - Incidents
  - Real-time information

- Machine Learning
  - Corridor Optimization
  - Network Optimization

Funded by FDOT
Highway Vehicle Movement Tracking

- Detecting and tracking highway vehicles
- Vehicle speed computation
- Trajectories – O/D, Exit and Enter Locations
AVIAN: Autonomous and Connected Vehicles Intersection Controller (NSF CPS + FHWA+FDOT)

Funded by NSF CPS
Predicting and preventing fatal crashes (FDOT D5)
Truck and Commodity Classification Using Machine Learning

WIM Dataset w/ Truck Attributes & Commodity

WIM Data + Taxonomy + Commodity + Video + Machine Learning =

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Body type</th>
<th>Typical commodities</th>
<th>Typical industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Five-axle tractor semitrailer, 3-S2</td>
<td>(59%)</td>
<td>Vans/reefers</td>
<td>Produce</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Refrigerated goods</td>
<td></td>
</tr>
<tr>
<td>Six-axle tractor semitrailer, 3-S3</td>
<td>(19%)</td>
<td>Flat decks</td>
<td>Manufacturing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Equipment</td>
<td>Construction</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Building supplies</td>
<td></td>
</tr>
<tr>
<td>Nine-axle stub double, 3-S2-4</td>
<td>(6%)</td>
<td>Hoppers</td>
<td>Agriculture</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Grain</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Granular fertilizer</td>
<td></td>
</tr>
<tr>
<td>Eight-axle B-train double, 3-S3-2</td>
<td>(7%)</td>
<td>Tankers</td>
<td>Petroleum</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Petroleum products</td>
<td>Chemical</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Chemicals</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>Dumps</td>
<td>Construction</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Aggregate</td>
<td>Agriculture</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Grain</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>Refuse</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Containers</td>
<td>Refroid</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Palletized cargo</td>
<td>Retail</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Freight of all kinds</td>
<td></td>
</tr>
</tbody>
</table>

FHWA Vehicle Classifications

1. Motorcycles
2. Passengear Cars
3. Pickups, Panel, Vans
4. Single Unit 1 or 2-Axle Trucks
5. Single Unit 3 or 4-Axle Trucks
6. Single Unit 5 or More-Axle Trucks
7. Single Unit 5 or More-Axle Trucks
8. Single Unit 6 or More-Axle Trucks
9. Single Unit 3 or 4-Axle Trucks
10. Single Unit 5 or More-Axle Trucks
11. Multi-Trailer 2 or Less-Axle Trucks
12. Multi-Trailer 3 or More-Axle Trucks
13. Multi-Trailer 5 or More-Axle Trucks
14. Multi-Trailer 6 or More-Axle Trucks
15. Multi-Trailer 7 or More-Axle Trucks
16. Multi-Trailer 8 or More-Axle Trucks
17. Multi-Trailer 9 or More-Axle Trucks

[Diagram of vehicle classifications]
The developed algorithms can achieve a high recall (80+ %) with a competitive recognition accuracy.

Funded by FDOT
Conclusions

• Our current transportation related projects are leveraging novel physical and cyber infrastructure
  • Autonomous and connected vehicle deployment
  • Advanced sensors and cameras through smart intersection
  • Intelligent data stores, cloud computing and artificial intelligence

• With the following objectives
  • Manage traffic congestion and improve safety by using big data and related technologies
  • Use data driven approaches for decision making, planning, evaluation and measurement
  • Support efficient tracking and movement of goods, services and people

• While Working with a number of key stakeholders from city, county and state
UFL Team: Artificial Intelligence and Machine Learning for Transportation

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