IoT and Big Data for Smart Transportation Systems

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Why?

Reckless Driving

Fault Detection & Prediction

Fuel Fraud

IoT

Data Analytics

Smart Driving

Driving Anomaly Detection

Tracking & Surveillance

Smart Driving

IoT

Data Analytics
Smart Driving – Solution Architecture

- Real-time analysis
  - Driving anomaly detection
  - Fuel fraud
  - Geo fencing
  - Vehicle fault detection

- Historical analysis
  - Driver profiling
  - Driver coaching
  - Predicting sensor failure
  - Case analysis
TOYOTA’s Activites towards SMART MOBILITY SOCIETY

Toyota aims to create a smart mobility society where people feel secure and happy in transport and everyday life.

COMFORT

Connected with people...

The vehicle will become a trusted partner through close communication with the driver.
- The vehicle complies with the driver’s verbal and nonverbal commands.
- The vehicle predicts driver’s actions in order to provide services and prevent dangers.

SAFETY

Connected with vehicles and roads...

Toward the realization of Toyota’s ultimate goal: zero casualties from traffic accidents.
- Vehicles exchange their locations and speeds at all times.
- Vehicles receive useful information from roadside infrastructure.

ECOLOGY

Connected with the community...

Optimizing the energy use of the entire community
Achieving eco-friendly lifestyles with high quality of life.
- Actualizing a low-carbon society where homes and vehicles share energy with each other.
- Promoting local energy production/consumption.
- Creating communities that are strong enough to withstand natural disasters.

CONVENIENCE

Connected with society...

Building a stress-free traffic environment where everyone can move around as they wish.
- Utilizing big data generated from vehicles to improve traffic control and disaster-related measures.
- Implementing an ultra-micro EV sharing service integrated with public transportation.
Help with finding a parking space

30 percent of drivers in cities are looking for a parking space. Intelligent machine-to-machine (M2M) solutions make life easier in the city.

1. **Sensors** "detect" whether a parking space is occupied or vacant and...
2. ...transmit data to the central server

3. **Smartphone app** "requests" a parking space and guides drivers to the free space

4. **Parking fee** is paid directly through the app

5. **Special permit** Administration of - parking and local resident IDs - permits for taxis, coaches, deliveries

6. **Legitimation** Access control to restricted traffic areas such as loading zones, residential parking

Source: Deutsche Telekom
OBD2 Based Analysis

- OBD – On Board Diagnostics
  - Available in many vehicles since 1996
  - OBD2 – In most vehicles since 2005
  - Speed, RPM, Odometer, Coolant Temperature, Padle Position, Oxygen, Mass Air Flow, etc.
App-Level Processing – Real-Time Dashboard
Fuel Economy & Coolant Temperature Monitoring

- Implemented using Siddhi Complex Event Processor on smartphone
- Minimum impact on battery level
  - Bandwidth saving due to local processing → Reduce energy consumption
Trip Logs

- Standard car ➔ High-end Car
Backend Processing – Reckless Driving

- Hard accelerations & deceleration count above a threshold
  - Per 100 Km
  - Per 1 Hour
- Count depends on average speed of vehicle in last $t$ seconds
- Implemented using Siddhi CEP
- Computed values stored in RDBMS
Driver Profiling

- Detection of anomalies
  - Hidden Markov Model based on acceleration profile
  - Model implemented in BAM
  - Validator implemented in CEP
Sensor Failure Prediction

- Mass Air Flow (MAF) sensor value has a linear relationship with engine RPM
- When sensor fails, gradient between MAF & RPM reduces with time
- Rate of change of gradient can predict date of failure
Fuel Consumption Prediction

- Long-distance bus fitted with a GPS unit & high-precision fuel sensor
- Could you
  - explain variability in fuel consumption
  - predict fuel consumption of a journey
  - give tips to improve fuel consumption
Dataset

- From 13 May 2015 – 31 August 2015
- Parameters
  - Timestamp (date and time)
  - Longitude (Min: 5.918611° N, Max: 9.835556° N)
  - Latitude (Min: 79.516667° E, Max: 81.879167° E)
  - Bearing (0° to 360°)
  - Elevation (Min: 0m, Max: 2,524m)
  - Distance traveled (km) – between two samples
  - Speed (kmh-1)
  - Acceleration (kmh-2)
  - Ignition status (1 – Ignition On or 0 – Ignition Off)
  - Current battery voltage (Min: 0v, Max: 29v)
  - Fuel level (Min: 0L, Max: 218L)
  - Fuel consumption (L)
Bus Route
Fuel Usage

Total Fuel Usage

Total Fuel Consumption Summary Vs Day

Days:
- Sunday
- Monday
- Tuesday
- Wednesday
- Thursday
- Friday
- Saturday
Factors Contributing to Fuel Usage

Total Fuel Consumption Summary Vs Journey

Fuel Consumption and Elevation
Factors Contributing to Fuel Usage
(Cont.)
Factors Contributing to Fuel Usage (Cont.)

Total Fuel Usage VS No of Harsh Acc/ Deacc

- Fuel usage in each day
- Number of harsh acc/ deacc

Date

05/13 05/16 05/20 05/23 05/26 05/29 06/01 06/04 06/07 06/10 06/13 06/16 06/19 06/22 06/25 06/28 07/01 07/04

Fuel usage in each day (L)

Number of harsh acc/ deacc

5 10 15 20 25 30 35
Factors Contributing to Fuel Usage (Cont.)
Predicting Fuel Consumption – Random Forrest

Actual Fuel Consumption: 84.08L
Predicted Fuel Consumption: 91.77L
Error: 9.1%
Predicting Fuel Consumption – Gradient Boosting & Neural Network
Driver Feedback to Promote Fuel Efficient Driving

<table>
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<th>Cluster No</th>
<th>Mean Speed (km/h)</th>
<th>Mean Acceleration (km/h²)</th>
<th>Mean Elevation Change (m)</th>
<th>Is Idling (Mode)</th>
<th>Hour (Mode)</th>
<th>Weather Condition (Mode)</th>
<th>Mean Fuel Usage (km/L)</th>
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On Going Work

- Dashboard design
- Driver profiling
  - Beyond acceleration profile
  - Correlating with location, time, traffic, & weather
  - Usage-Based Insurance (UBI)
- Quantifying passenger comfort
- Case analysis
  - Traffic, weather
- Driver feedback
  - Real-time & long-term
- Process re-engineering
Publications

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Q&A
Demo

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