6th International Naturalistic Driving Research Symposium (NDRS)
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Monitoring distraction through smartphone naturalistic driving experiment

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Scope

The development of the OSeven Smartphone application (www.oseven.io/) was initiated by the need for collecting and analysing driving behaviour data:

- from naturalistic driving conditions
- of a large-scale
- through cost effective solutions
- and transmit them in real time

Started in late 2014 and continuously progressing.

Past limitations

Limiting barriers existed so far:

- Mobile phone technology
- High cost of:
    - In-vehicle data recording systems (e.g. OBD)
    - Data transmission plans
    - Cloud computing
- Low penetration rate of smartphones and social networks
- Inability to manage and exploit Big Data

...have now been eliminated.

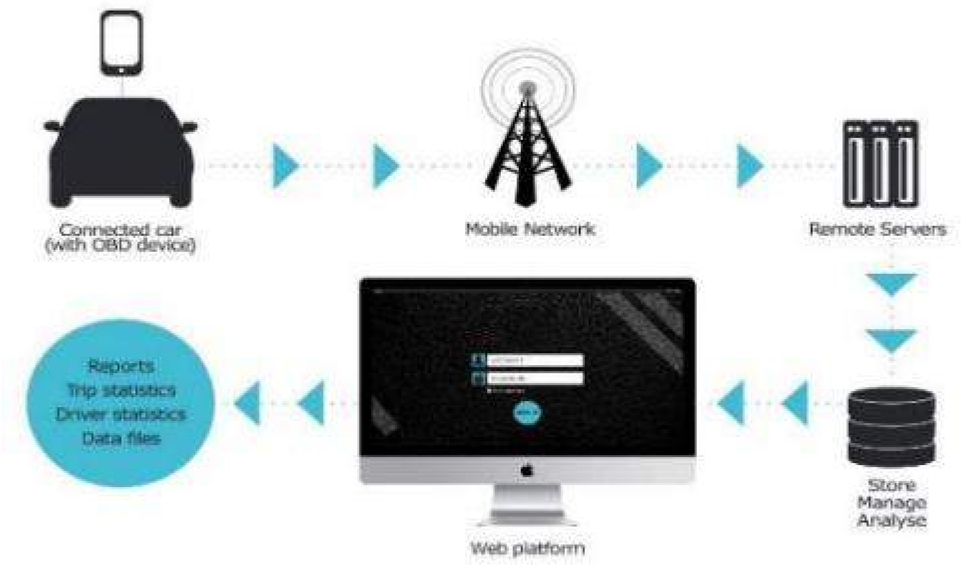
Current technological advances make it substantially easier for experts to collect and exploit data easier and more accurately through mobile phones.

Data flow (1/2)

- A mobile App recording user's behaviour using mobile phone sensors (automatic start / stop)

- A variety of APIs to read sensor data recorded and temporarily store it to mobile phone

- Data transmission from the mobile App to the central database via an appropriate communication channel such as:
  - Wi-Fi network (online)
  - Cellular network such as a 3G/4G network (online)
  - Bluetooth (offline)



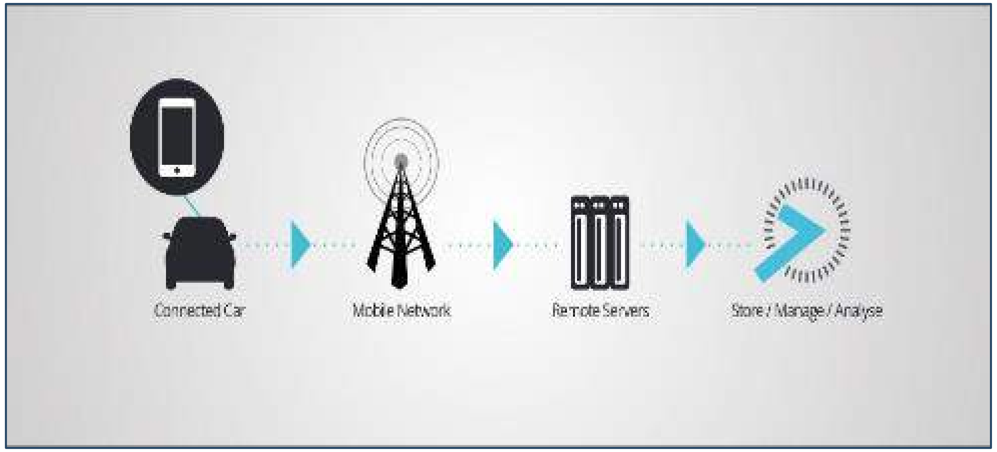
Source: OSeven Telematics

Data flow (2/2)

- Data is stored in a sophisticated database where managed and processed

- Indicators result from the mobile phone data process using
  - Machine learning algorithms
  - Big data mining techniques

- Results Visualization
- Mobile App
- Web Portal



Source: OSeven Telematics

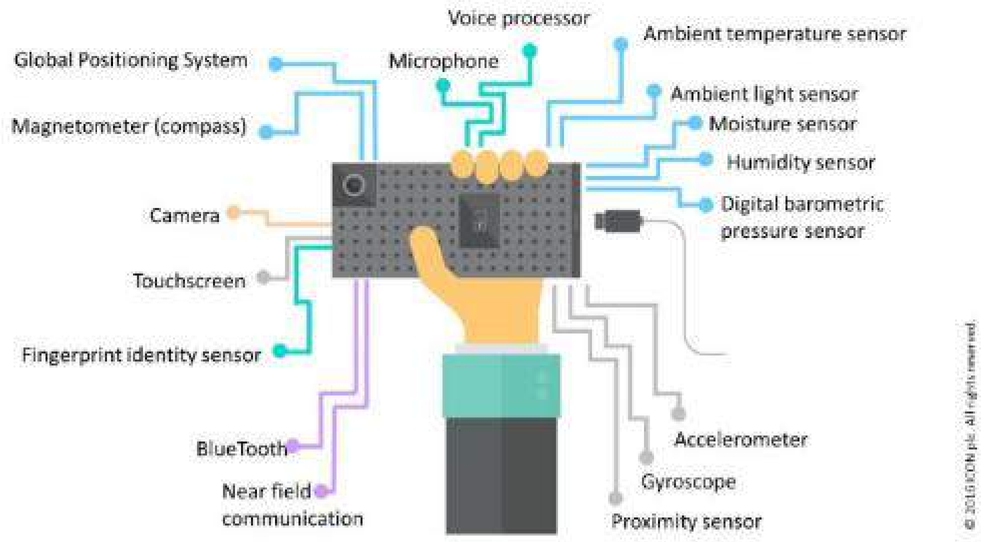
Smartphone data

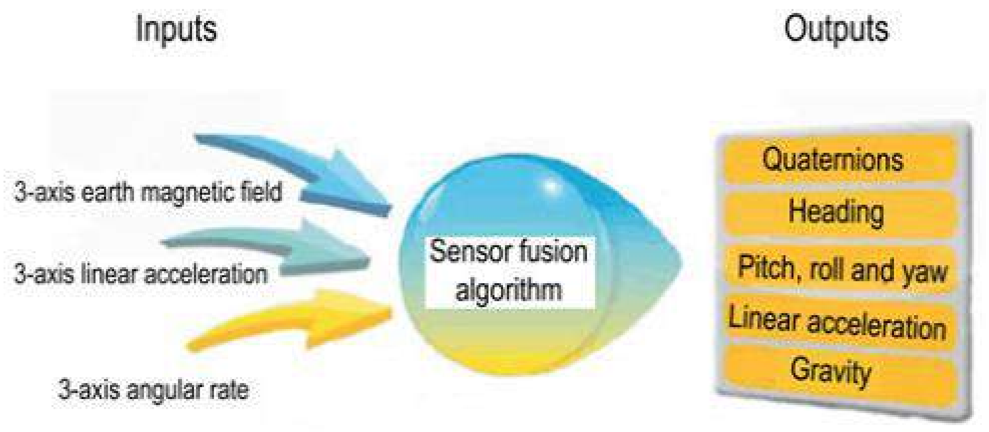
Indicatively, mobile phone integrates technology sensors:
- Accelerometer*
- Gyroscope*
- Magnetometer
- GPS (speed, course, longitude, latitude)

- Fusion Data provided by iOS and Android:
- Yaw, pitch, roll
- Linear acceleration*
- Gravity*

*(x, y, z components)

Recording at a minimum frequency of 1Hz





Risk exposure indicators

- Total distance (mileage)
- Driving duration
- Type(s) of the road network used (given by GPS position and integration with map providers e.g. Google, OSM)
- Time of the day driving (Rush hours, Risky hours)
- Weather conditions
- Trip purpose

combined with other data sources (speed limits and detailed accident maps).

Driving behaviour indicators

- Speeding (duration of speeding, speed limit exceedance etc.)

- Number and severity of harsh events
- Harsh braking (longitudinal acceleration)
- Harsh acceleration (longitudinal acceleration)
- Harsh cornering (angular speed, lateral acceleration, course)

- Driving aggressiveness (e.g. braking, acceleration)

- Distraction from mobile phone use

Additional parameters

In more advanced setups, when sufficient amount of data is available, new additional or composite parameters might be used such as:

- seat belt use
- alcohol consumption
- vehicle maintenance

Eco-driving could also be exploited in the future as it is proved to have a significant correlation with crash risk since fuel consumption is strongly correlated with aggressive and speeding driving

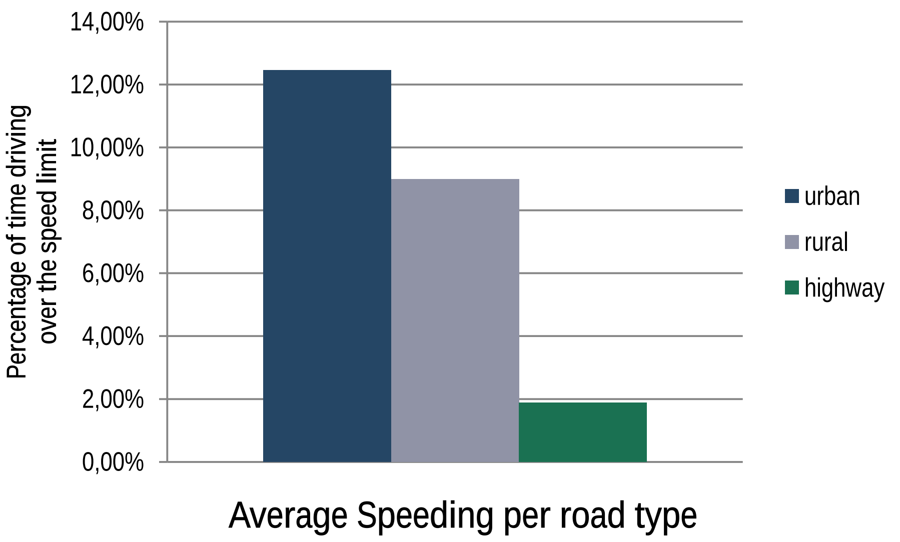
Sample

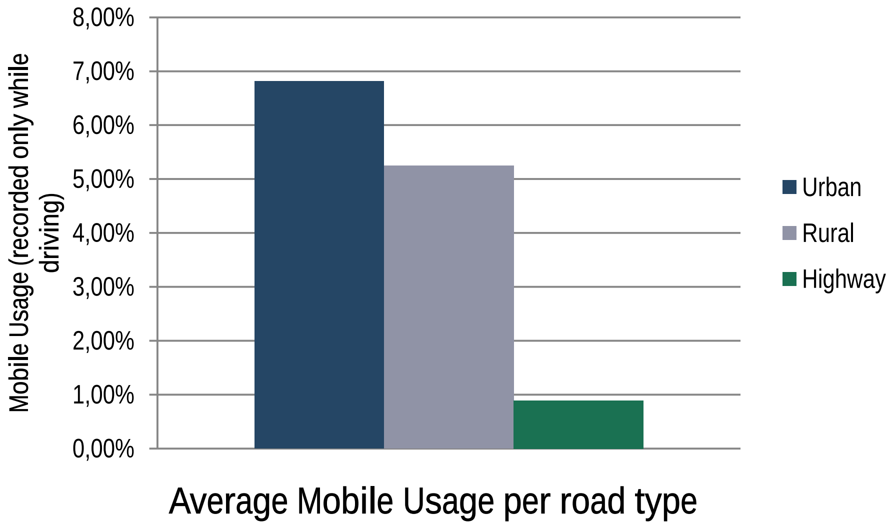
Smartphone data driving experiment:

- 100 drivers
- 4 months
- 18.850 events

Descriptive Statistics:

- Highest percentage of time driving over the speed limit is found to be on urban road network
- Highest mobile usage is found to be on urban road network





Linear Regression Model - Harsh events per distance

A **linear regression** model to investigate the driving characteristics influencing the **number of harsh events per distance travelled**. Parameters found to influence:

- mobile phone usage
- trip duration
- speed standard deviation
- average speed limit exceedance
- driving during morning rush hour

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
Constant	.408	.008		54.374	0.000
Driving during morning rush hour	.050	.007	.051	7.023	.000
St. Deviation of Speed	-.001	.000	-.023	-2.680	.007
Average Speed limit exceedance	.193	.024	.068	8.231	.000
Mobile Usage	.039	.015	.019	2.580	.010
Duration (hr)	-.163	.009	-.144	-18.943	.000

a. Dependent Variable: total number of events per kilometres travelled

Binary logistic model – predicting mobile phone use

A **binary logistic** model to **predict the possible use of a mobile phone** while driving based on the observation of different driving measures. Parameters found to influence:

- average angular speed
- trip duration
- average percentage of time driving over the speed limit
- driving during morning rush hour
- driving during afternoon rush hour

Variables in the Equation	B	S.E.	Wald	df	Sig.	Exp(B)
St. Deviation of Speed	.007	.002	8.852	1	.003	1.007
Driving during morning rush hour	-.209	.042	25.310	1	.000	.811
Driving during afternoon rush hour	.126	.036	12.140	1	.000	1.135
Duration (hr)	1.369	.064	461.442	1	.000	3.930
Average Angular Speed	.117	.006	366.534	1	.000	1.124
Average percentage of time driving over the speed limit	.646	.138	21.910	1	.000	1.907
Constant	-1.898	.076	616.145	1	.000	.150
Refers to the Utility function of mobile phone usage = 1						

Impact (1/2)

- Distraction originating from smartphone usage has a serious impact on the number of harsh events that occur per kilometre and subsequently on the relative crash risk.

- Data analysis implemented through statistical methods led to the quantification of this impact.

- Mobile phone usage was found to be predictable using driving characteristics such as travel duration, time of the day driving, speeding, etc.

Impact (2/2)

- The quantification of change in driving behaviour can constitute a measure of evaluating driver's performance and thus, it can potentially lead to the implementation of a driving risk model based on:
    - driving behaviour
    - degree of exposure

- It may also contribute towards the practice of evaluating driver's traffic and safety behaviour as well as to classify drivers in different safety categories depending on their relative level of risk

Future challenges (1/2)

Monitoring driver behaviour through mobile phones makes gradually possible the continuous driver assessment, opening a new great potential for traffic and safety behaviour improvement, used either:

- Independently by the drivers in order to:
  - raise awareness and engagement on safe and eco-driving
  - receive feedback and support on driving performance and risks

- Through customized insurance schemes by correlating driving exposure and behaviour with insurance premiums:
  - pay-as-you-drive (PAYD)
  - pay-how-you-drive (PHYD)

Future challenges (2/2)

Advanced machine-learning algorithms

Big data analysis – handling - mining

Correlation between accidents and driving indicators

Developing user-friendly Apps for driving recording

User engagement

Battery consumption

Personal data privacy

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