Detection of inattentive drivers

Papers presentation

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Papers

Driver Distraction Detection Methods: A Literature Review and Framework

Alexey kashevnik, Roman Shchedrin, Christian Kaise, Alexander stocker

Review of the published scientific literature

Driver Distraction Recognition Based on Smartphone Sensor Data

Jie Xie, Allaa R.Hilal, Dana Kulic

A direct research experience

Introduction and motivation

25% of police-reported crashes involve some form of driver inattention such as the driver is distracted, fatigued or lost in thought

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Vehicle manufacturers, suppliers, start-ups and researchers are devoting more and more resources to better understand and measure the causes of driver distraction and inattention

↓

Developing of warning and prevention mechanisms for drivers and increasing the automation level of vehicles

Background

Driver distraction

the diversion of attention away from activities for safe driving toward a competing activity

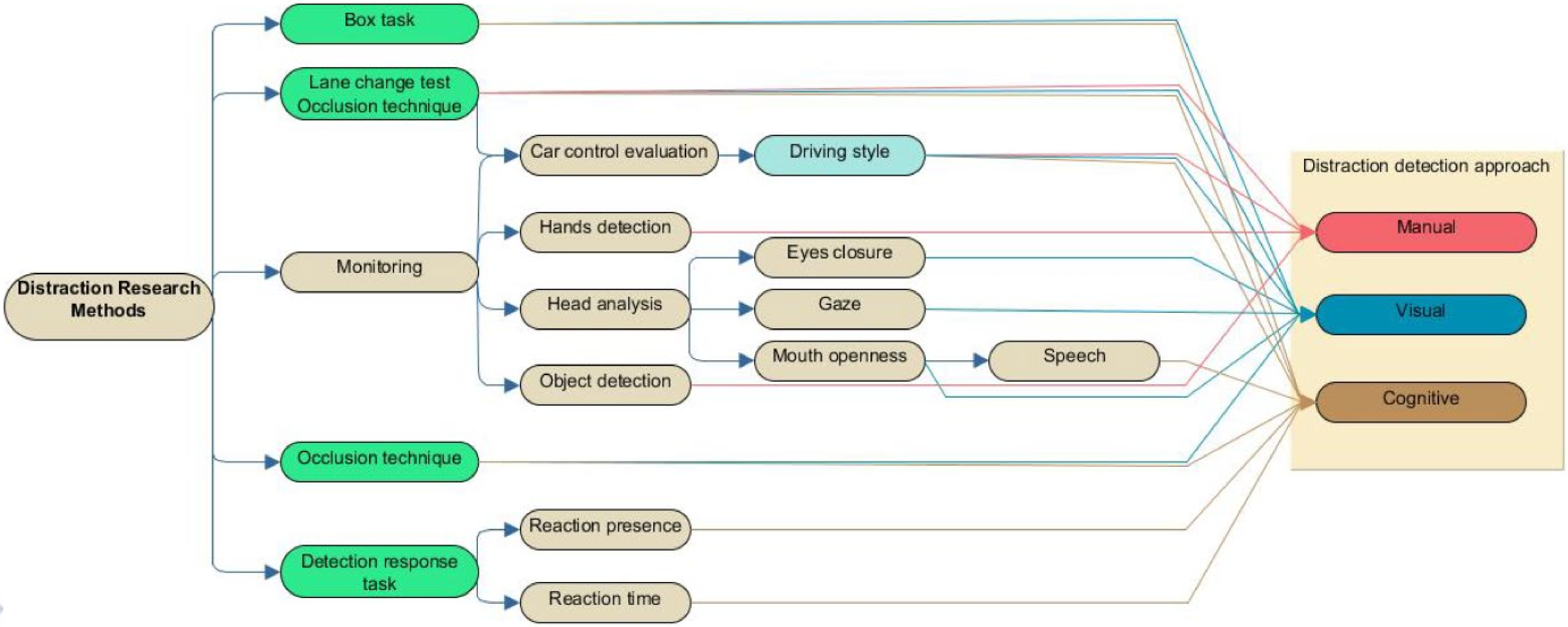
Types of distraction

Visual distraction
Manual distraction
Cognitive distraction
Auditory distraction
Vocal distraction
Verbal distraction

6 levels of driving automation

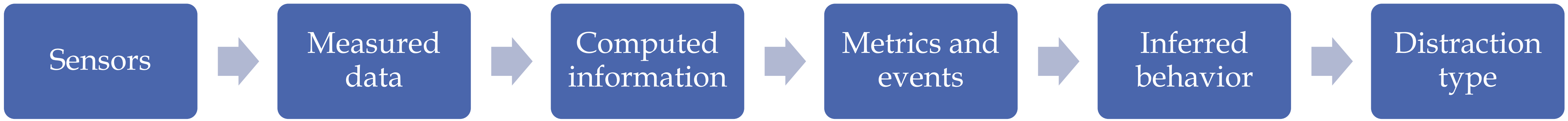
No automation
Driver assistance
Partial automation
Conditional automation
High automation
Full automation

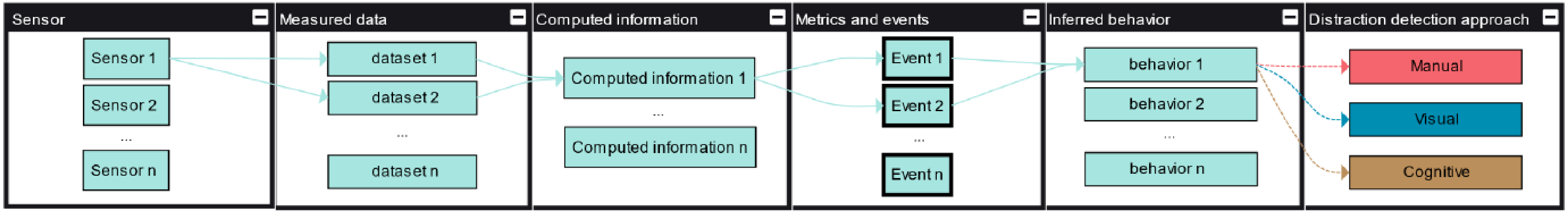
Driver distraction evaluation methods

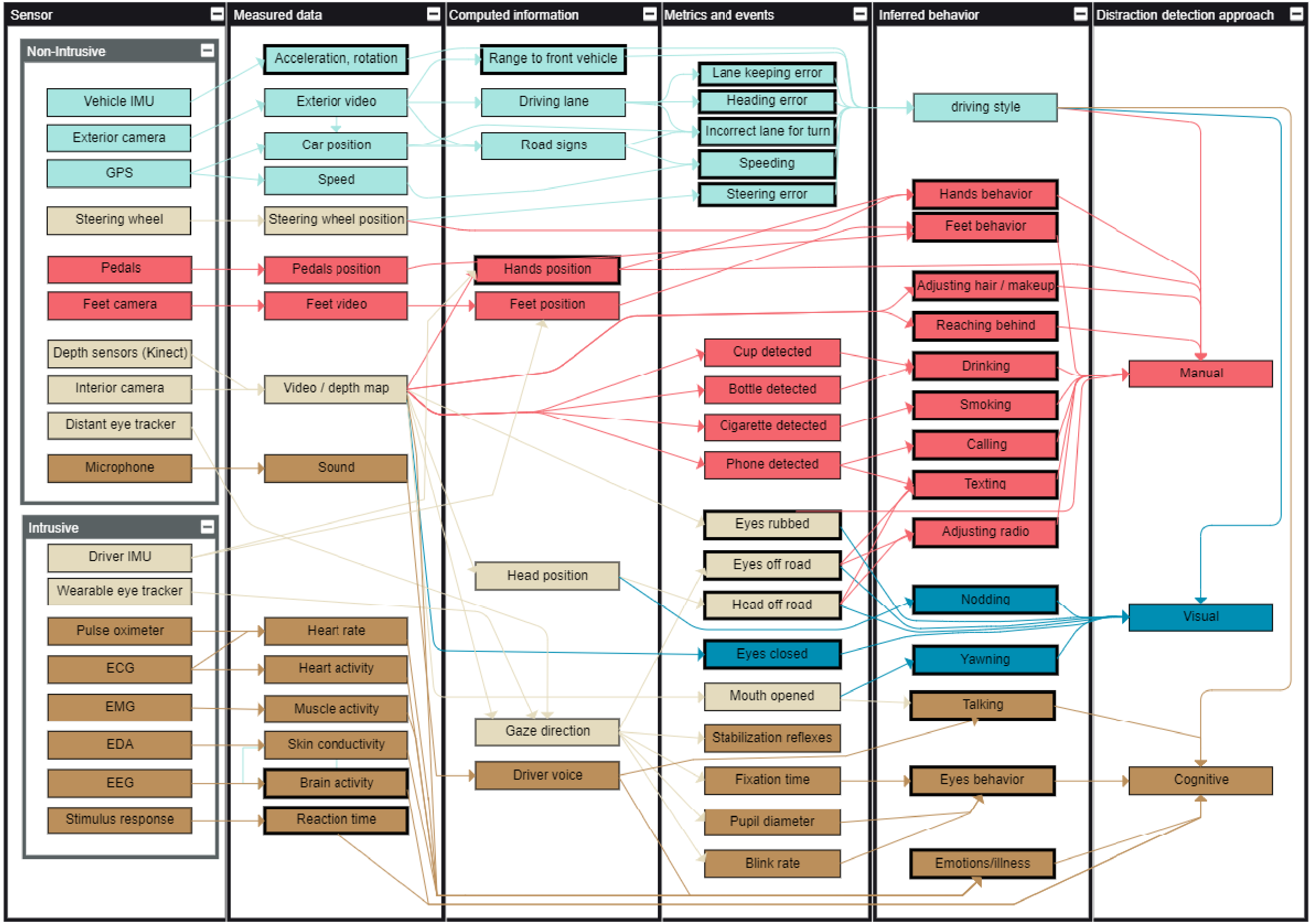


- Laboratory environment only
- Both laboratory and real driving conditions on public roads

Distraction detection process







Sensor
Measured data
Computed information
Metrics and events
Inferred behavior
Distraction detection approach
Non-Intrusive
Vehicle IMU
Exterior camera
GPS
Steering wheel
Pedals
Feet camera
Depth sensors (Kinect)
Interior camera
Distant eye tracker
Microphone
Intrusive
Driver IMU
Wearable eye tracker
Pulse oximeter
ECG
EMG
EDA
EEG
Stimulus response
Acceleration, rotation
Exterior video
Car position
Speed
Steering wheel position
Pedals position
Feet video
Video / depth map
Sound
Heart rate
Heart activity
Muscle activity
Skin conductivity
Brain activity
Reaction time
Range to front vehicle
Driving lane
Road signs
Hands position
Feet position
Head position
Gaze direction
Driver voice
Lane keeping error
Heading error
Incorrect lane for turn
Speeding
Steering error
Cup detected
Bottle detected
Cigarette detected
Phone detected
Eyes rubbed
Eyes off road
Head off road
Eyes closed
Mouth opened
Stabilization reflexes
Fixation time
Pupil diameter
Blink rate
driving style
Hands behavior
Feet behavior
Adjusting hair / makeup
Reaching behind
Drinking
Smoking
Calling
Texting
Adjusting radio
Nodding
Yawning
Talking
Eyes behavior
Emotions/illness
Manual
Visual
Cognitive

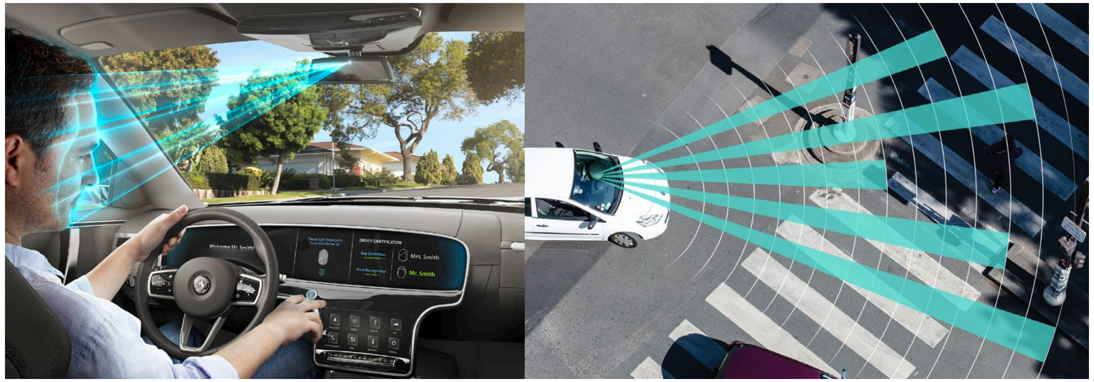
Intrusive VS non-intrusive sensors

Intrusive sensors

- Can obtain more accurate data regarding certain causes of distraction
- More useful for research purposes and to collect ground truth

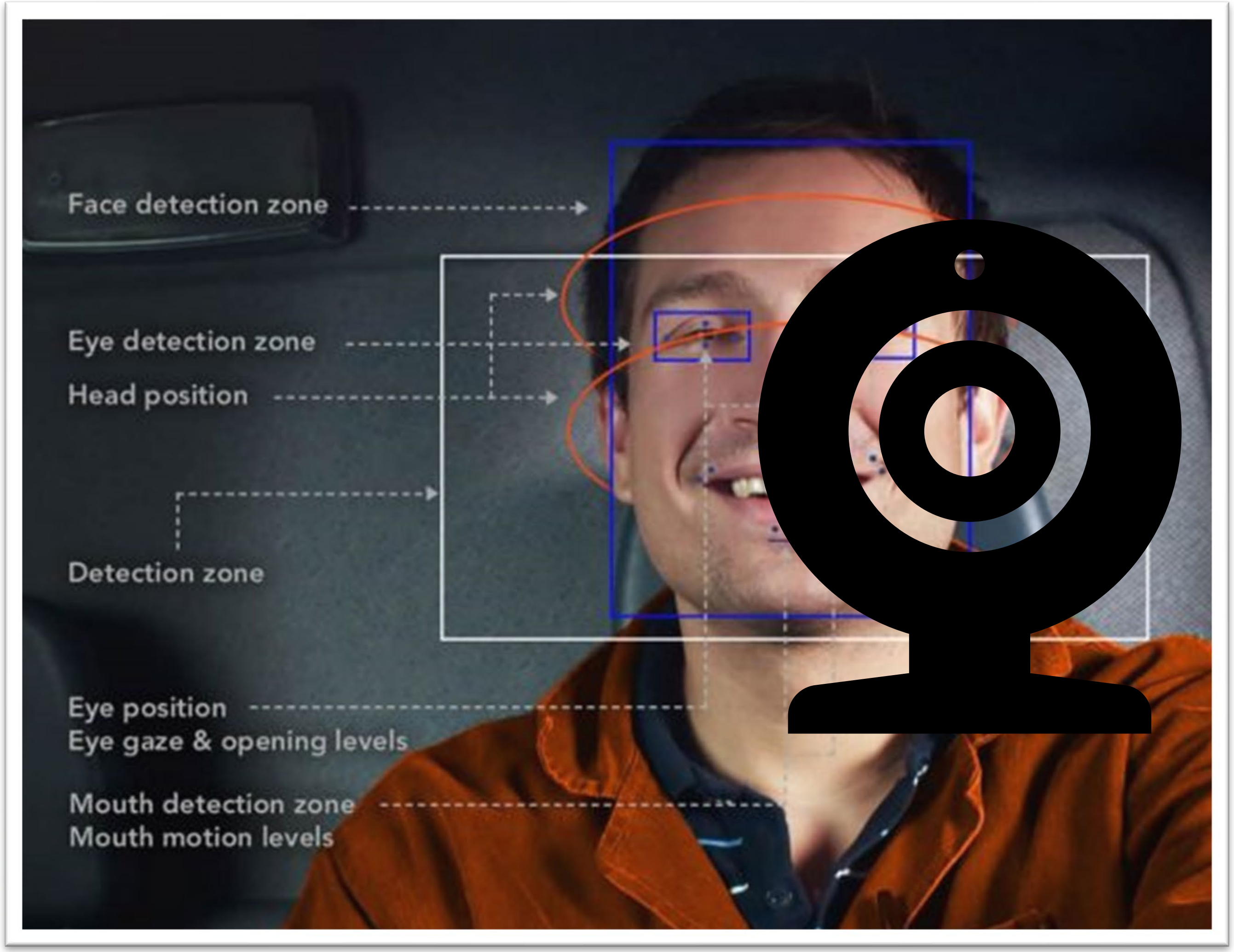
Non-intrusive sensors

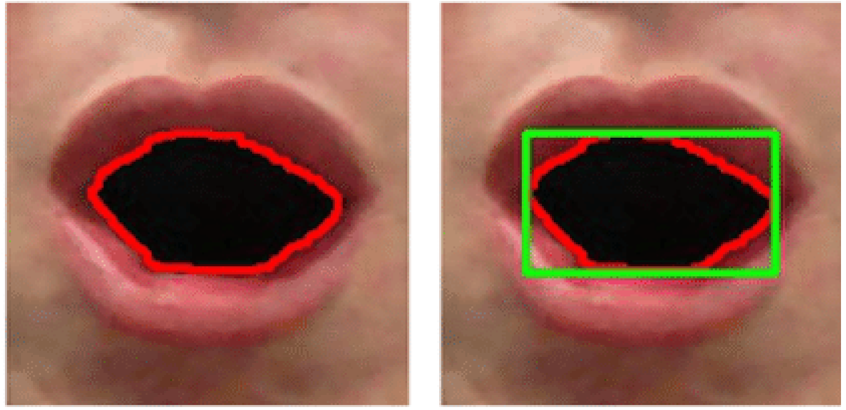
- Do not distract the driver
- Are more adequate for commercial systems
- Do not interfere with the movements and poses of the driver



How to detect distraction (non-intrusive sensors)

1/4





- SVM-based algorithms to detect eye closure.
- Perspective-N-Points solution combined with RANSAC to analyze head pose.
- ML regression algorithms directly on captured image data

How to detect distraction (non-intrusive sensors)

- Neural networks or computer vision algorithms used to estimate gaze direction
- In case the driver's hands are not fully captured by the camera AdaBoost classifier should be used

How to detect distraction (non-intrusive sensors)

- Features extracted from optical flow can be passed to a Hidden Markov Model (HMM) and argue that this might help to predict pedal misapplications

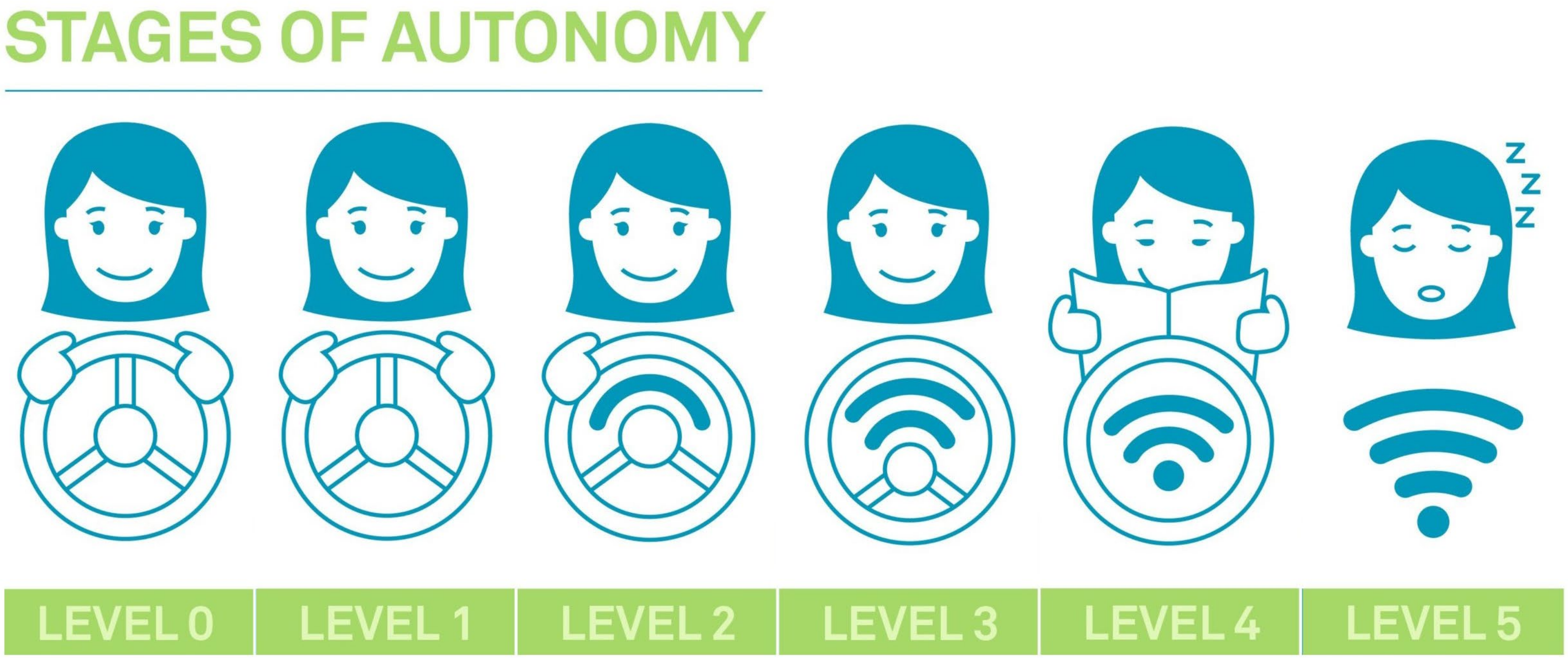
How to detect distraction (non-intrusive sensors)

- Training a ML algorithm on MelFrequency Cepstral Coefficients features (but other features and approaches can also be used)

How to detect distraction (intrusive sensors)

- It is also possible to evaluate a lot of aspects from analyzing the eye behaviour while driving in different conditions.

Conclusions



- Drivers will still have to be attentive
- Vehicle manufacturers will expand sensors technologies for a better interpretation of vehicle external and internal environment
- Distraction detection systems will be more and more important both if the autonoumous level increase or decrease

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Introduction

Driver distraction is one of the leading causes of vehicle accidents and injury

Study

The study develops a smartphone sensor based driver distraction system using an ensemble learning method.

Experiment

24 drivers between 21 and 52 yo were recruited to participate, driving on a route consisting of suburban and highway driving.

Previous studies

1

VGG-19
PRETRAINED MODEL

80%

2

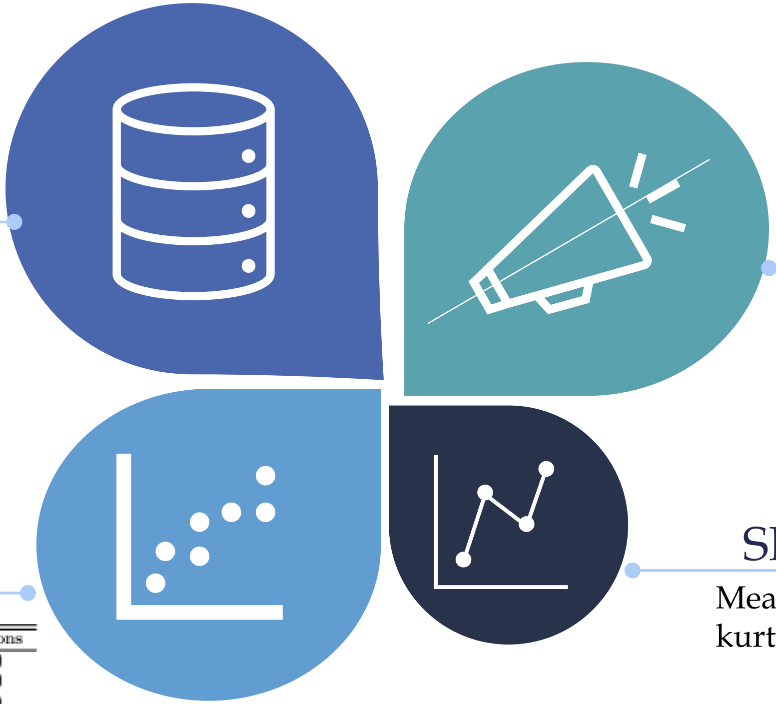
- Detection of driver cognitive distraction at stop-controlled intersection by using a **driving simulator** for collecting data
- 3 types of features: **scenario-based, sensor-based** and **eye-movement features.**

LIMITS OF THESE STUDIES:

- Only video data for driver distraction recognition
- Limitated usability while driving at night
- Privacy issue

Objective of this work

Estimate driver distraction from the driver's mobile device, using only **motion data** collected by the IMU and GPS sensors.



DATA COLLECTION

INTERPOLATION AND NOISE REDUCTION

SLIDING WINDOW FOR FEATURE EXTRACTION

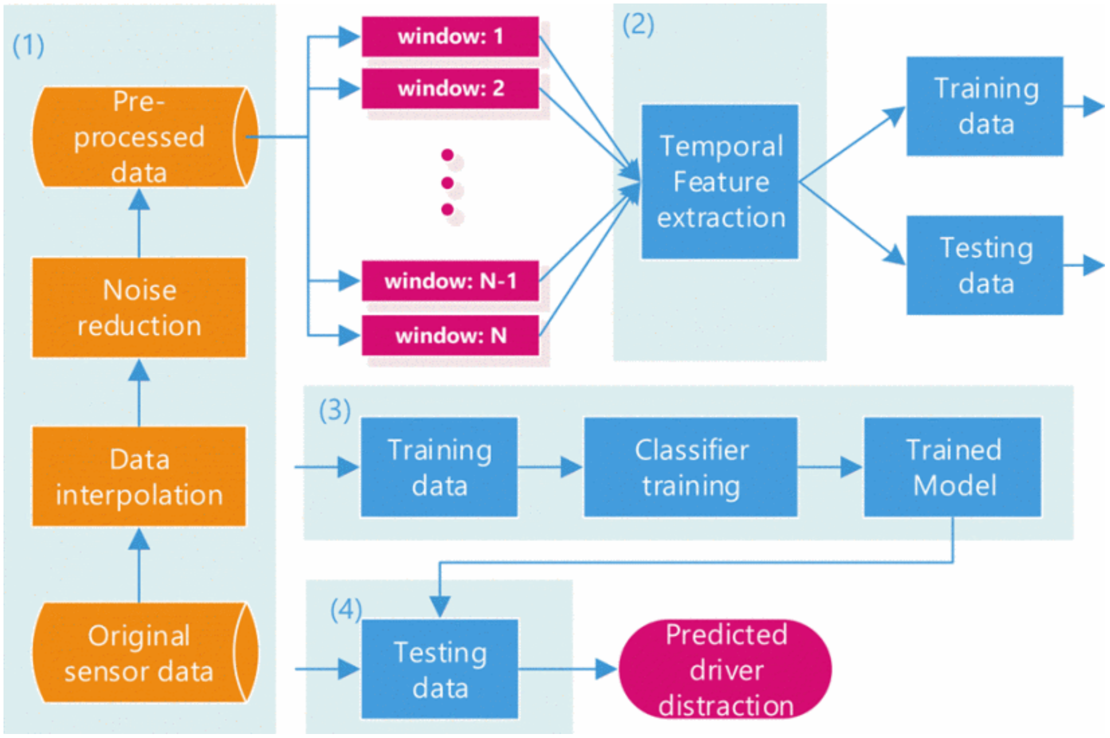
Sensor Information	Notations	Sensor Information	Notations
Linear velocity (km/h)	v(t)	Gyro in X (rad/s)	$g_x(t)$
Acceleration in X (m/s^2)	$a_x(t)$	Gyro in Y (rad/s)	$g_y(t)$
Acceleration in Y (m/s^2)	$a_y(t)$	Gyro in Z (rad/s)	$g_z(t)$
Acceleration in Z (m/s^2)	$a_z(t)$		

SIGNAL FEATURES

Mean, variance, median, range, kurtosis, skewness, root-mean-square

Pipeline

Driver distraction recognition system consists of 4 steps:



IMU sampling rate: 100 Hz

Linear velocity (from GPS) sampling rate: 1 Hz

3 road conditions:
- Parking lot
- Highway
- City road

Feature extraction

Before feature extraction, **noise reduction** is applied:

- *moving median* (outlier removal from signal) filter
- *moving mean* (smoothing filtered signal) filter

18) zero-crossing rate: $zcr = \frac{1}{2}\sum_{n=0}^{L-1}[sgn(x(n)) - sgn(x(n+1))]$

19) short-time energy: $ste = \frac{1}{L}\sum_{n=0}^{L-1}x(n)^2$

For each sliding window, 19 temporal features were considered:

#	Function	Description
1	mean	mean of a signal
2	min	minimum value of a signal
3	max	maximum value of a signal
4	var	variance of a signal
5	median	median of a signal
6	range	difference between the max and min
7	min-m	difference between the mean and min
8	max-m	difference between the max and mean
9	iqr	interquartile range
10	prctile	the 25^{th} and 75^{th} percentiles
11	sk	skewness of a signal
12	kur	kurtosis of a signal
13	slope	ratio between the range and the location of maximum and minimum
14	mad	mean absolute deviation of a signal
15	curv	curvature of both half signals and the whole signal
16	sk-hist	skewness of the histogram of a signal
17	jerk	standard deviation of the derivative of an acceleration signal

Label generations for dataset

After feature extraction, all features are concatenated together to form a feature vector of dimension 273.

Then, the **normalization** is conducted as follows: $v_i = \dfrac{v_i - \mu_i}{\sigma_i}$

Algorithm 1: Label generation for our dataset

Input : Start and stop talking timestamps (t_s and t_e) of each windowed signal. θ is empirically set at 0.5. $t_{win}(k)$ is the duration of the sliding window k.

Output: Label of each data window k: $L(k)$.

```
begin
    Step 1: Calculate talking time: t_d = t_e - t_s
    Step 2:
    if t_d ≥ t_win × θ then
        L(k) = 1
    else
        L(k) = 0
```

Classification

4 standard classifiers:

- K-NN
- Logistic Regression
- Naive-Bayes
- Random Forest

+

Ensemble learning:

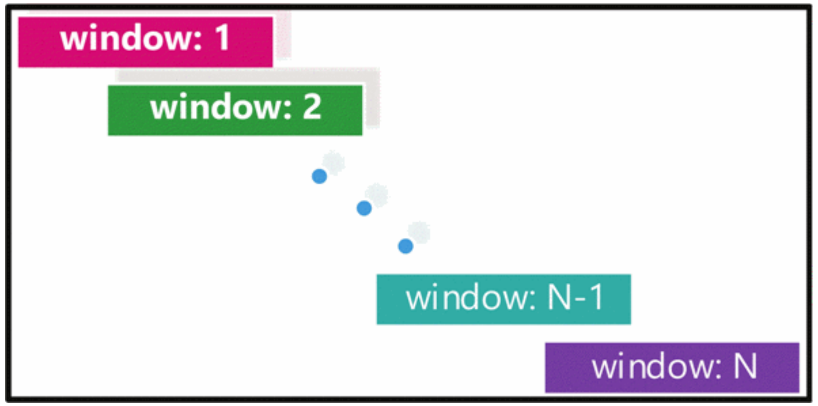
Returns labels as *argmax* of the sum of predicted probabilities

GridSearch is used to optimize the parameters using *5-fold-cross-validation*.

Algorithm	Parameter	Values
K-NN	K	1, 3, 5, 7, 9
RF	n_estimators	100, 300, 500
	min_samples_leaf	1, 7, 15
	max_features	'auto', 'log2', 'None'
	min_samples_split	10, 30, 50

Evaluation

For each classifier output, a label is assigned to each sliding window that is re-converted back to sample labels for the evaluation.

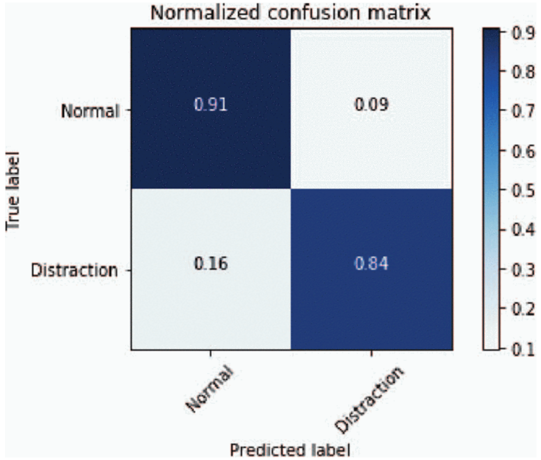


$$If \sum_{i=1}^{N} column(i) > 1 \longrightarrow$$ DISTRACTED DRIVING

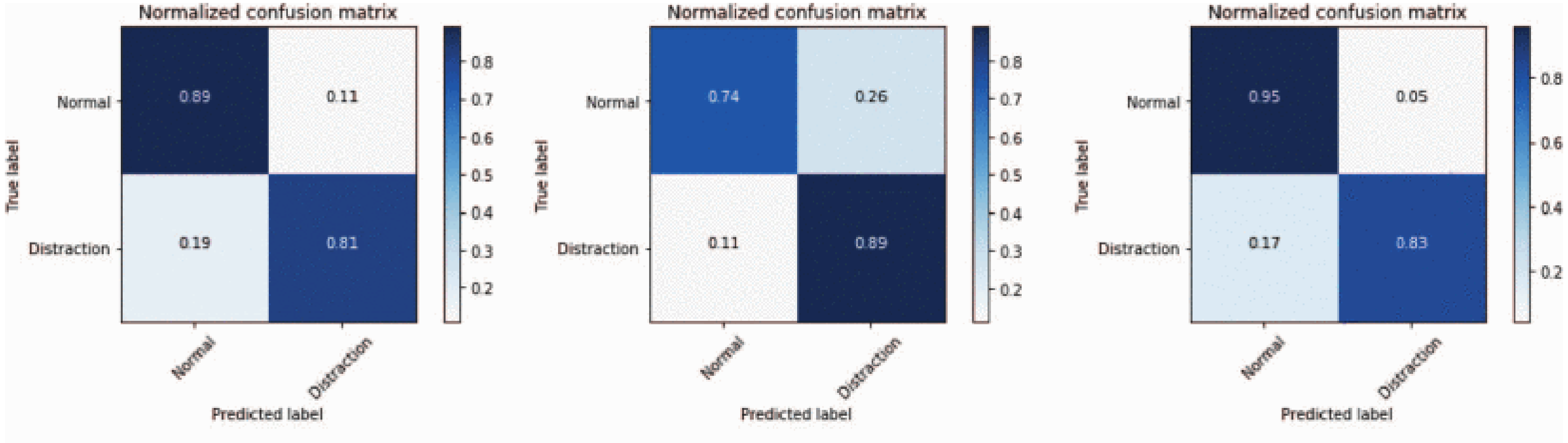
The proposed system is evaluated using a weighted ***F1-score***, defined as follows:

$$F1\text{-}score = \sum_{i=1}^{n} 2 \cdot \frac{precision(i) \cdot recall(i)}{precision(i) + recall(i)} * r_i$$

Results (1/2)



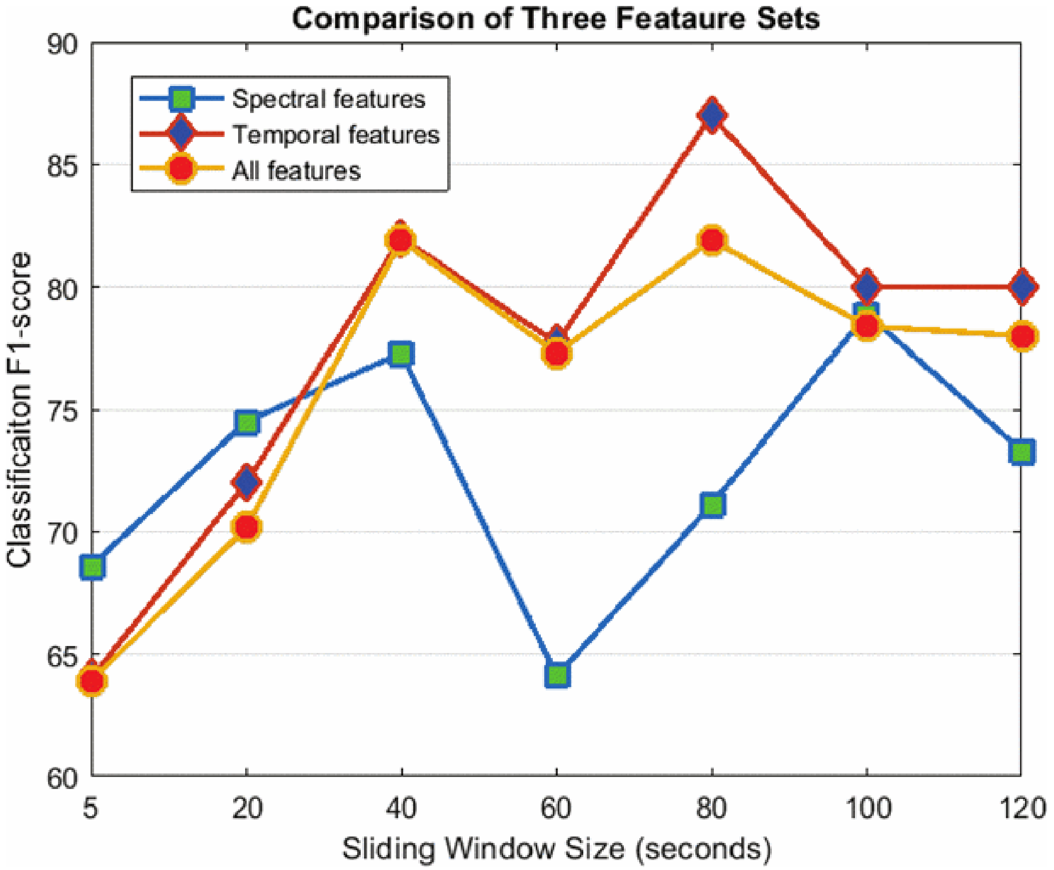
Labeling method	Size / Overlap	5s	20s	40s	60s	80s	100s	120s
All label ($\theta = 1$)	No overlap	0.71	0.74	0.77	0.77	0.84	0.79	0.82
	50%	0.64	0.72	0.82	0.77	0.87*	0.80	0.80
	80%	0.74	0.64	0.67	0.83	0.78	0.71	0.74
Strong label ($\theta = 0.8$)	No overlap	0.71	0.74	0.77	0.75	0.82	0.76	0.76
	50%	0.63	0.72	0.81	0.76	0.84	0.75	0.80
	80%	0.74	0.63	0.66	0.82	0.76	0.68	0.72
Half label ($\theta = 0.5$)	No overlap	0.71	0.74	0.75	0.77	0.78	0.77	0.72
	50%	0.63	0.70	0.80	0.73	0.82	0.72	0.76
	80%	0.73	0.62	0.65	0.78	0.70	0.64	0.67

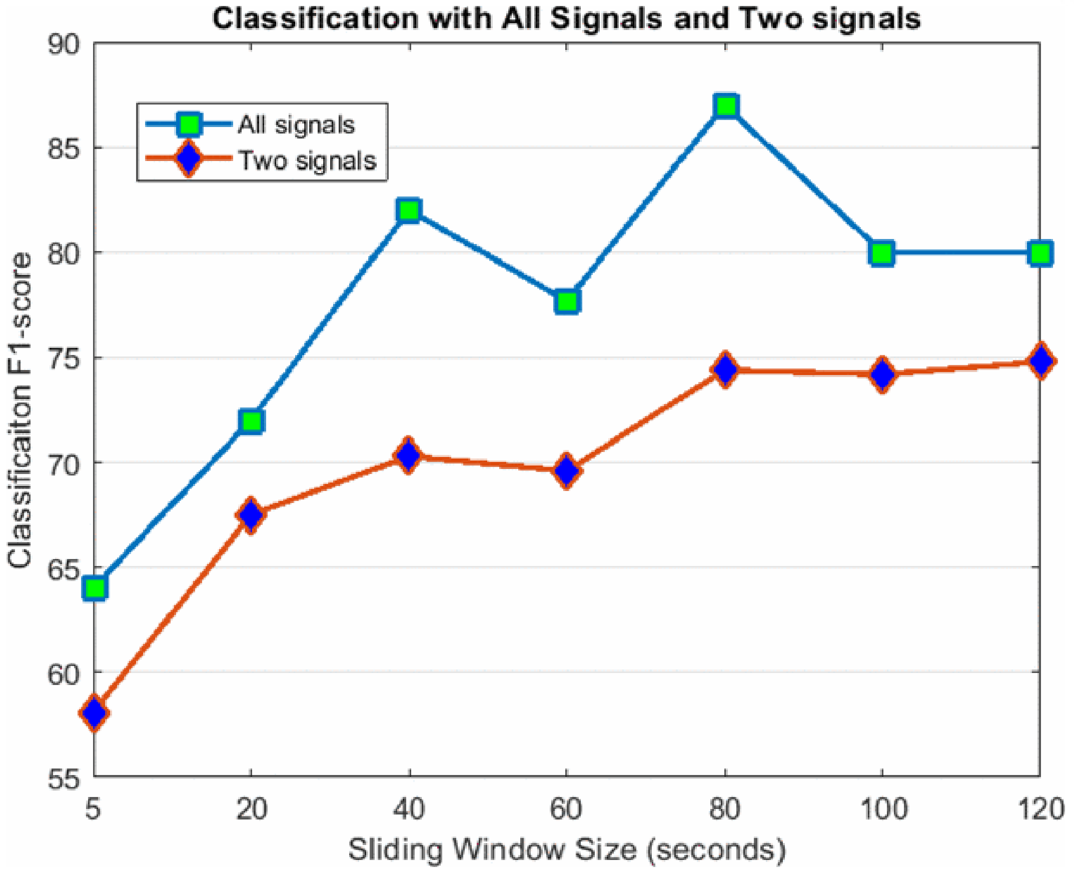


(a) Lane keeping (b) Stop or near stop (c) Lateral maneuvers

F1-score: 74.3% 83.8% 87.3%

Results (2/2)





- v(t) and $g_z(t)$ -> most important signals
- min, mean-min and median -> most important features

Conclusions

- A driver cognitive distraction recognition systems relying only on the mobile phone was developed, which do not require viewing the driver or knowing the driver or the outside conditions.

- Do not need to perform maneuver detection, but performance is improved when the driver is performing more difficult maneuver.

- Only one cognitive distraction is tested by talking to the passenger while driving.

THANK YOU FOR THE ATTENTION