Automated Road Friction Estimation using Car-sensor Suite: Machine Learning Approach

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More than 10% of all accidents occur because of slippery conditions

In the US: yearly approx 500 000 accidents of which 1800 are deadly

Sweden 15 Jan 2013

Why road friction is important ?

Friction ="grip" between tyre and road determines maximum acceleration and deceleration longitudinally and laterally

Assumed friction ↓ / True friction →	Low (snow)	High (dry asphalt)
Low (snow)	Vehicle speed is adapted to friction	• False slippery warnings • Vehicle will drive unacceptably slow
High (dry asphalt)	• Vehicle speed is too high • High frequency of accidents	Vehicle speed is adapted to friction

Problem formulation

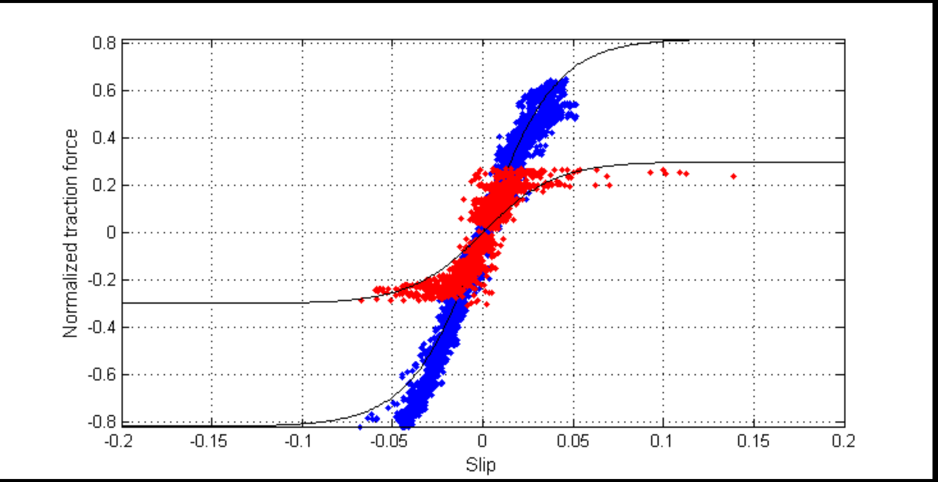
Can Machine Learning be an alternative approach for road friction estimation than state-of-the-art ?

- Higher accuracy of friction estimate ?
- Which features are useful ?
- Possible to use a front-looking camera & machine learning to predict road surface condition ?

State-of-the-art friction estimation methods

Use the tyre as a sensor with an internal model of the force-slip tyre characteristics (referred to as “baseline”)

- Contact based method
- Just software
- Requires sliding in tyre contact patch
- Requires large accelerations



Use an optical measurement device

- Contact-less method
- Requires extra hardware
- Identifies just the surface
- Sensitive to dirt contamination

Why using Machine Learning ?

Use the tyre as a sensor require valid physical tyre models -> the tyre is too complex to model with high validity

An advanced driver could experience friction, but we do not fully understand the physics

We have access to >100 000 km data, **annotated by hand with “true friction”**

Vehicle data used to develop the algorithm

- In total 86 features, most of them collected through CAN and flexray
- Sensor features from:
  - Inertia measurement unit, Wheel speed sensors (Veh dyn sensors)
  - Brake system, Propulsive system and Steering system (Actuator systems)
  - Ambient thermometer and GPS (Environmental sensors)
  - Vehicle motion state estimator
- Features manually noted as metadata:
  - tyre type
  - road type (asphalt, gravel,...)
  - surface type (wet, dry,...)
  - true friction [0,1]

Feature ranking

Reduce complexity by reducing the number of features, conceptually by:

1. Remove features with low correlation to true friction
2. Remove redundant features

Methods applied:

1. Selecting features with more than 20% correlation
2. Selecting features with more than 1% F-score
3. Minimum Redundancy Maximum Relevance (mRMR)
4. Engineering experience

33 features were finally selected from 86

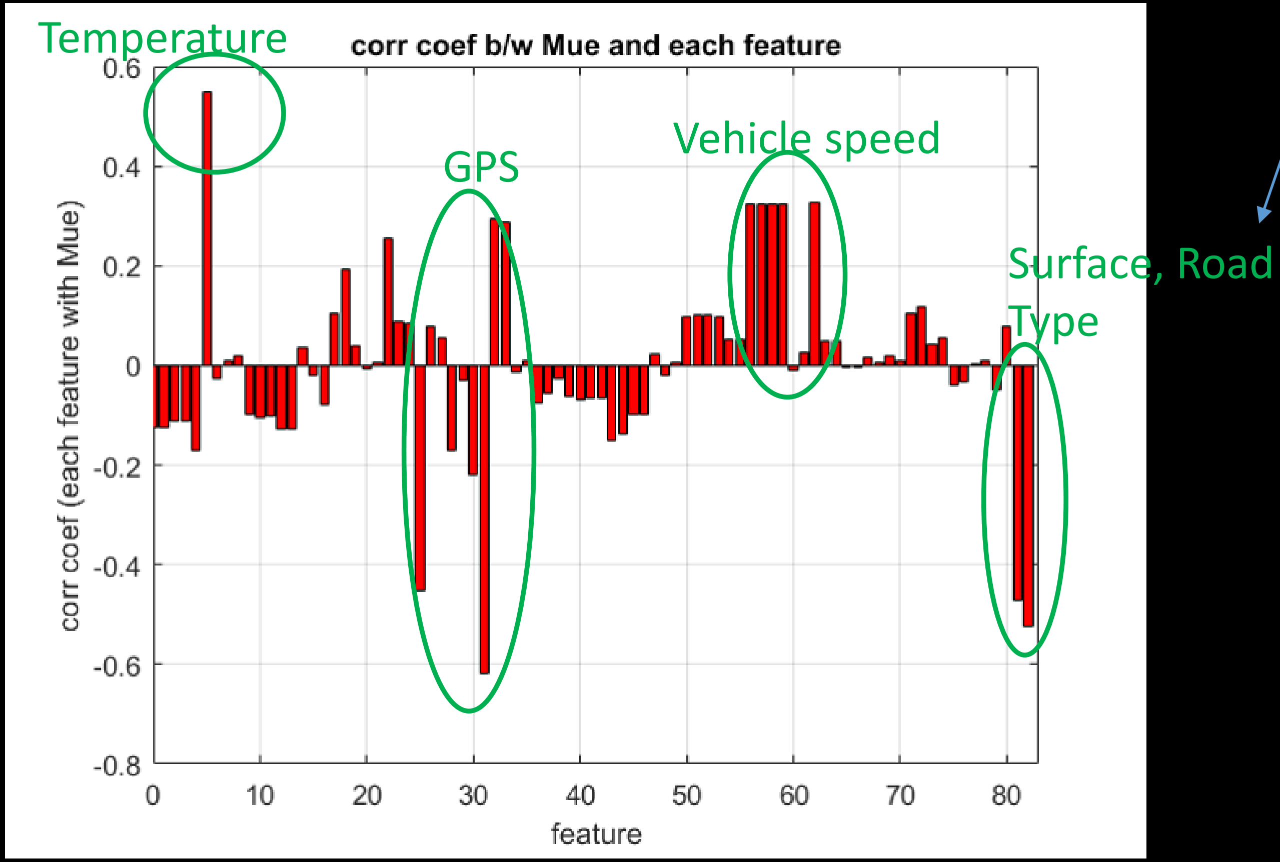
Top 5 features

Green= features selected by all 3 methods
Yellow= features selected by 2 of 3 methods
Red= features selected by 1 of 3 methods

Correlation	F-score	mRMR
GPSposLatitude	AmbTemp	RoadType
AmbTemp	SurfaceType	AmbTemp
RoadType	GPSposLatitude	GPSposAltitude
SurfaceType	GPSdop	WheelSpeed
GPSdop	RoadType	StabPtMaxMode

Feature and correlation to friction

Correlation to true friction



Surface & road type are not available in the sensor suite ->important to use a new sensor

Temperature, GPS, vehicle speed, surface and road type are important features for friction estimation

Features 1...86

Neural Network and Random Forest

Result for 33 features *excluding* Tyre, Surface and Road type:

	Training time (s)	Prediction time (s)	Testing accuracy (%)
Neural Network (Multiclass, 1 hidden layer, 60 neurons)	High	Low	83
Random Forest (Decision tree, multi class)	Low	Low	85

<3 min   <1 s

Random Forest (RF) has been selected as the best method

Training has been done with an Intel i7, 2.7GHz
Laptop with 8GB memory

Confusion matrix and 11 classes of friction

True friction →

Estimated friction ↓

	0	1	2	3	4	5	6	7	8	9	10
0											
1											
2				1 %							
3				12%							
4				1 %							
5											
6											
7											
8											
9											
10											

False Positive
(false slippery warnings)

False Negative
(missed warnings)

Accuracy=(TP+TN)/(TP+TN+FP+FN)

	Accuracy	FP	FN
Baseline	58%	14%	28%
Random Forest	85%	5%	17%

Motives to introduce a camera as a sensor

Road and surface type are both top feature and contributes to increase accuracy

The hypothesis was raised if a front-looking can be used to predict the road condition

Camera is not today used for friction estimation at Volvo Cars

The envisioned structure adding a camera

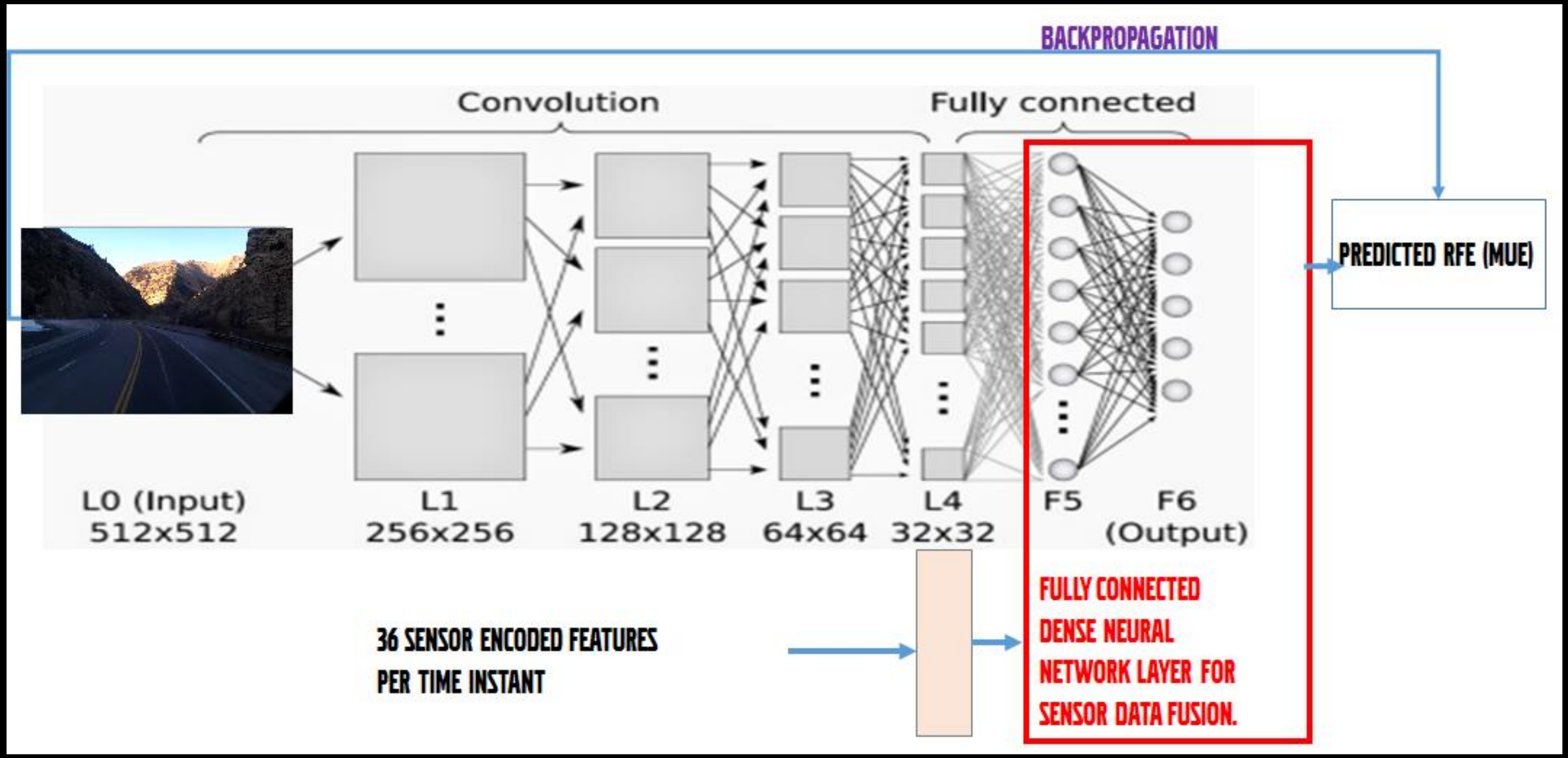


Image based road surface condition prediction

Dry Asphalt: Class 1

Wet/Water: Class 2

Slush: Class 3

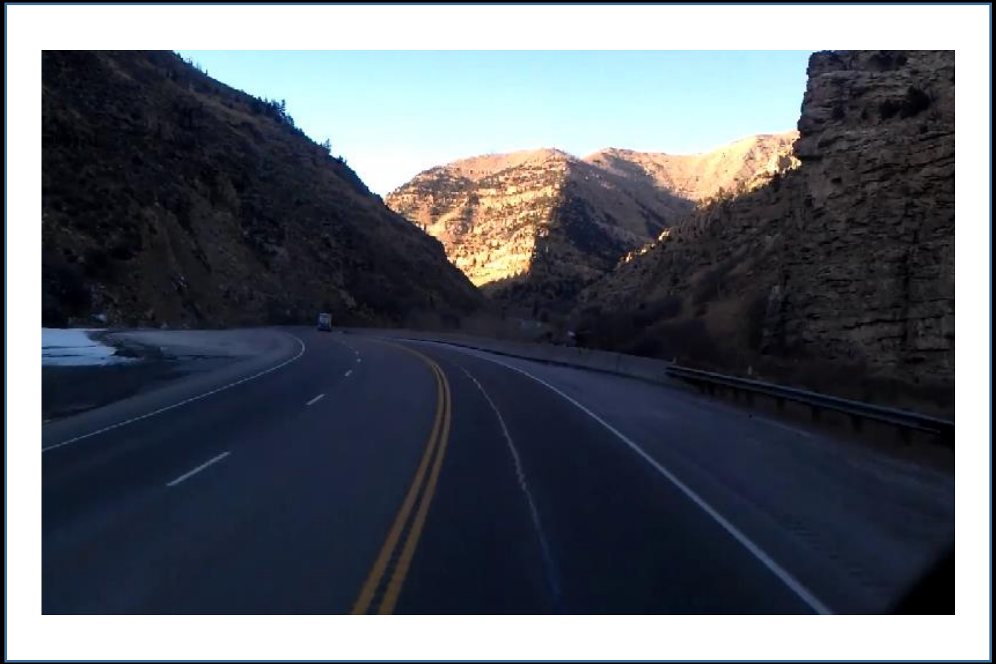
Snow/Ice: Class 4

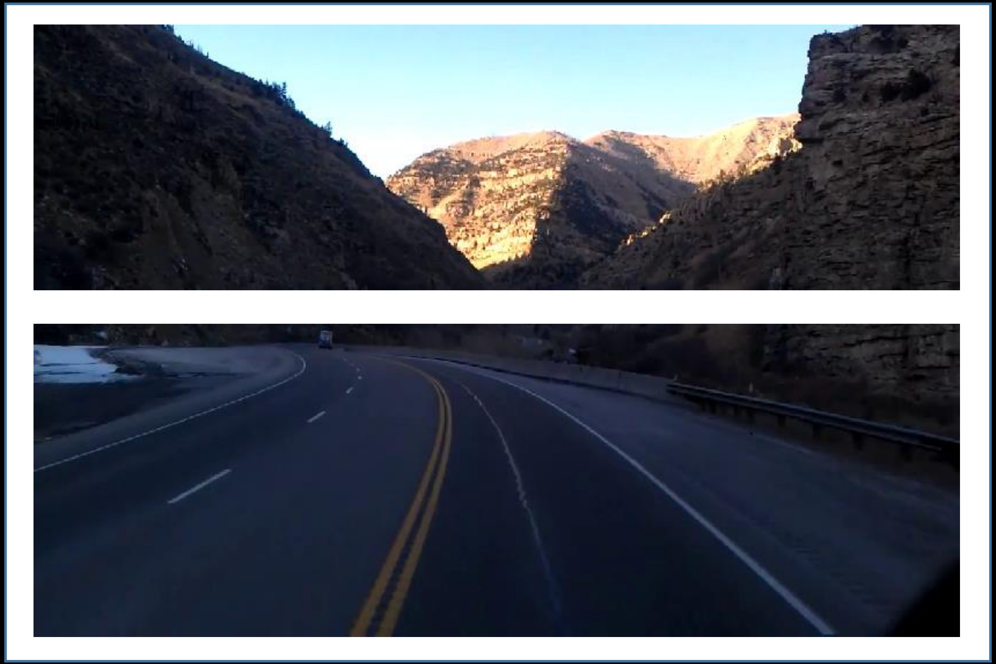
- Train Data: 40-100 frames per video (70%: random 3750 images. Interval between video frames>=1 second)
- Test Data: 40 frames per video (30%: random 1550 images. Interval between video frames>=1 second)

Proposed steps

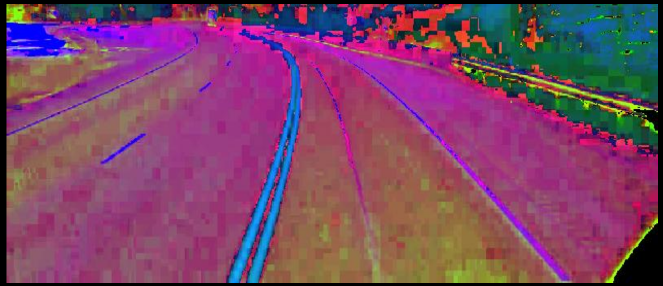
1. Extract GIST features from image=> Identify horizon

2. Partition Image to :
   I. Below Horizon (Drivable Surface + Surroundings)
   II. Above Horizon (Surroundings + Sky)





3. Extract HSV plane image



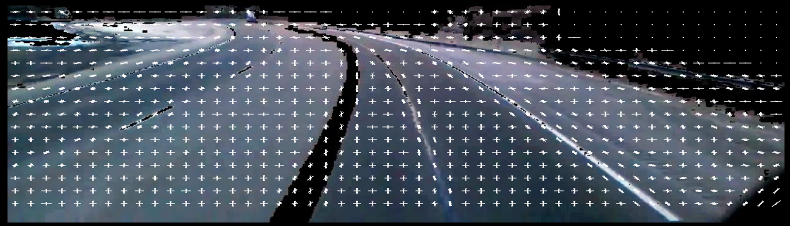
4. Divide the two sub images into four by detecting the surroundings

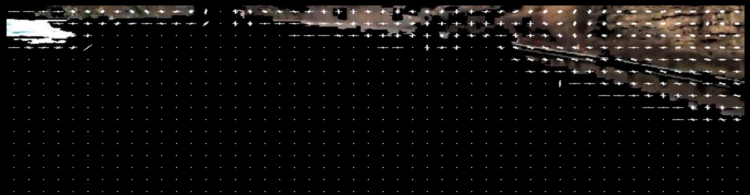
R1: Above Horizon: Surroundings

R2: Above Horizon: Sky

R3: Below Horizon: Drivable Surface

R4: Below Horizon: Surroundings





HOG Features for Texture

Results for road surface condition prediction

	3750 training images training time [s]	training accuracy	1550 testing images. test time [s] per image	testing accuracy	parameters
CNN (3 Conv Layers)	6hr	97.63%	0.02325690	92.52%	71673984
Squeezenet (AlexNet)	945.262	95.59%	0.00657387	92.26%	727428
ML (NN, 60features, 60neurons)	1012.880	91.87%	0.37160000	91.23%	7200

Neural Network was selected due to less parameters

Examples mis-classified images

Gound truth: **Dry**
Predicted as **Wet**

Gound truth: **Snow**
Predicted as **Slush**

Gound truth: **Wet**
Predicted as **Ice**

Challenges

Tyres sensitivity

Motion is generated in the tyre contact patch and tyres have individual characteristics

Generalizability of machine learning algorithms to various regions

Using e.g. GPS will require intensive training of algorithm in all markets

Ground truth

Friction is hard to measure

Machine learning is good only for scenarios it has been trained on

Conclusion

- Temperature, GPS data, vehicle speed, and Road&Surface Type are sensitive features for friction estimation
- The selected Machine Learning algorithm increases accuracy of friction estimate from 58% to 85% compared with the baseline.
- The Machine Learning algorithm for road surface images achieves 92% accuracy

end;