

A Prototype System for Truck Signal Priority using Video Sensors

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Research Sponsors

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Outline

1. Motivation
2. Object Classification in Images
3. Experimental Results
4. Conclusion

Why Truck Priority?

- Benefits:
 - Reduce the cost of goods transportation.
 - Reduce red light running.
 - Encourage trucks to use specific truck routes.
 - Reduce emissions.
- This requires the ability to detect and track trucks.

Video Sensors

- Video sensors have distinct advantages:
 - they are easy to install (or can be already installed),
 - they are inexpensive,
 - they can provide rich traffic description (e.g. road user tracking),
 - they can cover large areas,
 - their recording allows verification at any later stage.

Detecting and Tracking Trucks

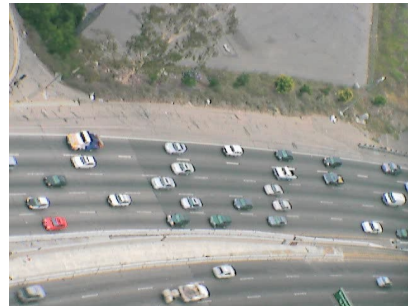
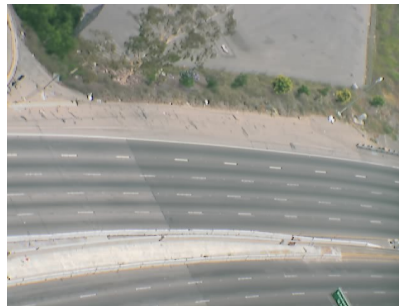


Image Sequence
+
Camera Calibration



Road User Trajectories



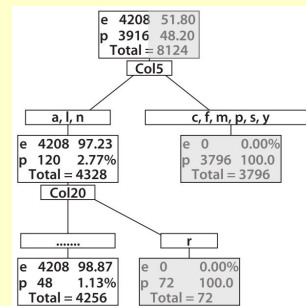
Background Model



Road User Classification



Labeled Truck Images



Truck Classifier

Object Detection in Images

- Two types of object description variables:
 - describing the appearance.
 - e.g. SIFT, HoG features.
 - describing the shape.
 - e.g. (3D-)models, moments.

Shape Description

- Extract a shape using background subtraction.



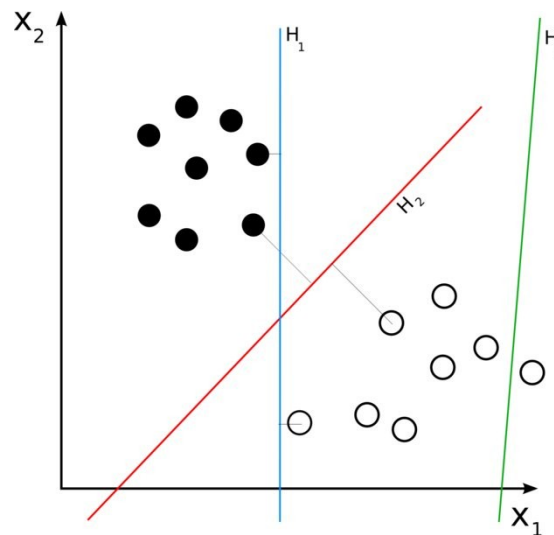
- Compute the moments of the shape.

$$m_{p,q} = \iint f(x,y) x^p y^q dx dy$$

$f(x,y)=1$ if the pixel at (x,y) is in the foreground
0 if the pixel at (x,y) is in the background

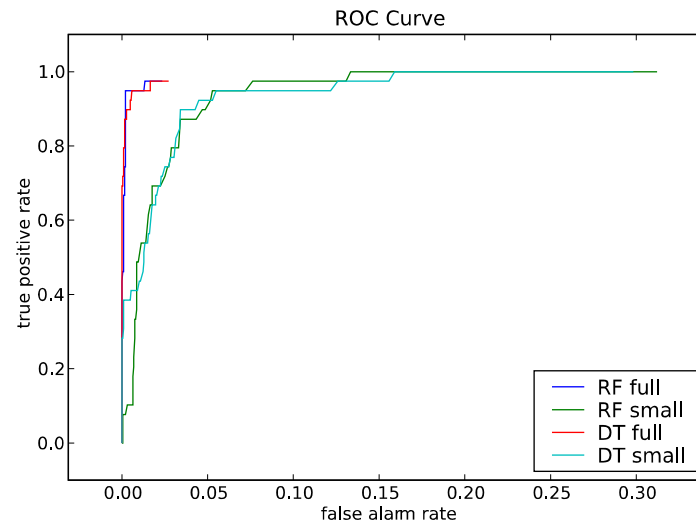
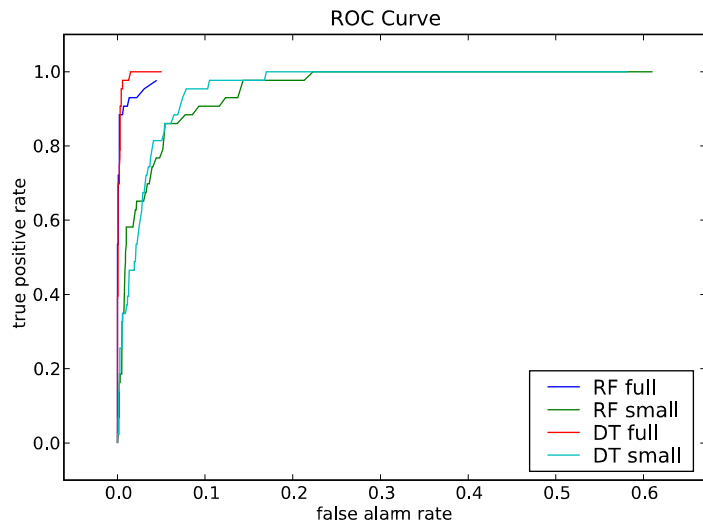
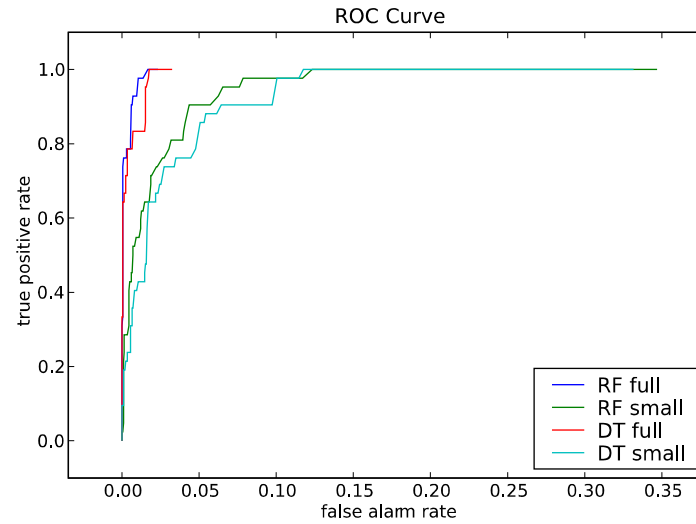
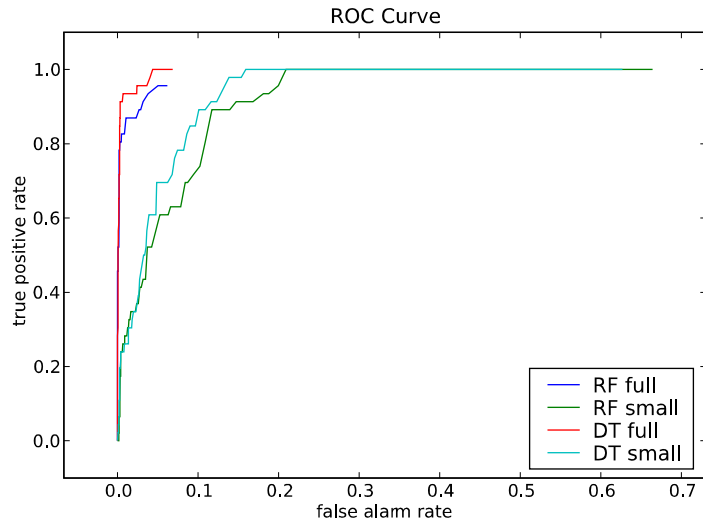
Learn a Truck Classifier

- Using machine learning to learn a binary classifier (truck vs. other road users).



- The classifier returns a decision for each shape at each instant. A threshold $nDetections$ is used to detect a truck.

Experimental Results



X axis:

$1 - \text{Recall}_{non-truck}$
also called false alarm rate

Y axis:

Recall_{truck}
also called true positive rate

DT: Decision Tree
RF: Random Forest

Experimental Results

- The recall for trucks reaches 78% to 95% on test data, with a false alarm rate below the 0.5% value used for the system simulation.

8:05 to 8:20	Decision Tree	Full	44	78.57
		Small	117	23.81
	Random Forest	Full	19	78.57
		Small	73	40.48
8:20 to 8:35	Decision Tree	Full	29	92.31
		Small	111	38.46
	Random Forest	Full	12	94.87
		Small	89	10.26

Experimental Results



Experimental Results: TkSP

- TkSP: green extension or red truncation.
- Conventional / Advanced TkSP: prediction of truck arrival time and queue dissipation time thanks to real-time tracking.
- Detection at 300m from the intersection.
- Simulation of the Knight St corridor in Vancouver B.C. (3 intersections with TkSP).
- The Advanced TkSP strategy outperformed conventional TkSP strategy.

Experimental Results: TkSP

- Especially effective
 - at two-phased intersections,
 - when traffic volume was less than that of the morning peak hour,
 - when truck proportion was equal to or less than 2%,
 - and when priority was not locked after a green extension or red truncation.
- Under the best conditions, average truck travel times were reduced by 9.16% and 0.93% in the peak and opposing directions, respectively.

Conclusion

- Prototype system for truck detection and tracking using video sensors.
- Tested on real world data: high recall for trucks, from 78% to 95%, and a false alarm rate below the 0.5% value used for simulation.
- Future work:
 - classify all road users and include other description variables,
 - multi-camera system.

Questions?