

## Chapter 67

# A Differential Evolution Based Multiclass Vehicle Detector and Classifier for Urban Environments

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### ABSTRACT

*Video analytics is emerging as a high potential area supplementing intelligent transportation systems (ITSs) with wide ranging applications from traffic flow analysis to surveillance. Object detection and classification, as a sub part of a video analytical system, could potentially help transportation agencies to analyze and respond to traffic incidents in real time, plan for possible future cascading events, or use the classification data to design better roads. This work presents a specialized vehicle classification system for urban environments. The system is targeted at the analysis of vehicles, especially trucks, in urban two lane traffic, to empower local transportation agencies to decide on the road width and thickness. The main thrust is on the accurate classification of the vehicles detected using an evolutionary algorithm. The detector is backed by a differential evolution (DE) based discrete parameter optimizer. The authors show that, though employing DE proves expensive in terms of computational cycles, it measurably improves the accuracy of the classification system.*

### 1. INTRODUCTION

Vehicle detection and classification is currently a hot focus area in the myriad web of intelligent transportation systems (ITSs) with immense potential for traffic flow control, security, and surveillance to name a few. ITSs are embracing data driven techniques (Zhang et al., 2011) wherein the data related to traffic density, incidents, etc. are relayed back to users of the traffic systems thereby empowering them

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to make real-time decisions about routes thereby promoting efficiency. Road side regulations, increasing density of vehicles on roads, and costs of overlaying the roads are some of the supplementary and rather critical reasons calling for ever more efficient utilization of our transportation networks. Robust vehicle classification systems that are able to compute the number and type of vehicles plying on a particular road or highway, provide a part of the solution.

Various vehicle detection and classification systems such as digital wave radars (Sharma et al., 2008), amplitude modulated laser radars (Mao et al., 2012), lidars (Levinson et al., 2011), magnetometers (Canoga, 2003) etc., have been proposed and some have been in continual use commercially with their inherent advantages and disadvantages. These systems can be broadly classified depending upon the type of sensors they use or on the basis of their installation vis a vis intrusive and non-intrusive. Most commonly used systems, use one or a combination of laser, piezoelectric, microwave, or video cameras. For example, inductive loop detectors are one of the most accurate and widely used systems for vehicle detection. But due to their intrusive nature, high equipment and installation costs, they are not often being applied (Middleton, Chara, & Longmire, 2009).

Video based vehicle classification has recently emerged as a low cost alternative to conventional intrusive systems primarily owing to their low cost, non-intrusive nature of installation, and operation. For example, there has been extensive use of video based vehicle detection systems in surveillance (Tian et al., 2015; Sivaraman & Trivedi, 2013; Wang, 2013). Other benefits include (Linda & Volling, 2003):

- Freedom from extensive sawing residue and extensive cleaning after installation and continual maintenance;
- Installation can be done year-round;
- No need for road closure for installation and maintenance thereby reducing the impact on traffic flow;
- Ease of operation;
- Provides rich data through which additional information and context can be approximated;
- Vision based systems integrate well with other object detection systems.

Their advantages notwithstanding, video based detection and classification systems have their own challenges, and pose many difficulties for researchers. Some of them may be categorized as (Tian et al., 2015):

- **Occlusion:** Vehicles and other objects on roads can block each other in the camera view leading to a false count;
- **Rapid illumination changes:** Weather changes may range from periods of very high brightness to very low intensities posing a problem for detection algorithms;
- **Vehicle edge/contour deformation:** Due to various continual changes in scene, the vehicle may not be detected with a perfect boundary leading to misclassifications;
- **Multiplicity of vehicle types:** There are highly varied types of vehicles ranging from a mid-sized sedan to transport trucks with different lengths, heights, and axles in between. Extracting individual features and correctly classifying vehicles becomes a challenge in this scenario. Add to that, pedestrian, bicycles and other objects, the problem becomes even more difficult.

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