# Vehicle Type Classification via Adaptive Feature Clustering for Traffic Surveillance Video

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# Contents

# Introduction

Vehicle type classification has become a significant task in machine learning because of its potential applications

- Intelligent Traffic Systems
- Autonomous Driving Systems

# Introduction

In this paper, a novel method is proposed to handle this task in the real road traffic surveillance video.

# Challenges

## Challenges

- low-resolution surveillance cameras
- different road conditions
- varying illumination conditions
- different camera viewpoints
- vehicles: colors, postures, manufacturers

# Traditional Methods

# Problems

## Problems

- It is hard to collect training samples under every circumstances
- Traditional methods fail to adapt to different situations in the real surveillance.

# Defination

Naturally, according to the vehicle size, vehicles can be divided into 3 categories:

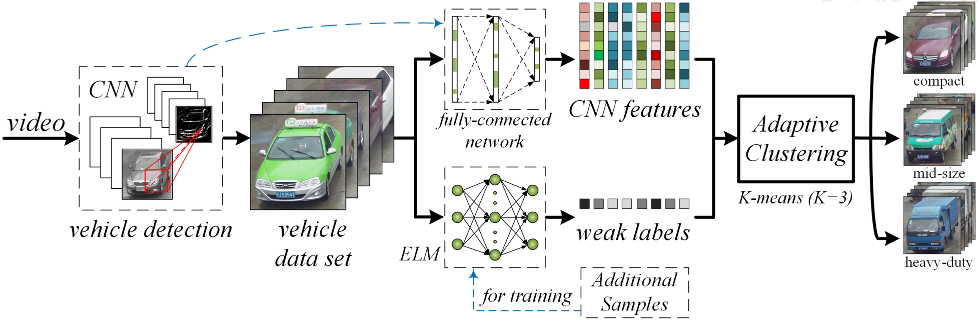
- **compact cars** (sedans, taxes)
- **mid-size cars** (vans)
- **heavy-duty vehicles** (buses, trucks)

# Proposed Method

## The algorithm has four steps

- Vehicle Detection and Dataset Generation
- Feature Extraction
- Unsupervised Learning
- Recognition and Classification

# Flowchart


video
CNN
vehicle detection
vehicle
data set
fully-connected
network
ELM
for training
CNN features
weak labels
Additional
Samples
Adaptive
Clustering
K-means (K=3)
compact
mid-size
heavy-duty

# More Details - Vehicle Detection

## Vehicle Detection

1.Set ROI

- limit the vehicle images to a suitable size range
- guarantee the integrity of vehicles
- decrease the detection area

2.Fast-RCNN

- output accurate vehicle coordinates

# More Details - Feature Extraction

## Feature Extraction

- Features from Deep Network
- Priori Features
- Feature Fusion

# More Details - Feature Extraction

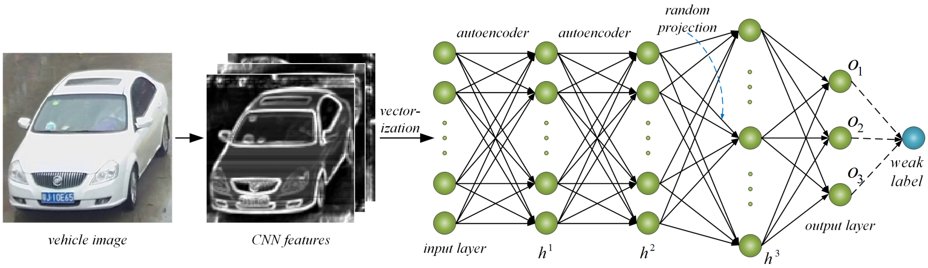
## Features from Deep Network

use the weights in the front fully-connected layers as the filters to extract features.

$$feature_1 = g(\boldsymbol{W} \cdot \boldsymbol{x} + \boldsymbol{b})$$

where $g(\boldsymbol{x}) = (1 + exp(-\boldsymbol{x}))^{-1}$ is the sigmoidal activation function.

# More Details - Feature Extraction



vehicle image

CNN features

## Priori Features

$$feature_2 = \underset{j}{\operatorname{argmax}}(o_j) - 2, \quad j = 1, 2, 3$$

# More Details - Feature Extraction

## Features Fusion

merge two features together according to the queue model.

$$f^{(i)} = [feature_1^{(i)}, \lambda \cdot feature_2^{(i)}]$$

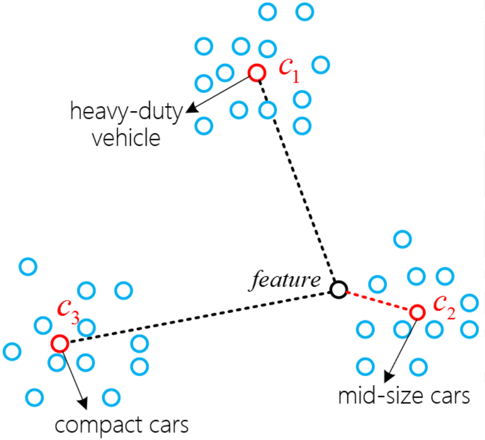
where $f^{(i)}$ is the features of the $i$-th vehicle image in dataset
$\lambda$ is a positive parameter

# More Details - Recognition and Classification

## Recognition and Classification

Finally, vehicle type will be recognized according to the closest distance principal.

$$r = \underset{k}{\text{argmax}} \|f - c_k\|, \quad k = 1, 2, 3$$



# Experimental Environment

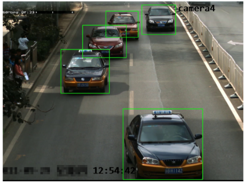
## Training Environment

Sugon I450, with NVIDIA Telsa K20C for GPU parallel computing.
21296 images (with 10000 negative samples) for training CNN network.
13860 images for training ELM network.

## Testing Environment

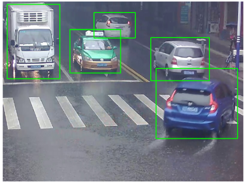
Visual Studio 2013 environment in Core i5, 3.2GHz CPU with 8-GB RAM.

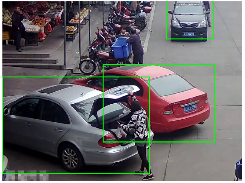
# Vehicle Detection



(a) daylight


(b) night


(c) rain


(d) occlusion

## Specifications

| PARAMETER | VALUE | UNIT |
|---|---|---|
| Detection Rate | **98.63** | % |
| Error Detection Rate | <0.1 | % |
| Training Time | 10.58 | hour |
| Testing Time (GPU) | 1.5 | s/frame |
| Testing Time (CPU) | 150 | ms/frame |

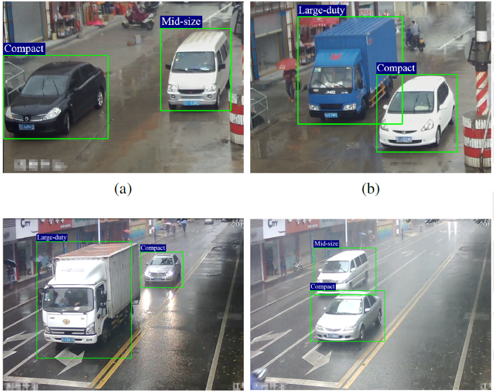
# Vehicle Classification

## Classification Results

THE VEHICLE TYPE RECOGNITION ACCURACY OF SEVERAL METHODS

| Methods | Accuracy (%) |
|---|---|
| HOG+SVM[*] | 81.42 |
| HOG+ELM | 82.80 |
| The proposed method | **85.56** |

[*] H. C. Karaimer, I. Cinaroglu, and Y. Bastanlar, Combining shape-based and gradient-based classifiers for vehicle classification, in 2015 IEEE 18th International Conference on Intelligent Transportation Systems, Sept 2015, pp. 800-805.




(a) (b) (c) (d)

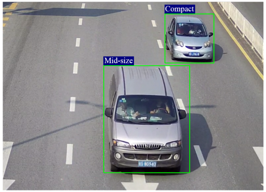
# Vehicle Classification

## CONFUSION TABLE

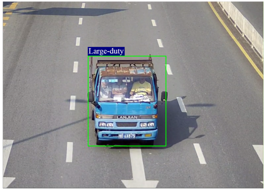
THE CONFUSION TABLE
BETWEEN DIFFERENT VEHICLE TYPES

| Actual \ Predict | Compact | Mid-size | Heavy-duty |
|---|---|---|---|
| Compact | **88.26** | 9.61 | 2.14 |
| Mid-size | 6.60 | **85.85** | 7.55 |
| Heavy-duty | 16.33 | 12.24 | **71.43** |

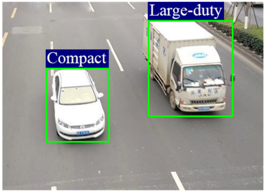
# Vehicle Classification



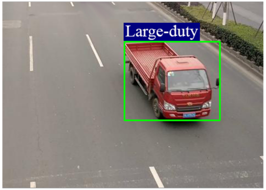

(a)



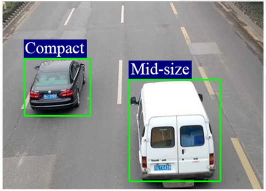

(b)



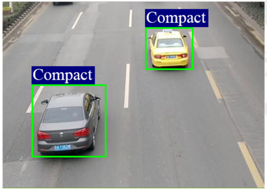

(c)




(d)




(e)




(f)

# Conclusion

## Conclusion

- Experimental results show that clustering results can largely distinguish these three types of vehicles.
- The proposed method outperforms other traditional methods, and has a very wide application prospects.
- This framework can avoid the uncontrolled effects of environment, such as various road situations.

# THANKS