On-Road Vehicle Detection

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ELECTRICAL & COMPUTER ENGINEERING
Outline

• Introduction
• Vision based detection vs. Radar based detection
• Challenge
• Why Active learning
• Types of Query
• Tracking
• Implementation and Results comparison
• Questions
Introduction

- Global Road Crash Statistics
  - 1.3 million people die each year
  - 3,287 deaths a day
  - 20-50 million are injured or disabled each year
  - 2.2% of all deaths
  - 9th leading cause of death
  - 1st leading cause of death ages 15-29
  - 5th leading cause of death by 2030, unless action is taken
  - $518 billion cost globally, 1-2% of individual countries’ annual GDP

Image from google image, https://02varvara.files.wordpress.com/2013/04/00-auto-accident-cartoon-01-04-13.jpg
Introduction

- United States Road Crash Statistics
  - 37,000 people die each year
  - 2.35 million are injured or disabled
  - 1,600 children under 15 die each year
  - 8,000 people are killed in crashes involving drivers ages 16-20
  - $230.6 billion per year, or an average of $820 per person

Image from google image, https://02varvara.files.wordpress.com/2013/04/00-auto-accident-cartoon-01-04-13.jpg
Introduction

• Automotive Safety system is important!
• Main types of automotive safety
  • Active Safety
    • ABS+EBD (Anti-lock breaking)
    • ESP (Stability control)
    • Cruise Control
    • Lane keeping
  • Passive Safety
    • Seatbelt
    • Airbags

Image from google image, http://belajarberbagi.blog.com/files/2014/02/Toyotas-philosophy.jpg
Vehicle Detection
Vision based vs. Radar based

- Radar based system becomes very popular
- Adaptive cruise control
- Cons of Radar based
  - Only detect vehicles directly in the front
  - Do not provide information on vehicles in neighboring lane
- Pros of vision based
  - Recognize and track vehicles across multiple lanes

Vision based Challenge

• Require robust performance
• Varying backgrounds and illuminations
• Diverse vehicles' Sizes and locations
• Vehicle-like regions spur false positives
Active Learning

- Initialization
- Query and Retraining
- Advantages
  - Significant drop in false positives
  - maintain a high vehicles recognition rate
Initialization

- Passively trained Adaboost classifier
- Cascaded 30 stages, each is based on a threshold of scores
- Weighted majority vote of weak learners
- Each stage reduces vehicle candidates set
- 7,500 positive training images
- 20,500 negative training images
Feature Extraction

- Haar-like rectangular features
- Rectangular features are sensitive to
  - edges
  - bars
  - vertical and horizontal details
  - symmetric structures
- Resolution requirement
  - HOG features requires higher image resolution than Haar feature
  - Influence on dimensionality
Types of Query

- **Query by Confidence (QBC)**
- Uncertainty and distance to the decision boundary
- Binary classification can be viewed as an inner product
- $h_n(x)$ are extracted features, $w_n$ are the weights

$$H(x) = \sum_{n=0}^{N-1} w_n h_n(x)$$

$$y(x) = \text{sgn}\{H(x)\}$$

Image from google, http://www.precision-crop-protection.uni-bonn.de/gk_research/project_3_06/image_3.jpg
Types of Query

- Logistic function maps $H(x)$ to interval $[0, 1]$

\[ p(y = 1|x) = \frac{1}{1 + e^{-2H(x)}} \]

- A query function $Q(x)$ returns samples close to the decision boundary

\[ Q(x) = \{x: |p(y = 1|x) - 0.5| < \epsilon\} \]
Types of Query

- **Query by Misclassification (QBM)**
- Human in the loop to label queried examples
- Mark correct detections, false positives and missed detections
- Example
  - Green: correct detection
  - Red: missed detection
  - Blue: false positives
- Correct detections retraining avoids overfitting
• Query and archiving interface for active learning
• Evaluate and allowing the user tag false positives and missed vehicles
• Archiving
  • missed vehicles + true positives = positive training examples
  • false positives = negative training examples
• Retraining
  • 10,000 positive images
  • 12,172 negative images
Examples of true positives outputs queried for retraining using QUAIL

Examples of false-positive outputs queried for retraining using QUAIL
Tracking

- Use the Condensation filter
- Example
  - Green: detector outputs
  - Middle red: Multiple hypotheses
  - Best tracking results
- Condensation Demo

Condensation Demo: http://www.robots.ox.ac.uk/~misard/index.html
ALVeRT

- Active-learning-based vehicle-recognition and tracking
  - Offline learning portion (white and red)
  - Online implementation portion (Green)
Implementation

• Data set
  • Caltech Vehicle Image 1999
    • 126 distinct static images of vehicles
  • LISA-Q Front FOV Video Datasets 1-3
    • Data1: 1600 consecutive frames
    • Data2: 300 consecutive frames
    • Data3: 300 consecutive frames
Implementation

• True positive rate

\[
TPR = \frac{\text{detected vehicles}}{\text{total number of vehicles}}
\]

• False detection rate

\[
FDR = \frac{\text{false positives}}{\text{detected vehicles} + \text{false positives}}
\]

• Average FP/Frame

\[
Avg = \frac{\text{false positives}}{\text{total number of frames processed}}
\]

• Average FP/Object

\[
Avg = \frac{\text{false positive}}{\text{true vehicles}}
\]
Result of Caltech 1999 Dataset
### Result of LISA-Q Dataset

#### Experimental Data Set 1: January 28, 2009, 4 P.M., Highway, Sunny

<table>
<thead>
<tr>
<th>Recognition/Tracking System</th>
<th>TPR</th>
<th>FDR</th>
<th>FP/Frame</th>
<th>TP/Frame</th>
<th>FP/Object</th>
</tr>
</thead>
<tbody>
<tr>
<td>Passively Trained Vehicle Recognition</td>
<td>89.5%</td>
<td>51.1%</td>
<td>4.2</td>
<td>4.1</td>
<td>0.94</td>
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<tr>
<td>Active Learning Vehicle Recognition</td>
<td>93.5%</td>
<td>7.1%</td>
<td>0.32</td>
<td>4.2</td>
<td>0.07</td>
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<tr>
<td>ALVeRT</td>
<td>95.0%</td>
<td>6.4%</td>
<td>0.29</td>
<td>4.2</td>
<td>0.06</td>
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</tbody>
</table>

#### Experimental Data Set 2: March 9, 2009, 9 A.M., Urban, Cloudy

<table>
<thead>
<tr>
<th>Recognition/Tracking System</th>
<th>TPR</th>
<th>FDR</th>
<th>FP/Frame</th>
<th>TP/Frame</th>
<th>FP/Object</th>
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<tbody>
<tr>
<td>Passively Trained Vehicle Recognition</td>
<td>83.5%</td>
<td>79.7%</td>
<td>4.0</td>
<td>1.0</td>
<td>3.3</td>
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<td>Active Learning Vehicle Recognition</td>
<td>80.2%</td>
<td>41.7%</td>
<td>0.72</td>
<td>0.98</td>
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<td>ALVeRT</td>
<td>91.7%</td>
<td>25.5%</td>
<td>0.39</td>
<td>1.14</td>
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#### Experimental Data Set 3: April 21, 2009, 12:30 P.M., Highway, Sunny

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<th>Recognition/Tracking System</th>
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<th>FP/Frame</th>
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<tr>
<td>Passively Trained Vehicle Recognition</td>
<td>98.1%</td>
<td>45.8%</td>
<td>2.7</td>
<td>3.16</td>
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<td>Active Learning Vehicle Recognition</td>
<td>98.8%</td>
<td>10.3%</td>
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<td>ALVeRT</td>
<td>99.8%</td>
<td>8.5%</td>
<td>0.28</td>
<td>3.17</td>
<td>0.09</td>
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Future

• Combing with the technology of AR display
• Applications
  • cruise control
  • safe merging
  • Auto’s information capture
Reference


Questions

• Under current estimation, will the traffic accidents cause of death increase or decrease
• What are two main automotive safety systems
• What is the advantage of vision based vehicle detection compared to radar based
• Briefly describes the loop inside of the active learning
• What algorithm is used for tracking
• Define the Average FP/Frame