Evolving Cascades of Voting Feature Detectors for Vehicle Detection in Satellite Imagery

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The objectives

- Use a compound GP classifier to detect vehicles in satellite imagery (visible band)

Characteristics of the task:
- extreme disproportion of the positive and negative classes,
- heterogeneity of the positive class,
- low spatial resolution,
- uncontrolled lighting,
- partial occlusions,
- strong sunlight reflexes from wind shields, man-made objects that closely resemble cars (air conditioning equipment on rooftops, cargo containers, etc.)
Binary classification task with [extremely] low share of positive examples

- cars occupy around 1.5% of image area,
- a priori probability of the positive class: 0.0001

The idea: use a *cascade* of classifiers.

Each classifier:

- processes only the examples classified as positive by all its predecessors,
- is trained to retain (accept) all (almost all) positive examples, while rejecting as many negative examples as possible,
Cascade of detectors

- Only examples that pass through all cascade nodes are classified as positive
- Famous representative: Viola & Jones [2001] face detector
Our contributions

- Employ GP to induce the base classifiers
- Use quad-tree-based features instead of Haar wavelets
A quad tree stacked over $32 \times 32$ input window
- Tree nodes correspond one-to-one to rectangular image regions (tiles).
- The nodes at consecutive depths correspond to $16 \times 16$, $8 \times 8$, $4 \times 4$, and $2 \times 2$ tiles; there are, 4, 16, 64, and 256 of them $\Rightarrow$ total of 340 tiles.
- Each tile uniquely identified by quad key – a variable-length sequence of quaternary digits.

Feature $d(m, n) =$ difference between mean brightness values in two tiles identified by $m$ and $n$.

Total number of features: $340 \times 340 = 115,600$

A clever trick (integral image) makes extraction of such features very effective (4x memory access + 3 subtractions).
Exemplary tree and accessed features

An exemplary GP tree (base classifier):

\[
\begin{align*}
&+ \\
&\text{Avg} \\
&\quad d(2, 100) \\
&\quad -0.21 \\
&\quad d(032, 021) \\
&\quad d(21, 1)
\end{align*}
\]

The tiles accessed by particular features (16x16 grid not shown):
## The Experiment: Tasks and Settings

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual</td>
<td>5 GP trees</td>
</tr>
<tr>
<td>Population size</td>
<td>1024</td>
</tr>
<tr>
<td>Population initialization</td>
<td>standard ramped half-and-half</td>
</tr>
<tr>
<td>Selection</td>
<td>tournament (7)</td>
</tr>
<tr>
<td>Crossover</td>
<td>tree-swap, probability 0.9</td>
</tr>
<tr>
<td>Mutation</td>
<td>subtree-replacement, probability 0.1</td>
</tr>
<tr>
<td>Elitism</td>
<td>no</td>
</tr>
<tr>
<td>Tree depth limit</td>
<td>10</td>
</tr>
<tr>
<td>Number of generations</td>
<td>100</td>
</tr>
</tbody>
</table>

- Evolutionary Computation in Java, ECJ
- Runs repeated 5 times
F-measure = the harmonic mean of precision $p$ and recall $r$ (sensitivity)

$$fitness = F_{measure} = \frac{2pr}{p + r}$$

$$p = \frac{TP}{TP + FP}, \quad r = \frac{TP}{TP + FN}$$
The Experiment: Data

- 33 true-color satellite images of spatial resolution 0.2m/pixel
The Experiment: Data

- Different environments: urban, rural, parking lots, bridges, etc
- 4 to 378 cars per image, \(22 \times 9\) pixels on average
- Training example = 32x32 window of the original image
  - positive example: window centered on a vertically aligned car
  - negative example: any window non overlapping with any car
- Training set: 659 cars extracted from 24 training images,
- Testing set: 635 cars extracted from 9 testing images,
- All images converted to grayscale for further analysis
<table>
<thead>
<tr>
<th>Cascade node</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>374</td>
<td>11865</td>
<td>135</td>
<td>285</td>
</tr>
<tr>
<td>2</td>
<td>368</td>
<td>87</td>
<td>48</td>
<td>6</td>
</tr>
<tr>
<td>3</td>
<td>367</td>
<td>18</td>
<td>30</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>367</td>
<td>5</td>
<td>25</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>367</td>
<td>8</td>
<td>17</td>
<td>0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>367</td>
<td>11983</td>
<td>17</td>
<td>292</td>
</tr>
</tbody>
</table>

On the training data, this detector attains precision $p = 0.956$, recall $r = 0.557$, and F-measure of 0.704.
Evaluation on test images

Input image → Image rotation (different $\alpha$'s) → Feature extraction → Cascade of voting GP classifiers → Detection density map (sum over $\alpha$) → Vehicle locations
Evaluation on test images

Detection density map (DDM):

- aggregated over 8 rotated versions of the test images (every 22.5 degrees)
- each detection increases the belief in vehicle presence at the particular location and its surroundings (Gaussian distribution with $\sigma = 2.6$)
- local maxima in DDM with belief values greater than $t$ lead to detections
Detections
**ROC curve**

- Obtained by varying the $t$ threshold of the DDM
- Detection within a true vehicle contour counted as TP, otherwise FP
Some false positives and false negatives

FP

FN
Decent performance on a challenging task using simple features

No contextual information used (particularly road/street locations)

Further work: different aggregation schemes, colour, multiobjective evolutionary search for precision and recall