Ongoing Work on Traffic Lights

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Abstract

Research in traffic light recognition (TLR) has stagnated compared to related computer vision areas, such as pedestrian detection and and traffic sign recognition. We focus on the detection sub-problem, since this is the most challenging problem and solving this is the key to a successful TLR system. This is done by looking at four detectors from different author groups and their reported results. From surveying existing work it is clear that currently evaluation is limited primarily to small local datasets. In order to provide a common basis for future comparison of TLR research an extensive public database is collected based on footage from US roads. The database consists of continuous test and training video sequences, totaling 46,418 frames and 112,971 annotated traffic lights. The sequences are captured by a stereo camera mounted on the roof of a vehicle driving under both night and day conditions with varying light and weather.

1. Introduction

Driver assistance systems are gaining a lot of momentum currently, as evident in top models from prominent car manufacturers. Recognition of traffic lights (TLs) would be a desirable addition, but judging by the state of current research in this area, consumer-ready systems are not on the immediate horizon. Traffic light recognition (TLR) consists of three sub-problems, detection, classification, and tracking. Figure 1 illustrates the typical flow of such a computer vision system. A similar breakdown is done for traffic sign recognition in [13].

The detection and classification stages are executed sequentially on each frame, whereas the tracking stage feeds back spatial and temporal information between frames. For

![Figure 1: Breakdown of a vision based TLR system.](image-url)
object detection, and visual odometry, with the purpose of reducing the bias and providing real-world test scenarios. The purpose is similar for the recently introduced VIVA Challenge, which is used for benchmarking proposed methods on difficult tasks associated with drivers, occupants, vehicle dynamics, and vehicle surroundings. For now, it includes datasets for hands, faces, and signs captured under challenging naturalistic drive settings. The TL dataset published with this work is eventually going to be included in the VIVA Challenge[12].

The contributions made in this survey paper are thus threefold:

1. Provide an overview of four different approaches to TL detection from four author groups.
2. Introduce a common evaluation procedure for TL detectors.
3. Publish an extensive high resolution, stereo video database, with day and night video sequences, accompanied by TL annotations.

The paper is organized as follows: Section 2, explains the possible appearances of TLs, along with common challenges that TL detection systems are subject to. Related research is summarized in section 3. In section 4, we present a new database for evaluation of TL detection systems. Finally, concluding remarks are found in section 6.

2. Traffic Lights: Structure and Challenges

TLs are by design made to stand out and be easily visible. Their primary components are bright colored lamps. These lamps are commonly circular or arrow shaped, they are surrounded by a uniform, often dark box. The purpose of TLs is the same across the world, they must safely regulate the traffic flow, by informing drivers about the right of way. Right of way is given in a manner which minimize conflicts between vehicles and pedestrians traveling incompatible paths through the intersection during the same time span. The most common TL configuration is the basic red-yellow-green signal, where each state indicates whether a driver should stop, be prepared to stop, or keep driving. Worldwide there are many variations in TL designs; however, all follow a few general guidelines. A TL consists of a box that holds differently colored, and sometimes differently shaped lamps. The orientation, color, size, and shape of the box will vary country to country and even city to city. In the U.S. TLs are regulated by the Federal Highway Administration in the Manual on Uniform Traffic Control Devices [8] and most European countries have signed the Vienna Convention on Road Signs and Signals [18], requiring TLs to meet a common international standard.

2.1. Challenges in recognizing traffic lights

Although TLs are made to be easily recognizable, influences from the environment and sometimes sub-optimal placement can make successful detection difficult, if not impossible. Issues include:

- Color tone shifting and halo disturbances because of influences from the atmosphere and glass that the light passes through[3]. Fig. 2(c).
- Occlusion and partial occlusion because of other ob-

![Figure 2: (a) Examples of TLs from the collected dataset.](image)
sumption that TLs will only appear above this line. They reducing the search area considerably, relying on the as-
in a given video sequence

tion is not available. The detector reaches a detection rate
number of false candidates is very high and color informa-
tion. Specifically, rejection is done based on criteria
which leads to an initial high number of false candidates.
segmented using the white top-hat morphology operation,
color distortion. Areas brighter than their surroundings are
in [5] and it relies purely on intensity from grayscale im-
are selected based on being recent and by representing a
nich in current TL detection.
The first approach of interest is found in [17, 2, 5] which
share the same TL detector. The detector is first presented
in [5] and it relies purely on intensity from grayscale im-
ages. This has the advantage of being more robust to
color distortion. Areas brighter than their surroundings are
segmented using the white top-hat morphology operation,
which leads to an initial high number of false candidates.
False candidates are filtered out based on the shape infor-
mation. Specifically, rejection is done based on criteria
such as, dimensional ratio, the BLOB being hole free and
approximately convex. Furthermore, the areas of BLOBs
are compared to the areas of regions grown from extrema
in the original grayscale image. This is especially effective
for removing false candidates found in bright uniform areas
such as the sky. This detector relies heavily on a competent
classifier for further rejection and state estimation, since the
number of false candidates is very high and color informa-
tion is not available. The detector reaches a detection rate
of more than 90%. The detection rate is described as the
ratio between correct TL recognitions and the ground truth
in a given video sequence

[19] begins by detecting the vanishing line and thereby
reducing the search area considerably, relying on the as-
sumption that TLs will only appear above this line. They
then apply the white-top hat operation, similarly to [17, 2,
5]. This is done on the intensity channel V from the HSV
color space. The top-hat operation yields a greyscale like-
hood map which is thresholded to create a binary candi-
date map. Remaining candidates are filtered based on sta-
tistical measurements of the hue and saturation ranges of
red and green lights. All pixels outside these ranges are
rejected while the remaining pixels are selected as candi-
dates. Candidate BLOBs assigned scores based on size
and height-width ratio. They then look for black bounding
boxes around the BLOBs based on gradient information
and the blackness of the inside of box candidates. These
metrics are also translated into a score and combined with
the BLOB score. Finally, candidates are confirmed if their
scores are high. Their system reaches an accuracy of 85%.
The accuracy is the overall recognition rate taking true posi-
tives, false negatives, and false positives into considera-
tion.

[11] extracts candidate BLOBs from RGB images by ap-
plying a color distance transform proposed in [15]. The
transform emphasizes the chosen color in an intensity im-
age, which is thresholded to remove to suppressed colors.
This is followed by shape filtering to reduce noise using
width/height ratio and the solidity of BLOBs. The solid-
ity is calculated based on the ratio between the area of the
BLOB and it’s bounding box. When evaluating their sys-
tem, they count a success if the TL was detected just once
in the sequence, this allows them to reach a detection rate
of 93%.

An easy way of improving the segmentation is to reduce
the search area. A popular and simplistic approach is to
limit the search to the upper half of the input image. A so-
plicated and precise approach is seen in [7], where an
off-line database containing prior knowledge of TL loca-
tions is used. The off-line database is created using the
input image combined with accurate GPS measurements, and
then manually hand-labeling of the areas with TLs on a pre-
captured image sequences. Given that the route which the
TLR system is used upon is hand-labeled, such an off-line
database can reduce the searching window and the detection
problem significantly. However, collecting and maintaining
such a database is very time-consuming. Besides the use of
prior knowledge, [7] uses color and shape information for
final localization of candidates. With the use of their prior
map their approach reach a precision of 99% and a recall of
62%.

Table 1 provides an overview of the four mentioned TL
detectors along their reported performance measurements.
Note that detector performance is reported using different
measures and on vastly different data sets, making compar-
ison difficult.
Table 1: Overview of recent studies in TLR. GT is an abbreviation of ground truth

<table>
<thead>
<tr>
<th>Paper</th>
<th>Year</th>
<th>Color Space(s)</th>
<th>Segmentation</th>
<th>Filtering</th>
<th>Dataset(GT TLs)</th>
<th>Conditions</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>[17, 2, 5]</td>
<td>2009</td>
<td>Grayscale</td>
<td>Top-hat spot light detection</td>
<td>BLOB filter, shape, structure</td>
<td>10,339 (ParisTech)</td>
<td>Urban day</td>
<td>90% Detection rate</td>
</tr>
<tr>
<td>[19]</td>
<td>2014</td>
<td>HSV</td>
<td>Top-hat spot light detection</td>
<td>BLOB filter, color, shape, structure</td>
<td>3,767</td>
<td>Good, challenging, very challenging</td>
<td>85% Accuracy</td>
</tr>
<tr>
<td>[11]</td>
<td>2013</td>
<td>RGB</td>
<td>Color thresholding</td>
<td>BLOB filter, shape</td>
<td>12,703</td>
<td>Night</td>
<td>93% Detection rate</td>
</tr>
<tr>
<td>[7]</td>
<td>2011</td>
<td>-</td>
<td>Prior knowledge of TL location</td>
<td>BLOB filter, color and shape</td>
<td>1,383</td>
<td>Morning, afternoon, night</td>
<td>99% Precision, 62% Recall</td>
</tr>
</tbody>
</table>

4. LISA Traffic Light Database

As it was concluded in the traffic sign survey paper [13], the general approach for testing and validating a proposed method is to use a privately collected dataset. This is considered sufficient for preliminary testing and validation. But, when trying to estimate the performance of a contribution, it becomes difficult to compare the work with others’. The only currently public dataset is provided by Robotics Centre of Mines PariTech in France. The dataset consists of 11,179 frames from a single 8m 49s long video. It contains 9,168 hand-labeled instances of TLs. More information about this dataset can be found in Table 2.

A public database for computer vision should support the three part stereo vision bottom-up paradigm described in [16]. [16] provides an overview of vehicle detection systems based on both monocular and stereo vision since 2005. Both monocular and stereo vision are widely used for solving this problem, but an interesting finding in this work is the stereo vision bottom-up paradigm which consists of visual odometry, feature points in 3D, and distinguishing static from moving points, which is also mentioned in [4]. The motivation for having a public TL database with stereo images is therefore that all three parts in this paradigm can help reduce the amount of false positives. This notion is reinforced in [1] where the main technical challenges in urban environments are occlusions, shadow silhouettes, and dense traffic. The introduction of stereo has shown promising results in solving these challenges.

The database that is collected and released together with this paper is focused on TLR and contains TLs that are found in San Diego, USA. Even though it was collected with TLR in mind, it could also become useful for evaluation of other related computer vision challenges, since it contains numerous traffic signs, vehicles, pedestrians, etc. The stereo image pairs are acquired using the Point Grey’s three lens CCD camera, Bumblebee XB3 (BBX3-13S2C-60) with a resolution of 1280 x 960, each lens has a horizontal Field of View(FoV) of 43° and a focal length of 6mm. The stereo camera supports two different baselines, 12 and 24 cm, whereof a baseline of 24 cm is used for the LISA TL database. The stereo images are uncompressed and rectified on the fly, and captured with a frame rate of 16 FPS. Capturing was done by mounting the stereo camera centrally up front on the capturing vehicle’s roof. The database provides two day and two nighttime sequences for testing and 18 shorter video sequences intended for training and additional testing. They are organized as seen in Table 3, which gives a detailed overview of all the video sequences that are made available with this paper. The number of annotations is the accumulated number of hand-labeled TLs on a frame-by-frame bases. The number of TLs is the physical number of TLs in the physical world. Camera gain and shutter speed were manually set to avoid oversaturation as well as to minimize flickering from the TLs. For all day clips, a shutter speed of 1/5000s and 0 gain was used. For all night clips, a shutter speed of 1/16s and 8 gain was used. A Triclops calibration file is provided along with the stereo images. This file contains the factory calibration for the used Bumblebee XB3 camera, which can be used with Point Grey’s Triclops SDK.

Each sequence in the database comes with 2 hand labeled annotations for the left stereo frame. The annotations for a given video sequence contain the following information: frame number, rectangular area around the lit TL lamp or TL box, and the state of that area. Labeling is done for every visibly lit TL lamp. An example of annotated TLs is seen in Figure 3. The purple annotations are available which only mark the lit TL lamp. The green annotations cover most of the TL box and are meant for detectors that aim at detecting the entire box. The LISA Traffic Light Database is made freely available at http:
Table 2: Overview of current public TL databases. Ambiguous means that it could not be decided whether the light was a TL during annotation, these are ignored when evaluating.

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>#Classes 4 (green, orange, red &amp; ambiguous)</td>
<td>7 (go, go forward, go left, warning, warning left, stop, &amp; stop left)</td>
</tr>
<tr>
<td>#Frames / #Annotations 11,179 / 9,168</td>
<td>46,418 / 112,971</td>
</tr>
<tr>
<td>Image spec. 640 x 480, 8-bit, RGB</td>
<td>Stereo, 1280 x 960, 8-bit, RGB</td>
</tr>
<tr>
<td>Place of origin Paris, France</td>
<td>San Diego, USA</td>
</tr>
<tr>
<td>Video included</td>
<td>Yes, 8min 49s @25FPS</td>
</tr>
<tr>
<td>Description 1 urban day time sequence 4 test sequences ≥ 5min and 18 clips ≤ 2min 49s, morning, evening, night</td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Overview of the video sequences in LISA Traffic Light Database.

<table>
<thead>
<tr>
<th>Sequence name</th>
<th>Description</th>
<th># Frames</th>
<th># Annotations</th>
<th># TLs</th>
<th>Length</th>
<th>Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day seq. 1</td>
<td>morning, urban, backlight</td>
<td>4,800</td>
<td>10,267</td>
<td>25</td>
<td>5min</td>
<td>Go, warning, warning left, stop, stop left</td>
</tr>
<tr>
<td>Day seq. 2</td>
<td>evening, urban</td>
<td>9,586</td>
<td>11,154</td>
<td>29</td>
<td>6min 10s</td>
<td>Go, go forward, go left, warning, stop, stop left</td>
</tr>
<tr>
<td>Night seq. 1</td>
<td>night, urban</td>
<td>4,992</td>
<td>18,889</td>
<td>25</td>
<td>5min 11s</td>
<td>Go, go left, warning, stop, stop left</td>
</tr>
<tr>
<td>Night seq. 2</td>
<td>night, urban</td>
<td>6,533</td>
<td>23,776</td>
<td>54</td>
<td>6min 48s</td>
<td>Go, go left, warning, stop, stop left</td>
</tr>
<tr>
<td>Day clip 1</td>
<td>evening, urban, lens flare</td>
<td>2,161</td>
<td>6,474</td>
<td>10</td>
<td>2min 15s</td>
<td>Go, stop</td>
</tr>
<tr>
<td>Day clip 2</td>
<td>evening, urban</td>
<td>1,031</td>
<td>2,230</td>
<td>6</td>
<td>1min 4s</td>
<td>Go, go left, warning, stop, stop left</td>
</tr>
<tr>
<td>Day clip 3</td>
<td>evening, urban</td>
<td>643</td>
<td>1,087</td>
<td>3</td>
<td>40s</td>
<td>Go, warning, stop</td>
</tr>
<tr>
<td>Day clip 4</td>
<td>evening, urban</td>
<td>397</td>
<td>859</td>
<td>8</td>
<td>24s</td>
<td>Go</td>
</tr>
<tr>
<td>Day clip 5</td>
<td>morning, urban</td>
<td>2,667</td>
<td>9,717</td>
<td>8</td>
<td>2min 46s</td>
<td>Go, go left, warning, stop, stop left</td>
</tr>
<tr>
<td>Day clip 6</td>
<td>morning, urban</td>
<td>468</td>
<td>1,215</td>
<td>4</td>
<td>29s</td>
<td>Go, stop, stop left</td>
</tr>
<tr>
<td>Day clip 7</td>
<td>morning, urban</td>
<td>2,718</td>
<td>8,189</td>
<td>10</td>
<td>2min 49s</td>
<td>Go, go left, warning, stop, stop left</td>
</tr>
<tr>
<td>Day clip 8</td>
<td>morning, urban</td>
<td>1,040</td>
<td>2,025</td>
<td>8</td>
<td>1min 4s</td>
<td>Go, go left, stop, stop left</td>
</tr>
<tr>
<td>Day clip 9</td>
<td>morning, urban</td>
<td>960</td>
<td>1,264</td>
<td>4</td>
<td>59s</td>
<td>Go, go left, warning, stop, stop left</td>
</tr>
<tr>
<td>Day clip 10</td>
<td>morning, urban</td>
<td>48</td>
<td>109</td>
<td>4</td>
<td>3s</td>
<td>Go, stop</td>
</tr>
<tr>
<td>Day clip 11</td>
<td>morning, urban</td>
<td>1,052</td>
<td>1,268</td>
<td>6</td>
<td>1min 5s</td>
<td>Go, stop</td>
</tr>
<tr>
<td>Day clip 12</td>
<td>morning, urban</td>
<td>152</td>
<td>229</td>
<td>3</td>
<td>9s</td>
<td>Go</td>
</tr>
<tr>
<td>Day clip 13</td>
<td>evening, urban</td>
<td>693</td>
<td>873</td>
<td>8</td>
<td>43s</td>
<td>Go, warning, stop</td>
</tr>
<tr>
<td>Night clip 1</td>
<td>night, urban</td>
<td>591</td>
<td>1,885</td>
<td>8</td>
<td>36s</td>
<td>Go</td>
</tr>
<tr>
<td>Night clip 2</td>
<td>night, urban</td>
<td>2,299</td>
<td>4,205</td>
<td>25</td>
<td>2min 24s</td>
<td>Go, go left, warning, stop, stop left</td>
</tr>
<tr>
<td>Night clip 3</td>
<td>night, urban</td>
<td>1,051</td>
<td>1,476</td>
<td>14</td>
<td>1min 6s</td>
<td>Go, go left, warning, stop, stop left</td>
</tr>
<tr>
<td>Night clip 4</td>
<td>night, urban</td>
<td>1,104</td>
<td>2,538</td>
<td>9</td>
<td>1min 9s</td>
<td>Go, warning, stop</td>
</tr>
<tr>
<td>Night clip 5</td>
<td>night, urban</td>
<td>1,453</td>
<td>3,242</td>
<td>19</td>
<td>1min 31s</td>
<td>Go, go left, warning, stop, stop left</td>
</tr>
</tbody>
</table>

//cvrr.ucsd.edu/LISA/datasets.html for educational, research, and non-profit purposes.

5. Evaluation

A wide variety of approaches and metrics have been used to evaluate detector performance. A standardized methodology would make comparison more straightforward. For evaluations on the LISA Traffic Light database we suggest using: precision and recall, which are defined in equation (1) and (2). TP, FP, and FN are abbreviations for true positives, false positives and false negatives. The TPs, FPs and FNs should be evaluated on a per frame basis.

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (1)
\]

Precision is the ratio of correct TL detections to the total number of detections made by the detector.

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (2)
\]

Recall is the ratio of correct TL detections to the actual number of TLs.

For presenting and evaluating the overall system performance, we suggest generating a precision-recall curve and using the area-under-curve (AUC) as performance measure. A high AUC indicates good performance, an AUC of 100% indicates a perfect system performance for the testset. An example of a precision-recall curve is seen in Figure 4.

The Pascal overlap criterion defined in equation (3) is used to determine TPs:

\[
a_0 = \frac{\text{area}(B_d \cap B_{gt})}{\text{area}(B_d \cup B_{gt})} \geq 0.5 \quad (3)
\]

\(a_0\) denotes the overlap ratio between the detected bound-
Figure 4: Example of a precision-recall curve

We propose that future DAS focused TLR systems are evaluated on a frame-by-frame basis. Furthermore, a proposed system’s accuracy should be calculated using AUC for a PR curve. The proposed evaluation terms are listed below:

- True positives are defined according to equation (3).
- Precision, as seen in equation (1).
- Recall, as seen in equation (2).
- Area-under-curve for Precision-Recall curves.

6. Concluding Remarks

We have presented an overview of four state of the art approaches to traffic light detection, which have been published in recent papers on traffic light recognition (TLR). None of the examined TL detection approaches rely on machine learning. This raises the question of whether learning based approaches would be able to outperform these heuristic model based detectors on a challenging dataset such as the one presented in this paper. Because the systems are evaluated using different methodology and on very different datasets it is not clear which approach is the best. The approach proposed in [7] has the major advantage of using prior maps, which significantly ease the detection problem. Only one public database with traffic lights (TLs) is currently available and it is not widely used. We therefore contribute with the LISA Traffic Light Database, which contains TLs captured using a stereo camera on roads in San Diego, USA under varying conditions. The database is supposed to enable comparable evaluation on a large and varied dataset, and provides the possibility of including stereo vision for improving TLR. Along with the dataset we propose a standardized method for evaluating TLR systems, which should enable easy comparison between future detectors. The dataset will eventually be included in the VIVA Challenge [12].

References


