A Traffic Light Recognition Device

49

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Abstract

Traffic lights detection and recognition research has grown every year. Time is coming when autonomous vehicle can navigate in urban roads and streets and intelligent systems aboard those cars would have to recognize traffic lights in real time. This article proposes a traffic light recognition (TLR) device prototype using a smartphone as camera and processing unit that can be used as a driver assistance. A TLR device has to be able to visualize the traffic scene from inside of a vehicle, generate stable images, and be protected from adverse conditions. To validate this layout prototype, a dataset was built and used to test an algorithm that uses an adaptive background suppression filter (AdaBSF) and Support Vector Machines (SVMs) to detect traffic lights. The application of AdaBSF and subsequent classification with SVM to the dataset achieved 100% precision rate and recall of 65%. Road testing shows that the TLR device prototype meets the requirements to be used as a driver assistance device.

Keywords

Traffic light detection and recognition · Support vector machines · Computer vision · Expert systems

49.1 Introduction

A study published by [1] shows that in August/2016, advancing the red sign in traffic light was the second main infraction associated with fatal accidents involving motorcycles, cars and bus in the city of São Paulo, Brazil.

Traffic lights are widely used as a traffic regulator device. Although it is a simple and logical device, drivers frequently cross the red light causing accidents with serious consequences as death to drivers, passengers, and pedestrians.

Some situations can be pointed as probable causes to these infractions:

- Poorly located traffic lights;
- Faulty/off traffic lights or in very dim light;
- Ambient light that disturbs the vision of the driver;
- Visual impairment of the driver;
- Doubt if there is enough time to cross the traffic light when the signal turns yellow;
- Number of traffic regulator items to be observed.

The first two listed items can be easily solved with the effort of the traffic regulator in arranging and maintaining traffic lights optimally on the streets. However, the problematic presented by the remaining items could be minimized by using a Traffic Light Recognition Device—TLR to assist the driver.

The main task of a TLR is to avoid accidents and save lives by informing the presence of a red or yellow traffic light to the driver in a non-intrusive way. In addition, an even more complex TLR can bring other information such as which is the main traffic light for a route when there is more than one and how far the traffic light is.

Another information that could be extracted from a more complex TLR is what speed the driver must maintain to advance the largest number of green signals in sequence on a given avenue.

A TLR would also be very useful for pedestrians who are visually impaired. Although several crossings for pedestrians have signaled adapted for visually impaired people, few adaptations include sound signaling. In addition, there are many crossings that do not have pedestrian traffic lights, thus

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leaving the visually impaired dependent on others to cross the street in safety.

The device used to build a TLR and how it is positioned at the vehicle has a big influence in the TLR success. For example, if the device has a faulty camera the images may not reflect the scene reality. Also if the device can not see clearly the road, or it is not stable, the images can be blur or miss some important information from the real world.

In this paper we evaluate a TLR layout prototype using a detection and recognition method proposed by [2]. The proposed TLR uses a smartphone as camera and processing unit. The results shows that the proposed layout is valid and can be used to test TLRs, build traffic light datasets, and build other image datasets related to traffic and vehicles.

49.2 Related Work

An object recognition mechanism works in two phases in order to recognize objects from an image: (1) an initial phase to detect targets as possible objects, and (2) a second phase to classify the targets.

When working with object detection/recognition we need to define which object features shall be used to guide the algorithms. In traffic light recognition, features such as light, shape, and color are commonly used.

Concerned literature shows that Neural Networks, Saliency Map, and Blob Detection are the most common techniques used to detect traffic lights.

Weber et al. [3], John et al. [4–6] used Convolutional Neural Network—CNN to detect possible traffic lights, while [7] used a PCAnet NN.

Philipsen et al. [8] used a learning algorithm based on image feature channels and Histogram of Oriented Gradient—HOG to detection and recognition.

Saliency Maps was used as a detection tool by [9–12] and [5]. We also observed fine examples of Blob Detection use in [13–15].

Geometric transforms were used in detection phase by [16, 17] and [18], which applies the Hough Circular Transform and [19], which used the Radial Symmetry Fast Transform.

Some less common techniques used alone or in association with the ones cited before are Adaptive Filters [2], Template Matching [20], Gaussian Distribution [21], Probability Estimation with CNN [3], and Top Hat [22].

Processing image algorithms are also commonly used to detect traffic lights. Color or shape segmentation was used by [23] and [24]; and threshold was used by [25] and [26].

To recognize traffic lights, most works used Machine Learning algorithms, mainly CNN and variants, Support Vector Machines—SVMs, and Fuzzy systems. Chen and Huang [14] used CNN whereas [3] used a PCAnetwork, a NN that simulates a CNN using less layers. SVMs were used by [2, 7, 12–14, 27–31] to recognize traffic lights, sometimes along with a NN. Fuzzy was also used in [10] and [32].

Other techniques were used as ML substitutes, to improve false positives detection or to make the connection between detection output and recognition input. Zhou et al. [13], Michael and Schlipsing [28], Ji et al. [12], Almeida et al. [11], and Almagambetov et al. [33] used Histograms. Balcerek et al. [34], Cai [35], Omachi and Omachi [18] and [36] used Transforms. John et al. [5], Choi et al. [37], Fan [38], and de Charette and Nashashibi [39] used Template Matching. John et al. [6] used Saliency Map and [40] used Probability Histograms.

Normalized Cross Correlation was observed in [41] to recognize pedestrian traffic lights. Hidden Markov Models—HMM were used in [42] to recognize common traffic lights.

To highlight regions of interest—ROI at the image, [2] proposed an Adaptive Background Suppression Filter—AdaBSF. In the algorithm, a 4-channel feature map W_i, where i represent the 4-channel feature map index, are generated extracting R, G and B channels and calculating the normalized gradients of the input image.

To search for vertical and horizontal traffic lights, the window size for W_i is fixed as 16×8 pixels and 8×16 pixels, respectively. As each window is 4-dimensional the pixel amount is $D = 16 \times 8 \times 4$ per window. Each window is represented by a feature vector x of size $D = 512$. The multi-scale problem was solved by down-sampling the original image to different scales while the window detection remains with fixed size.

The aim of AdaBSF algorithm is to design an Finite Impulse Response (FIR) filter specified by the vector $w = [w_1, w_2, \ldots, w_D]^T$ in a way that $y = w^T x$. The output y assigns a score to each detection window, which represents how likely the detection window covers a traffic light [2].

To classify the ROI found by AdaBSF, [2] used Support Vector Machines—SVM. The author created a cascade of SVM classifiers that begins classifying the ROI whether it is a traffic light or not. If it is a traffic light the next SVM classify the ROI into "red type" or "green type". After this the traffic light is classified in more specifics types considering if it has an arrow and its direction by the next SVM using a '1-vs-1' voting method.

In this paper, the method proposed by [2] was applied at images obtained by a TLR device that uses a smartphone as camera, and with possible use as a processing unit. The TLR follows a specific layout to use the TLR in real-time. This layout is specified in the following sections.

In order to validate the method presented in [2], the algorithm was reimplemented in Python language. SVMs and AdaBSF algorithm was trained with traffic light samples made available by the author and used in [2]. Negative samples, i.e. background samples, was extracted from four random test sequences also made available by the author, once the negative samples used in [2] was not accessible.

The algorithm was tested with the test sequences that was not used to generate the negative samples for training, obtaining a precision rate of 90%. In Fig. 49.5 it is possible to see the reproduction result in comparison with the original work result. There is little difference between the reproduction results and the original results, what validates the reproduction and the original work. Section 49.3.1 presents a detailed discussion over these result.

49.3 Traffic Light Recognition Device Prototype

A main question when prototyping a TLR Device is where it will be positioned at the vehicle, once it has to be in a position that allows it to observe the traffic clearly without compromising the vision of the driver. Another critical observation is that the device shall be protected from adverse meteorological conditions like rain, or be waterproof. The heat also might cause problems in some electronic devices, so the sunlight incidence at the device location may be considered as well.

As the vehicle moves, it is normal to observe some trepidation. However, this trepidation might have a negative influence in the device vision. Considering this, the device needs to be the most stabilized as possible. The device also has to be able to generate a warning sound to advise the driver, to see the traffic using a camera, and to have a computational unit to process the data. An accessible device that accomplishes these requirements and is commonly used to help drivers at traffic are the smartphones.

In this work, a smartphone was positioned inside a vehicle to capture real traffic scenes with and without traffic lights. Two kinds of supports are generally used to position a smartphone in a useful location to help the driver: air conditioning supports and windshield suction cups. Air conditioning supports can not be used to position a TLR Device because it has no outside view from the vehicle. Windshield suction cups supports are a possible choice, however, the support may fall down with or become very shaking if low quality suckers were used.

Fig. 49.1 TLR device support holding an iPhone 6

To overcome the smartphone supports problems and to meet the requirements specified previously we designed an stable device support using a two-sided tape and part of a windshield suction cup support. We remove the support part that holds the device from the cable with suction cup that is attached to the windshield. Then we fixed the first part centralized at the vehicle panel with the two-sided tape. This design allow the device to capture the traffic scene without a bias to the left or to the right. The proposed layout obligates the device to use the camera in landscape mode, minimizing the amount of sky captured and maximizing the traffic scene size obtained with more visible traffic lights (Fig. 49.1).

Three different smartphones was used to capture traffic videos containing traffic lights: Motorola G second generation, iPhone 6, and Galaxy S8+. All devices was configured to capture video with HD resolution. Figure 49.2 shows an example of images obtained with this devices. The images were extracted from videos at 5 frames per second (fps) rate.

49.3.1 Prototype Results

The images obtained by the TLR device using this support prototype were submitted to classification in a personal computer using the method applied in [2].

The images was obtained using three different smartphones. The first group obtained with Motorola G 2nd Generation did not present good results, for this reason it was not accounted in the results. The second group with images obtained by iPhone 6 contains 682 images, 209 negative samples and 473 traffic light samples. The third group is formed by 247 images obtained with Galaxy S8+, being 165 traffic light samples and 82 negative samples.

Fig. 49.2 Images obtained using the TLR Device support prototype with different smartphones. From top to bottom: image obtained by Motorola G 2nd Generation, by iPhone 6, and by Galaxy S8+

An amount of 929 traffic images were analyzed: 638 images containing green or red traffic lights and 291 images not containing traffic lights, the negative group.

Considering that most times there are two equal traffic lights for the same road, we account as one true positive for traffic light type when one or both of the traffic lights are recognized in image. So from each image we have one error or one hit. This also reflects the real life behavior when we just need to look at one traffic light to make a choice.

In Fig. 49.3 it is possible to see detailed results from each image group. The two groups achieved high precision rates, but the iPhone 6 group presented a low recall rate of 60%. This result can be can be explained by the fact that traffic lights samples used in training dataset are too different from some traffic lights present in the iPhone group dataset as shown in Fig. 49.4. If the training samples does not properly represent the real world some traffic lights can not be recognized.

Also the illumination condition in the dataset training are very different from the condition found in test dataset due to geographic/meteorological issues and possibly the device used to obtain it. These conditions have influence in the final result as well.

The distance from the TLR device to the traffic light is crucial to recognition. So far the device was able to correctly classify the traffic lights from second car line, considering the traffic stopped at red traffic light.

The iPhone group low recall rate influenced the final rates of TLR tests, as observed in Fig. 49.5. In comparison with the results obtained by [2] and by our reproduction using data from [2], the TLR result is valid to justify its use in future research.

49.4 Conclusion

This work presents a TLR device layout prototype used to capture road scenes. The tests achieved a 100% precision rate and 65% recall rate. The results demonstrate the prototype feasibility. The recall rate can be improved by training the applied algorithm with more representative samples, which will be done in the future along with cross-validation tests. The results also show that Galaxy S8+ and iPhone 6, two different mobile platforms, can be successfully used as TLR devices. Another future work includes real-time tests, investigating other detection and recognition models that could fit better with the obtained dataset, and expansion of the dataset itself.

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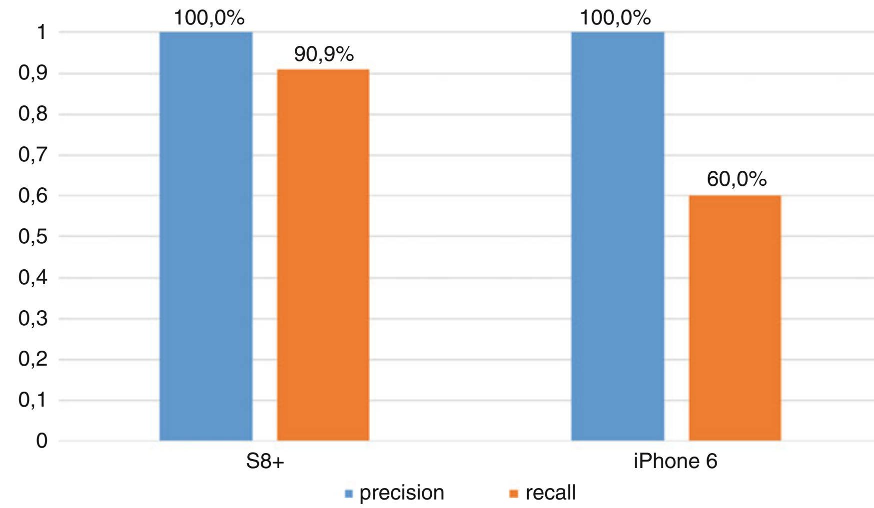

Fig. 49.3 Precision and recall rates by smartphone used to obtain the images

Fig. 49.4 From left to right: red and green traffic light sample used in training, red and green traffic light sample from the test dataset obtained with the TLR device prototype

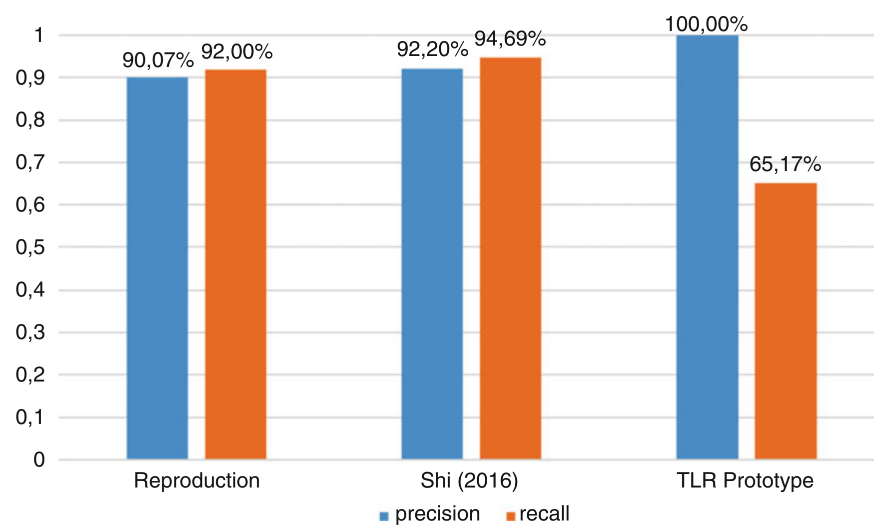

Fig. 49.5 Precision and recall rates on our reproduction of [2], original work from [2], and tests using the images obtained with the TLR device prototype, respectively

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