Traffic Light Recognition During the Night Based on Fuzzy Logic Clustering

Moises Díaz-Cabrera[1] and Pietro Cerri[2]

[1] University of Las Palmas de Gran Canaria, Spain
moisdc@gmail.com
[2] VisLab - University of Parma, Italy
cerri@ce.unipr.it

Abstract. Traffic light recognition in night conditions is explored throughout this paper. A system detecting suspended traffic lights in urban streets is proposed. Images are acquired by a color camera installed on the roof of a car. Fuzzy logic-based clustering provides robust color detection. Additionally, other techniques end up recognizing the traffic light state. The detection rate is quite high and the false positive proportion is really low.

Keywords: Traffic Lights Detection, Advanced Driver Assistance System (ADAS), Patter Recognition, Image Processing, Color Threshold Segmentation.

1 Introduction

Traffic light detection challenge is addressed in scientific literature [8,2,11,4]. Indeed, nowadays both highways and urban traffic networks are often controlled by traffic lights.

On one hand, Kim *et al.* [7] have dealt with this kind of recognition. They reported that there were many noises due to street lights, car headlights, and

Fig. 1. Traffic light recognition during the night in an urban road

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sign boards during the night. They got successfully rid of many false positives using a thresholding algorithm.

On the other hand, a different approach was presented in [5]. Fairfield *et al.* coped with a large set of traffic light images. They were able to detect traffic signs both in day and night conditions. A digital prior map helped to predict where a traffic light could be located in the world. A digital map with information about the pose of traffic lights could give more robustness to our system as well.

Nevertheless, others research groups around the world have performed maturate development in Vehicle-to-Infrastructure (V2I) communication technologies, based on Radio Frequency IDentification (RFID) or wireless networks. Although these technologies could potentially substitute system like the one presented, researches in Advance Driver Assistance Systems still deal with traffic light recognition.

This paper presents an extension of our last work [3]. Figure 1 shows a typical scene in which our algorithm was tested. Our focus of interest was the recognition of traffic lights during night, following the next steps:

1. A fuzzy logic-based clustering to create isolated images: each isolated image correspond to red, amber, green and black cluster.
2. Classical morphological operations: an erosion followed by a dilation.
3. Some rules based on traffic lights features.
4. A simple tracking to filter the remaining false positives.

Our recognition approach could slightly vary both during day and night, or even in case of different weather conditions, such as cloudy, rainy, foggy, etc.

The paper is organized as follows: in section 2 the developed algorithm is explained. The results are presented in section 3 and the paper closes with some conclusions and future work ideas in section 4.

2 Traffic Light Detector during Night

A fundamental requirement is that camera parameters, both intrinsic and extrinsic, must be previously computed. The intrinsic parameters were calculated using the classic Zhang method. In order to compute extrinsic parameters, a wall built by large blocks (1.2 meters) was used as a grid. The camera orientation parameters were estimated adjusting pitch, roll and yaw values matching the lines with the drawn grid. After that, the live video was processed according to next steps.

2.1 Fuzzy Logic for the Clustering

During night, spots of lights are usually framed in the image as a spot bigger than the real size, due to saturation effect. Moreover, colors saturate to white and it is quite impossible to distinguish between different traffic lamps. To avoid this drawback, the shutter time of the camera should be drastically decreased. As negative effect, the live video could become too dark, and the images could be used to detect brightest traffic lights only, such as LED lights. Shutter time was empirically tuned, taking into account these effects.

A controlled clustering process was performed on the images. Four images were created for each frame containing red, amber, green and black clusters. Red, amber and green clusters included pixels with R, G, B components similar to respective traffic light colors. Black cluster image contained very dark pixels. Black cluster also contained false positive colors, uncategorised samples and confusing samples, i.e. colors similar to red, amber and green lights colors but that cannot belong to a light.

The clustering process was based on a fuzzy logic trained using a large number of samples. The chosen R, G, B samples were selected from a number of random samples during the night. The R, G, B data from raw images and the R, G, B normalized data (R_N, G_N, B_N) from normalized images, were used to design the clustering algorithm. The normalized color space, used in this part, follows that relationship: $\chi_N = \frac{\chi}{R+G+B}$, being χ the channel R, G or B. All these six data were combined each other for each cluster. The mean and the standard deviation were calculated for each component combination. Then, their correspondent Gaussian functions were represented as their frequency intensity plot. Each normalized Gaussian curves represented the best membership curve for the fuzzy system. Since nineteen different combinations were found as the more relevant, according to mean and standard deviation, four Gaussian-based fuzzy set for each combination were computed. That combination were: $R, G, B, R_N, G_N, B_N, R-G, R-B, G-B, R_N-G_N, R_N-B_N, G_N-B_N, R-G-B, G-R-B, R+G-B, R_N-G_N-B_N, G_N-R_N-B_N, R_N+G_N-B_N$ and $R+G+B$, being the sub-index N the normalized component color. In Figure 2 the "R" combination is represented. Here, the four membership functions, which belong to mentioned clusters, were plotted. Using these values, a new test pixel could be evaluated according its "R" component value. If it is close to green mean curve, the test sample pixel could belong to the green cluster. If not, it could be difficult to discriminate between red and amber clusters using only the "R" component value due to the similarity of red and amber curves. Hence, false positive curve has a large deviation; therefore, this curve was not allowed to discriminate if a test pixel belongs to black cluster (false positive).

In addition, five fuzzy sets for each traffic lamp color (red, amber and green), according to the smallest standard deviation, were selected. The distances with other means were taken into account before the selection of these five values. The sum of these five components determined the final fuzzy value. The soft computing technique previously explained, was integrated into sequential rules. Therefore, several ranges based on RGB and RGB normalized components were established. Since red and amber components were extremely similar, the fuzzy logic was used to decide whether one component was red, amber or maybe false positive. Finally, four isolated monochromatic images were achieved at the end of

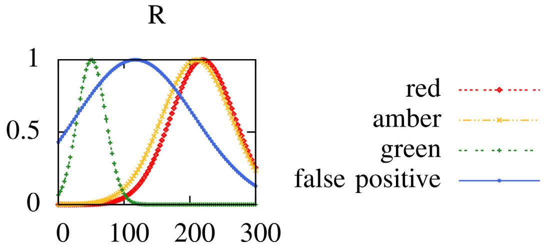


Fig. 2. Fuzzy Membership Function for the Red combination

this process, representing red, amber, green, and uncategorised or false positive pixels (black cluster) respectively. In the following steps the resulting images were managed.

Simple sequential techniques have been carried out for the clustering problem by other authors, for instance, A. Vu *et al.* [12], M. Omachi *et al.* ([10,11]) or even in our previous work [4]. Better results have been found in the present research by combination of fuzzy logic and sequential rules. Another similar approach is shown in [2], where hue and intensity images were combined together with illumination data to recognise traffic lights, then, possible traffic lights were obtained by fuzzification of all these data.

2.2 Morphological Operations and Labelling

Two processes were performed on each image: erosion and dilation. Therefore, after these processes, a new image was obtained for each color image: Img' = $((\mathrm{Img} \ominus e) \oplus d)$. This is a typical process carried out in many works [1,9]. Different thresholds were used for different colors, according to the results obtained in the first test, which highlighted the different brightness of the lamps.

The labelling process was a quite standard part. The three computed colors images, which contained red, amber and green information colors, were elaborated. All the connected areas in the image were detected using a flood fill algorithm [6]. Using the information of each label, it became possible to build a bounding box which contained the whole area.

2.3 Rules

Two simple rules, based on the aspect of the detected spot, were performed:

Bounding box features First of all, bounding box width and height were taken into account. The diameter of real lights in analysed traffic lights was 0.3 m for the red lights and 0.2 m for the amber and green lights. Using a perspective mapping transformation, and considering the height range in which lights can be found, it was possible to compute the minimum and maximum diameter of a traffic light for each image row.

Another obvious feature was that if the light is round, its bounding box is square: height and width should be ideally equals. This expression can therefore be considered, being ψ a threshold.

$$\frac{1}{\psi} \leq \frac{\text{height}}{\text{width}} \leq \psi \tag{1}$$

Color pixel density This rule consists on color density measurements. In an ideal case, if a pixel within the light was detected, the shape was a perfect circle. Consequently, the filled area of a color was: $A_{circle} = \pi \cdot r^2$ where r is the radius of the spot on the image. To filter false positive, the number of bright pixels which were contained within the bounding box were counted. To accept a candidate, this relationship must be satisfied:

$$\frac{N_{px}}{A} \leq \chi \tag{2}$$

Assuming that N_{px} was the number of illuminated pixels, A was the area of a square bounding box and χ was a threshold. In an ideal case, $\chi = \frac{\pi \cdot r^2}{(2 \cdot r)^2} \simeq 0.78$. This reference threshold was adapted to real conditions.

2.4 Tracking

A simple tracking stage was performed. This part provides robustness to the recognition. Information about the detected spot was stored: its color, its position in the image and its centre of gravity. Each detected spot can be matched to one previously detected. The number of detections of the same spot (age) and the number of missing detections were also used in this stage to provide a more robust output: if the age exceeded a threshold, the bounding box was validated and shown on the image; on the other hand if a light was missed for a consecutive number of frames higher than a threshold, it was removed.

Traffic lights transitions were also considered at this stage. When a light was turned off and another one was turned on, and the two lights were computed to lay approximately in the same columns of the image, a possible transition was issued. As lighting-up order are known, if an expected change was detected, the old light was removed and the new bounding box inherited its age.

3 Results

The algorithm was developed in C++. Its average processing time was around 70 ms, therefore, it could work under real-time conditions. The evaluated system was an Intel(R) Core(TM)2 Quad CPU Q9550 @ 2.83 GHz with 8GB RAM.

3.1 The Setup Acquisition System

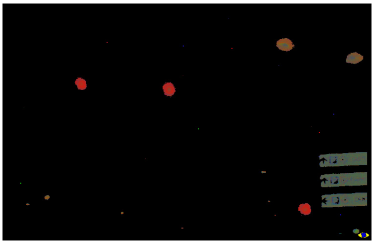
The used camera was installed on the roof of the test vehicle. It was a color 752×480 CMOS sensor camera (AVT guppy F-036C). Its position was pitched up to detect also traffic lights close to the vehicle. A traffic light closer than 10 meters could not be detected, as it was out of the field of view.

3.2 Detection Rate

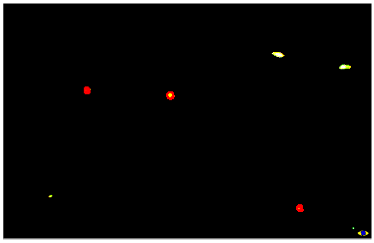
The obtained results encourage following this research line. More than 16000 night-time frames were tested, with 4600 frames containinf traffic lights. In the video sequences many distracting lights were present, especially coming from street lights. However, since they were clustered into a specific cluster, they generated a negligible number of false positives.

Table 1. Detection rate

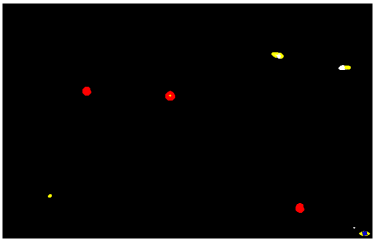
Duration (min)	Total frames	Correct Detection	False positive	Precision %
25	16176	4651	93	98.04



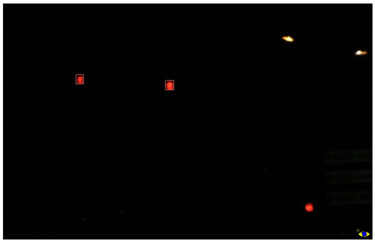
(a) RGB normalized image.



(b) Red, amber, green and black images merge in one image.



(c) Erosion and dilation image.



(d) Output detection result.

Fig. 3. Red detection during the night on a frame

Dirt on the housing of the traffic lights sometimes prevented the complete detection, and provided false negative. Saturation influence often produced a bigger bounding box and wrong color. Consequently, the range of the shutter was slightly low. Lamp traffic lights were more vulnerable to this effect than LED traffic lights because they were more visible. This problem was due to component colors difference between LED and lamp traffic light. Nevertheless, the detection rate was not under the influence of that drawback.

Our detection rate was calculated in terms of $Precision = \frac{TP}{TP+FP}$. The results were detailed in the Table 1. Furthermore, the major part of the frames in the sequences did not have any detected point because no traffic lights were present.

In Figure 3 we can see the algorithm procedure on a frame containing both traffic lights and street lights. Figure 3a shows a normalized color space image. As we can see, some other road object can be seen in this color space, such as the road sign on the right of the image. Both Figure 3b and Figure 3c represent the effect of the morphological operation on the possible detected signs. Finally, Figure 3d shows the correct output of the algorithm.

4 Conclusions and Future Work

A technique to detect suspended traffic lights during night, working in real time, is presented. Complex scenarios due to bright street lights have been taken into account. The shutter time was tuned and false positives were included into a cluster. Then, fuzzy logic combined with sequential rules are presented as a soft clustering process. More than 15000 frames were analysed, and a high detection rate has been achieved.

This approach will be extended to daylight conditions in our future researches. The processing time will be reduced parallelizing the functions of the method, so that the system could guarantee real time conditions. Finally, some ideas about distance estimation combined with ego motion computation are currently under tests to strengthen the tracking part of the algorithm.

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