# DETECTION OF TRAFFIC LIGHTS USING MACHINE LEARNING 

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#### Abstract

Real-time detection of visitors lighting from video feed has numerous actual-lifestyles applications, which include self-using motors, automated train sign detection, and many others. This paper describes a way to locate pink and green round visitors lights from a video feed recorded by way of a digicam established on a shifting automobile. In this technique, we first set thresholds for purple and inexperienced within the RGB shade area after which become aware of blobs inside the body that meet this threshold. After blob detection, we carry out a last operation to cast off gaps. We then become aware of the centre and radius of the round blobs and draw a circle around the detected visitors alerts. The software has been carried out on Matlab on an Intel i5 processor and examined numerous video samples to decide detection accuracy. Further, we also examined the overall performance of the gadget under noisy imaging situations. The method meets real-time processing requirements of 15 frames in step with second.


Key Words: Real-time, traffic-lights, video-feed, blobdetection, closing-operation, Matlab, noisy-imaging conditions

## 1. INTRODUCTION

Real-time detection of traffic lighting fixtures from a video feed unearths numerous applications in brand new global. Most of the trains in Indian Railways today rely on the manual detection of the train signal, increasing the possibility of injuries. In this state of affairs, a machine that robotically detects the visitors sign from the video feed and alerts the driver can enhance street and railway protection. This system also can assist the driving force in identifying traffic lighting fixtures inside the state of affairs of negative visibility because of fog or different environmental situations. Traffic lights are of various shapes, sizes, and colors. In this paper, we cognizance on the detection of purple and green round lighting fixtures. The identical technique can later be extended with slight changes for site visitors lights of other colorings and shapes.

### 1.1 Challenges

First, differentiating many bright purple-coloured and inexperienced-colored objects within the video from visitors lighting fixtures. Secondly, the environment wherein the video is recorded also impacts the accuracy of detection. The presence of fog or dirt particles or low mild situations decreases detection accuracy, main to extra fake negatives and false positives. Gaussian noise, which is brought due to electronic additives such as sensors, also reduces detection
accuracy. Finally, there's also a need to system the frames in real-time and make essential selections on accelerating or decelerating the car. This might necessitate hardware acceleration with the aid of implementing the program on an FPGA.

### 1.2 Related Works

Existing literature on visitors light detection predominantly focuses on picture processing and laptop vision algorithms to hit upon site visitors lighting fixtures. Second, using gadget studying to train the gadget to carry out classification of detected site visitors lighting and enhance performance. This paper focuses totally on Image Processing strategies for the detection of site visitors lighting fixtures.

## 2. IMPLEMENTATION \& RESULTS

### 2.1. Approach

First Step: Detect blob to pick out crimson and green site visitors indicators. To become aware of the blobs, we've got used a threshold for the RGB color values.

Second Step: Generate binary image from an RGB image with blobs having a value of 1 (represented as white regions of the image) and the rest having the value 0 . Fig. 2. shows a binary image after performing colour thresholding on the original frame.


Fig. 1. Source image that is used as a reference for further demonstrations.


Fig. 2. Binary image based on detected blobs
Third Step: Perform a closing operation in this binary photo to fill the gaps. The remaining operation is a morphological operation in digital photo processing which applies a dilation accompanied via erosion and gets rid of gaps and holes. Fig. 3. Shows the end result after performing a ultimate operation on the binary picture.


Fig. 3. Result of performing closing operation on binary image. Notice how the holes have been filled to form circular blobs

Fourth Step: Determine the define or contour of those blobs. For this cause, we decide the blobs' center and radius and use this data to draw a circle across the detected blobs inside the video. Fig. 4. Indicates body with pink coloration site visitors light detected and a cyan coloured circle drawn
around it for ease of identification. Fig. 5. Shows frame with inexperienced visitors lighting fixtures detected and a purple colour marking for ease of identity.


Fig. 4. Red traffic light detection


Fig. 5. Green traffic light detection
Fifth Step: Add Gaussian noise and apply an averaging filter to test the system's robustness under noisy imaging conditions. In Fig. 6. Notice the red circles indicating the large number of false positives detected after adding

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Fig. 6. Green Traffic light detection after adding Gaussian Noise to the original frame.


Fig. 7. Green light detection after filtering using Averaging filter.

### 2.2. Flow Chart

The below program has been implemented on an i5 processor.


## 3. ANALYSIS OF TESTING ON VIDEO SAMPLES (in no noise condition)

For the detection and recognition of traffic lights, two metrics - precision and recall are used.

Precision = true positives /(true positives + false positives)
Recall = true positives /(true positives + false negatives)
$\left.\begin{array}{|l|l|l|l|l|l|l|l|l|}\hline \begin{array}{l}\text { S } \\ \text { No. }\end{array} & \begin{array}{l}\text { Num } \\ \text { frames }\end{array} & \begin{array}{l}\text { Type } \\ \text { of } \\ \text { traffic } \\ \text { lights }\end{array} & \begin{array}{l}\text { Num } \\ \text { traffic } \\ \text { lights }\end{array} & \begin{array}{l}\text { True } \\ \text { positives }\end{array} & \begin{array}{l}\text { False } \\ \text { negatives }\end{array} & \begin{array}{l}\text { False } \\ \text { positives }\end{array} & \begin{array}{l}\text { Precision } \\ = \\ \text { TP/(TP+F }\end{array} \\ \text { P) }\end{array} \begin{array}{l}\text { Recall = } \\ \text { TP/(FN + } \\ \text { TP) }\end{array}\right]$

Table 1 - Test result of 6 sequences that contain red traffic lights

RC is the number of circular red lights in the above table, and GC is the number of circular green lights. The second
sequence shows a precision rate of $55.35 \%$ and a recall rate of $53.21 \%$.

Common objects being identified as false positives include car headlights, road signs, hoardings, and other red objects.

| $\begin{aligned} & \hline \text { S } \\ & \text { No. } \end{aligned}$ | Num frames | Type of traffic lights | $\begin{aligned} & \text { Num } \\ & \text { traffic } \end{aligned}$ lights | True positives | False negatives | False positives | $\begin{aligned} & \hline \text { Precision = } \\ & \text { TP/(TP+FP) } \end{aligned}$ | $\begin{aligned} & \text { Recall } \\ & = \\ & \text { TP/(FN } \\ & + \text { TP) } \end{aligned}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 185 | - | - | 0 | 0 | 0 | 0 | 0 |
| 2 | 455 | RC*2 | $\begin{aligned} & 455^{*} 2 \\ & =910 \end{aligned}$ | 0 | 0 | 25 | 0 | 0 |
| 3 | 390 | - |  | 0 | 0 | 12 | 0 | 0 |
| 4 | 42 | $\begin{array}{ll} \hline \mathrm{GC}^{*} 2 \\ \mathrm{RC}^{*} 1 \end{array} \quad+$ | 84 | 84 | 0 | 11 | 88.42\% | 100\% |
| 5 | 83 | $\mathrm{GC}^{*} 1+\mathrm{RC}{ }^{*} 1$ | 83 | 83 | 0 | 0 | 100\% | 100\% |
| 6 | 89 | GC*1 | 89 | 0 | 89 | 89 | 0 | 0\% |

Table 2 - Test result of 6 sequences that contain green traffic lights

In the above desk, the fourth series has 42 frames, and the type of site visitors lighting fixtures involved are two round green lights and one round crimson light, out which 84 round green lighting are being detected effectively at the side of eleven commonplace gadgets as false positives, so the precision rate decreases to $88.42 \%$. In the 6th series, real green mild isn't always being detected, but some different item constantly affords a fake green light, resulting in a zero\% precision charge. Common objects being diagnosed as false positives consist of inexperienced signboards, hoardings which can be green in shade.

## 4. SCOPE FOR IMPROVEMENT

Since the proposed algorithm continues to be a work-inprogress, we will improve the accuracy within the future. One can use gadget gaining knowledge of algorithms to classify detected lighting and forecasting strategies to enhance overall performance. Template matching with a circular mild interior may be used to identify the square outline of the site visitors sign template. As the automobile movements via specific roads, the traffic lighting fixtures in these areas exhibit a huge variety in brightness and color values, necessitating dynamic thresholding.

## 5. CONCLUSIONS

In this paper, we advise a gadget which could stumble on circular purple and inexperienced traffic lights. Colour extraction and blob detection are used to become aware of the visitors alerts. The software has been implemented on MatLab on an Intel i5 processor tested on several video samples, and the precision and keep in mind calculated. The
overall performance of the device changed into also examined beneath noisy imaging situations. Computer vision and Image Processing toolbox of MatLab are getting used to put into effect the layout. The device has been discovered to satisfy the actual-time processing requirement of 15 frames consistent with 2nd..

## REFERENCES

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