Brake Light Detection by Image Segmentation

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ABSTRACT
This paper describes a method to detect brake lights of road vehicles by color analysis and segmentation of forward-facing images, suitable for an autonomous vehicle.

KEYWORDS
brake light, tail light, image segmentation

INTRODUCTION

Detecting other vehicles is a challenging task in designing an autonomous vehicle system. Such a system must be able to track the speed and relative location of other vehicles on the road. In addition, the system should respond to information from other vehicles, such as turn signals and brake lights, which indicate the vehicles' intended actions. In this paper, I describe a system to robustly detect the presence of vehicle brake lights in arbitrary (not necessarily sequential) color images.

This problem has been approached in several other fields with interesting applications. Sukthankar[1] developed an integrated system for following vehicles at night that recognized brake lights and turn signals. Carswell and Chandran[2] identified vehicles by tail lights to recognize erratic or drunk driving. Several patents by Matsumoto, *et al.*[3], Slotkowski, *et al.*[4], and Stam, *et al.*[5] have also described tail light detection methods for automatically dimming head light intensity when other vehicles are detected in front of the sensor. These systems may be integrated into consumer vehicles, as in the *Auto Dimmer Module* featured below, from the patent file of Slotkowski, *et al.*.

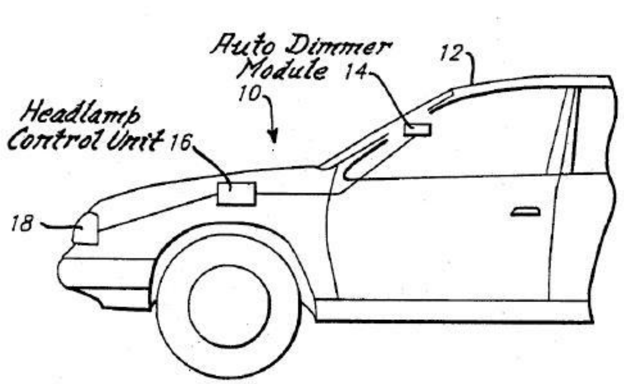

Figure 1: Tail light detection mechanism integrated with a consumer vehicle's head light controller. (Slotkowski, *et al.*)

METHODS

Given a forward-facing color image, I first extract pixels in a range of hue, saturation, and brightness that correspond to tail lights. Connected pixels are grouped (segmented) into regions. Region pairs are then classified by likelihood of being the outer two tail lights of a vehicle. Another round of segmentation is performed with relaxed saturation and brightness boundaries in order to capture the central brake light, which is often dimmer and smaller than the outer tail lights. Each region pair is compared to each relaxed region for likely candidates, based on several assumptions about the geometry of brake lights. Finally, the best candidates are returned as region triplets corresponding to brake lights.

Region Segmentation by Color

I assume that the light from brake lights occupies a narrow range of hue, saturation, and brightness. Given these ranges, I construct a binary image where white corresponds to the pixels of the color image within the ranges. Since the range of hue that I'm interested is chiefly red and the digital representation of red is 0 (of 255), I first shift the hue of the image by 128. Given this shift, manual measurements of brake light hue yielded a hue range of [110, 170], also pictured unshifted below.

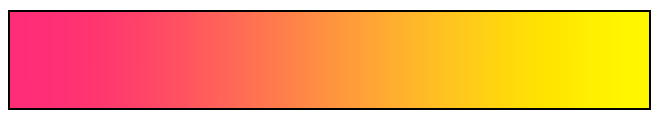

Figure 2: Brake light hue range (unshifted).

Two separate instances of region segmentation by color are performed. First, a segmentation with saturation range [160, 255] and brightness range [160, 255] produces a "narrow-range" image that is expected to contain the regions corresponding to the outer two tail lights of the vehicles. The second segmentation with saturation range [96, 255] and brightness range [128, 255] produced a "wide-range" image that is expected to contain the region corresponding to the central brake light of the vehicle. Each segmentation is performed on the hue-shifted color image. The first segmentation is necessarily a subset of the second.

With the binary image in hand, segmentation is relatively simple. First, a morphological closure (dilation and erosion with radius 1) is performed to remove any "holes" in regions or to connect regions that should be connected. Then, sets of 4-connected pixels are grouped together and assigned to distinct regions. For each region, I store the coordinates (x, y) of the center, the number of pixels n, and the maximum distance r from any point in the region to the center, which I define as the region's radius.

Pairing Regions

I consider each pair of regions in the narrow-range image as a candidate for the outer two tail lights of a vehicle. These pairs are pruned by three rules based on several assumptions about the size and distance of actual pairs. The following figure summarizes the rules for a regon pair a, b.

Size rule: $\left| \frac{a.n}{b.n} - \frac{b.n}{a.n} \right| \leq N$

Angle rule: $\left| \arctan\left(\frac{a.y - b.y}{a.x - b.x} \right) \right| \leq A$

Distance rule: $D_{\min} \leq \sqrt{\frac{(a.x - b.x)^2 + (a.y - b.y)^2}{a.r * b.r}} \leq D_{\max}$

Figure 3: Region pair pruning rules.

The size rule prunes pairs that are too dissimilar in pixel count. The angle rule prunes pairs that do not make an approximately horizontal angle. The distance rule prunes pairs that are too far apart or close together relative to their radii. In practice, the rules' parameters were manually fixed as N = 3, A = 0.1, D_{min} = 10, and D_{max} = 35. If each rule holds for a pair, then that pair is returned.

Detection

The final step is to consider each narrow-range region pair and each wide-range region. Consider the region pair (a, b). Based on the distance d between a and b, two rectangles are created, a positive area (green) and a negative area (red).

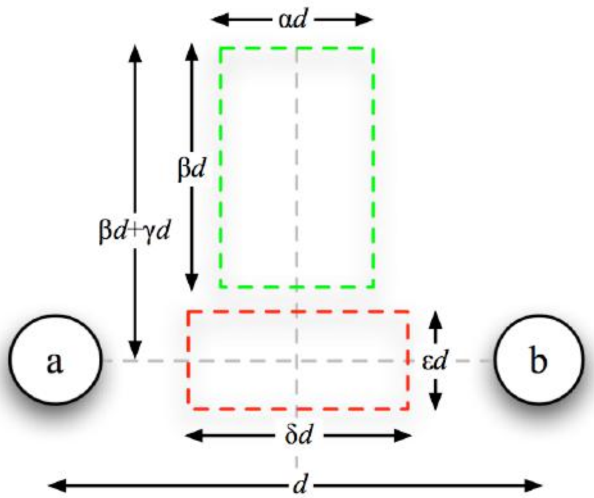

Figure 4: Positive and negative areas of a region pair.

The positive area is centered horizontally between a and b and is parameterized by α, β, and γ. Relative to d, the width of the area is α, the height is β, and the altitude is γ from the line connecting a and b. The negative area is centered absolutely between a and b and is parameterized by δ and ε. Relative to d, the width of the area is δ and the height is ε. Since a and b are not necessarily perfectly horizontal, this coordinate system may be arbitrarily rotated.

Given the pair a, b, the average size of these regions is $avgn = (a.n+b.n) / 2$. Let c be the n-maximal wide-range region in the positive area such that $c.n \leq avgn$. Let $negn$ be the sum of n of wide-range regions in the negative area. If $avgn > negn$ and c exists, then return the region triplet a, b, c as an instance of a brake light. This logic relies on the intuition that the central brake light should be the largest region in the positive area, but it should also be smaller than the outer tail lights. Also, there should not be much "noise" between the two outer tail lights, since there will not be lights in this part of the vehicle. In practice, the area parameters were manually fixed as α = 0.1, β = 0.25, γ = 0.05, δ = 0.5, and ε = 0.1.

EVALUATION

A set of positive- and negative-example images of brake lights were collected in the University Heights area of Cleveland, Ohio. In each image, the presence and location of brake lights was correctly determined. In the following images, the positive-example images have brake lights circled, and the negative-example images are unchanged.

Figure 5: Negative example.

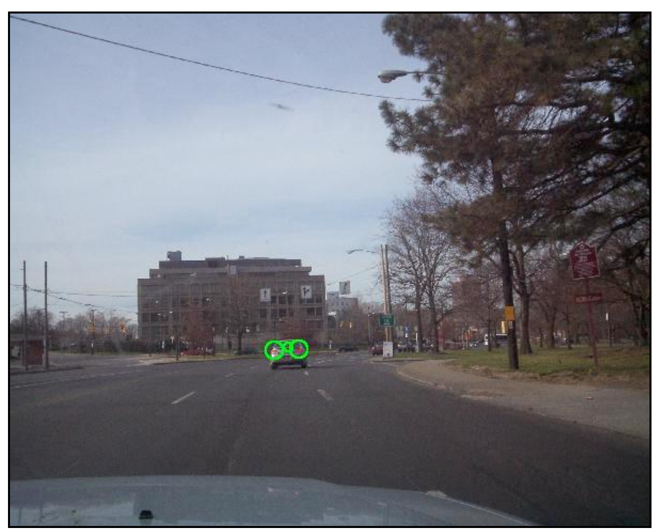

Figure 6: Positive example.

Figure 7: Positive example.

Figure 8: Negative example.

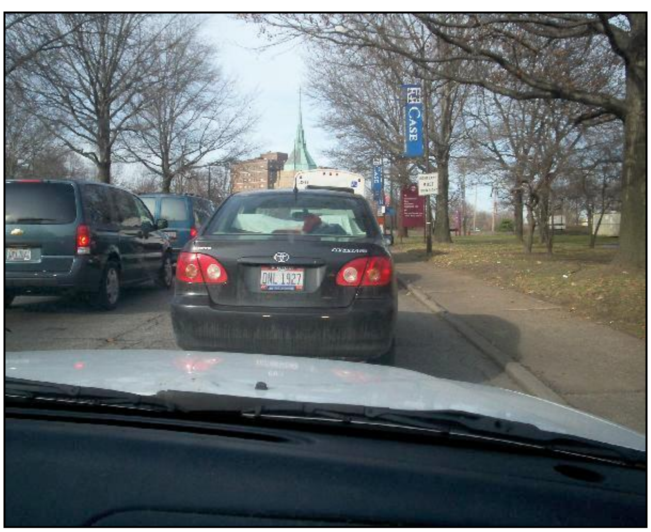

Figure 9: Negative example.

Figure 10: Positive example.

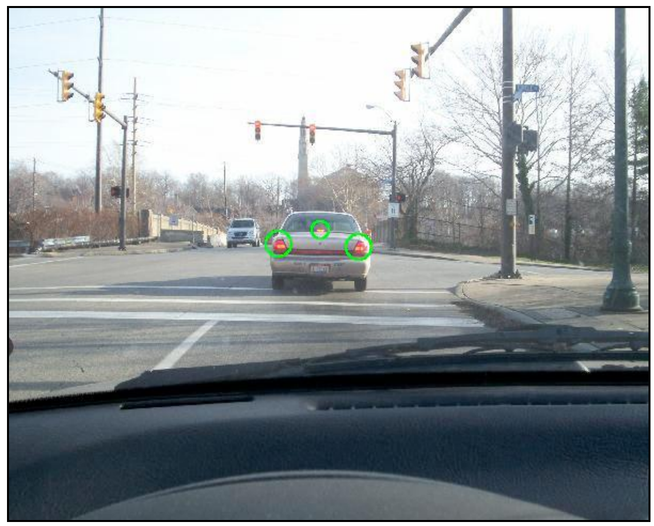

Figure 11: Positive example.

Figure 12: Negative example.

Figure 13: Positive example.

The following image illustrates how the positive and negative areas capture the central brake light and noise respectively. In this example, using the same image as figure 10, the negative regions were not significant in size compared to the outer tail light regions.

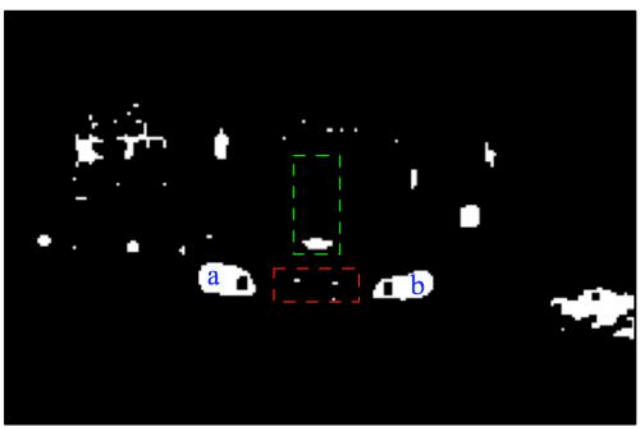

Figure 14: Positive and negative areas superimposed on wide-range regions.

CONCLUSION

The system is demonstrably capable of reliably recognizing brake lights under varied distances and during daylight. At present, the most significant limitations are the time required for each image (roughly 1-2 seconds on a Java platform) and the lack of rigorous testing.

Future work in this direction may seek to improve the segmentation ranges for different lighting conditions (*e.g.*, night, shadow) and further test the detection algorithm for different vehicle types (*e.g.*, buses, trucks).

REFERENCES

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