Vehicle Detection at Night Based on Tail-Light Detection

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ABSTRACT

Automated detection of vehicles in front can be used as a component of systems for forward collision avoidance and mitigation. When driving in dark conditions, vehicles in front are generally visible by their tail and brake lights. We present an algorithm that detects vehicles at night using a camera by searching for tail lights. Knowledge of colour, size, symmetry and position of rear facing vehicle lights, taken from relevant legislation, is exploited. We develop an image processing system that can reliably detect vehicles at different distances and in different weather and lighting conditions.

Keywords

vehicle detection, forward collision, advanced driver assist, automotive, image processing, rear light detection

1. INTRODUCTION

Statistics suggest that forward collision detection and avoidance - avoiding collision with a vehicle in front - is an important area of focus for road safety and accident prevention. For example, in the USA in 2003, 29% of total light vehicle crashes were rear-end collisions [1].

Demand for systems that can avoid or mitigate rear-end collisions is expected to grow as consumers grow increasingly safety conscious and insurance companies begin to recognise the impact such systems could have on the number of accidents occurring. Automotive manufactures have began to introduce such systems mainly implemented with active systems such as RADAR and LIDAR. A forward facing camera could be a low cost alternative or assistant to such active systems, as well as fulfilling many other functions. As there can be serious interference when multiple vehicles travelling in the same direction have the same type of active system [8], it is expected that the future of forward collision detection systems will be a combination of RADAR and forward facing optical camera. The approach we present could enable a collaboration or fusion relationship between such systems to continue to function in darkness. If a forward facing camera is on a vehicle performing functions in the day time, any useful functionality that can be achieved in dark conditions is a no-cost bonus feature.

While all vehicles will differ in appearance, with different styles of rear facing lights, they must adhere to certain guidelines governed by automotive legislation. These properties can be identified by image processing systems. When in direct view and not occluded, tail lights will be:

- amongst the brightest objects in the image;
- close to each other in pairs;
- symmetrical, same size and shape;
- red in colour.

This paper describes a system for detecting vehicles based on their rear lights. This system focuses on close range detection so that the distance in the image between the rear lights is large enough so that the individual lights are distinguishable. As the target vehicle gets further away, the rear lights tend to blur together, resulting in the distortion of the distinctive characteristics used for detection. Of course, the near range is also the area which is most critical in collision detection systems. We do not account for vehicles that do not meet legislative requirements, such as vehicles with broken lights or modified lights that do not meet the common legal specification of colour, brightness and position.

The algorithm can be summarised as follows. Firstly the image is converted into HSV colour space. Two colour thresholds reveal white and red regions. Red regions are used to mask the white thresholded image, resulting in white regions that are adjacent to red regions. A symmetry check attempts to group these regions into pairs. A brute-force axis of symmetry fit is avoided in favour of a simpler and less processing intensive comparison of size, aspect-ratio and alignment of centres. A bounding box containing the pairs is constructed. The aspect ratio of this box is checked to ensure that similar lights from different parts of the image aren't paired. Remaining bounding boxes are marked as detected vehicles.

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The layout of the remainder of the paper is as follows. In section 2 we present the legislative background to rear automotive lighting. This is followed by a review of prior research in the area of automotive forward collision detection in Section 3, with a particular emphasis on visual cameras and operation in dark conditions. In Section 4 our experimental data capture setup is explained. The image processing detection algorithm is outlined in detail in Section 5. Experimental results are outlined in Section 6. We conclude and consider directions for future work in Section 7.

2. LEGISLATION

Worldwide legislation states that rear automotive lights must be red and placed symmetrically in pairs at the extremities of the rear of the vehicle. These tail lights must be wired so that they light up whenever the front headlights are activated, and they must be constantly lit. Legislation also states that although tail lights and brake lights can be integrated into a single unit, there must be a minimum ratio between the brightness of the tail lights and the brake lights, so they can be easily distinguished.

There is no legislation governing the shape of rear automotive lights. Due to the advances in LED technology, light manufacturers are departing from conventional shapes of tail and brake lights. Thus it is important to have a detection method that is shape independent.

It has been compulsory for manufacturers to include a horizontal-bar brake light since 1986 in North America and since 1998 in Europe. This is a feature that could possibly be exploited in future systems, as an aid to detection and as a means to differentiate between tail lights and brake lights.

3. STATE OF THE ART

As rear lights must be red by law, several systems have utilised colour to aid vehicle detection. Chern et al [3] detect rear lights by colour filtering in RGB space to detect red and white regions. If a white region is surrounded for most of its perimeter by red pixels, it is regarded as a potential rear-light. They note that tail lights within 40 metres usually appear as white regions in the image as they are too bright for the image sensor. Their white filter was effective, however the red filter allowed through many different colours, resulting in bright objects such as street lamps being let through the filter. The candidates were paired by considering y-values, area and spacing.

The RACCOON system [7] uses two thresholds to find tail light pixels, one for brightness and one for redness. Detected tail lights are then tracked using a simple algorithm. The bearing of the target vehicle is estimated by the horizontal position of the centroid of the tail lights.

A very different approach is taken with the entirely hardware based solution described in [11]. No software signal processing is required. A signal is taken directly from the red channel of the RGB sensor, filtered and thresholded in hardware. This method has a zero processing overhead, but is not adaptable.

Symmetry is commonly used to filter potential candidates for vehicle detection as the rear of a vehicle is generally symmetrical during daylight and darkness. Some approaches fit an axis of symmetry e.g. [5]. While compute intensive, this approach is effective for daylight situations where the scene is more complex than darkness. Cucchiara et al [4] detect vehicles under day and night illumination in surveillance video, but approach the two environments with separate techniques. For detection at night, size and shape of thresholded lights are analysed. An axis of symmetry is determined, and reflections are distinguished from lights by examining the angle of the axis of symmetry. However this would not be effective from a observation point directly behind and square to the target vehicle. Vertical edges and shadows underneath the vehicle along with symmetry and tail light blobs have been used to detect vehicles by day and night in a particle filter framework [2]. The tail light pairing process can be simplified by making several assumptions [10]. They assume that the average car is around 170cm wide and the width/height aspect ratio of a highway vehicle is approximately 2.0.

Figure 1: Tail lights cause camera to saturate in places

Morphology has been used to detect vehicle lights [9]. The assumption is made that the lights will be circular or elliptical in shape. However the shape of rear lights is not specified in legislation and automotive designers are experimenting with different shapes as LED lights become more common. A temporal approach can also be used to improve detection rates. Blob trajectories can be grouped by their apparent motion [6], and Kalman filter tracking could be introduced to continue tracking through occlusion [12].

To aid detection, the lane ahead can be detected and a mask applied to reduce the area of the image that is searched for target vehicles [4][3].

4. EXPERIMENTAL DATA CAPTURE

For the approach presented here, the camera was mounted internally on the vehicle, behind the rear view mirror. The camera module has a resolution 640x480 and frame rate of 15Hz. It is important that the camera is mounted level. If it is not, it will interfere with the symmetry searches in the detection algorithm. Figure 1 shows a typical frame from the captured video.

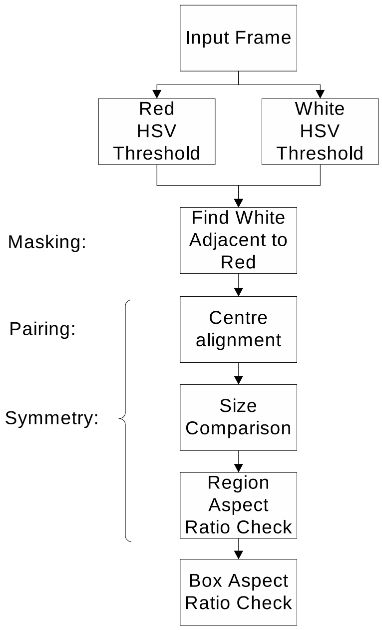

Figure 2: Detection procedure

Data was captured with different cameras in an effort to assess how sensor independent the system was. However due to the different way in which different sensors interpret colour it was found that the colour filter parameters of the red threshold had to be slightly adjusted for optimal operation between different sensors. Future work could involve introducing a calibration technique so camera sensors could be changed, and the system less sensor dependant.

A test plan was created with a view to capturing test data in simple situations. The plan involved video sequences with various permutations of the following options.

- Street lit environment / no lighting
- Tail lights / brake lights
- Indicator lights flashing intermittently
- Different distances
- Approaching target vehicle / target vehicle departing

Real world automotive video data was then captured in urban and rural situations. Data was also taken in bad weather conditions including heavy rain, as detection becomes more challenging when the road surface is wet as rear lights are reflected on it. Algorithm parameters were refined using the experimental test data.

5. REAR LIGHT DETECTION

In this section we outline the structure of an image processing system to detect rear lights from frames of automotive video. Objects such as street lamps, traffic lights, indicators lamps, reversing lights and oncoming headlights need to be filtered out, while retaining the rear lights of the target vehicle. A flow chart outlining the structure of the system is shown in Figure 2.

Table 1: Red HSV Filter Parameters

	Greater Than	Less Than
Hue	340	30
Saturation	0	30
Value	80	100

Table 2: White HSV Filter Parameters

	Greater Than	Less Than
Hue	ALL	ALL
Saturation	0	20
Value	99	100

5.1 Colour Filter

It was observed that during darkness tail and brake lights tend to appear as white spots in the video output. This can be attributed to most cameras automatic exposure adjustment for dark scenes. These white spots appear with a red halo region around the perimeter of the light where the intensity level of the light falls off.

We exploit these features to detect vehicles from the rear by applying two colour thresholds to the image to search for white regions and red regions. It was observed that it was impractical to implement the red filter in the RGB space, as contiguous RGB values could not represent the desired colour range for the filter to allow through. A more natural and practical colour space for this problem is the HSV (Hue-Saturation-Value) colour space, which is more representative of the way humans observe colour. HSV can be represented as an inverted cone, with Hue as the angle, Saturation as the radius and Value as the height. Hue is a cyclical dimension between 0 and 360, which is representative of the tint. Red is centred around the hue value of zero. Saturation is equivalent to shade, and has values of between 0 and 100. Value is tone, and also has values from 0 to 100. The parameters of the HSV space colour thresholds are displayed in Table 1 and Table 2.

Tail lights in the white filtered binary image generally appear as full circles with centres on the same level. In the red filtered binary image, tail lights can appear as a ring or annulus. This can be observed in Figure 3.

5.2 Image Masking

The binary images resulting from the two colour thresholds are filtered to remove noise. A binary mask is created from the bounding box rectangles of the red regions. This mask is applied to the white thresholded image. White regions containing any of the remaining pixels are transferred to the next stage of the process. This results in an image containing only white regions that are adjacent to red regions. This process is effective at selecting regions from the target vehicle at different distances.

5.3 Symmetry Check

As we are focusing on close range detection, we make the assumption that the target vehicle in front will be at the same tilt (pitch, roll and yaw) as the observing vehicle. In other words, we assume that, for close range application, the road in the short distance in front of the vehicle is tilted

Figure 3: Vehicle rear lights and the result of the red and white colour thresholding operations.

at the same angle as the observing vehicle and is therefore relatively level to the vehicle. The rear of the target vehicle will therefore appear square to the observer and the tail lights of the target vehicle will appear symmetrical. We make no assumption about shape, as there are no regulations governing the shape of tail lights, only that they must be placed symmetrically in pairs.

We employ a simple pseudo-symmetry check to avoid processor intensive brute force symmetry searches. The binary image resulting from the masking is searched for pairs. The first criterion that is applied is centroid alignment. All connected objects in the images are labelled, and their centres calculated. The image is then traversed, and objects with centres aligning in the y-dimension within a certain number of pixels are marked as potential pairs. The number of pixels that they must align by is proportional to the size of the regions. This is because the nearer and larger the lights, the greater the error is in their horizontal alignment.

The two objects of the potential pair are then compared in terms of size. The smaller of the two must have at least seventy percent of the number of pixels of the larger object. If this is not the case then they are removed. The concluding stage in the symmetry check is the comparison of the aspect ratios of the light candidates. This is to prevent objects of different shapes but similar size and position being paired.

5.4 Aspect Ratio Constraints

As a final check, the width to height aspect ratio of the bounding box containing the tail-lights must meet the following constraints.

$$3 \leq \frac{bounding\ box\ width}{bounding\ box\ height} \leq 8 \tag{1}$$

This ensures that similar objects a large distance apart, such as lights from vehicles in different lanes, are filtered out of the pairing process.

6. RESULTS

This entire process essentially amounts to a symmetry check. If a bounding box above a certain size is detected then the driver is alerted that a vehicle is close. Experimental test video was used to develop the algorithm as described in Section 4. This section presents some preliminary results drawn from video of a real road environment. In an 11.47 second sample video of 172 frames, the target vehicle was approximately 10m ahead. The vehicle in front, the target vehicle, was successfully detected in 164 of 172 frames, resulting in a detection rate of 95.3%. Bounding boxes resulting from white regions appeared incorrectly, not identifying the target vehicle, 5 times in the 172 frames, resulting in a false positive rate of 2.9%. These results refer to only a subset of the total video data.

Figure 4: Examples of successful tail light detection at different distances.

The algorithm has demonstrated that it works well in both well lit urban areas and dark rural areas. It also works effectively in wet conditions where the rear lights reflect off the road. Figure 4 is an example of tail light detection at multiple distances.

7. CONCLUSION

In this paper, we have discussed the need for a system to avoid or mitigate forward collisions during darkness. A background to the relevant automotive rear light legislation, showing characteristics that can be recognised by image processing, was given. We have presented an algorithm for forward collision detection at night using a visual camera. Our technique filters red and white colours in the HSV colour space. White regions adjacent to red regions are searched for symmetrical pairs, and aspect ratio constraints are applied to resulting bounding boxes. This produces detected rear target vehicle lights. We have shown promising preliminary results, and intend to expand and improve the system. An important next step is to introduce a temporal dimension and track targeted vehicles in video sequences to improve the detection rate, and to detect imminent collisions. It is envisaged to expand the range of test scenarios to make the system more robust.

Future work, could involve experimenting with different exposure times and High Dynamic Range (HDR) technology to achieve different views of rear lights in darkness. The algorithm could also be used to detect brake lights during the day and at night. Preliminary work has shown that the algorithm can be adapted to detect brake lights during the daytime. Future work could also include detecting the light-level at which night-time processing begins and day light processing stops. Several factors would have to be considered including a crossover procedure, and possibly a period when both night and day systems continue to function and co-operate, fusing information. It is envisaged to also make the system more sensor independent and develop an effective calibration technique.

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