Night Time Vehicle Detection for Driving Assistance LightBeam Controller

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***Abstract*— In this paper we present an effective system for detecting vehicles in front of a camera-assisted vehicle (preceding vehicles traveling in the same direction and oncoming vehicles traveling in the opposite direction) during night time driving conditions in order to automatically change vehicle head lights between low beams and high beams avoiding glares for the drivers. Accordingly, high beams output will be selected when no other traffic is present and will be turned on low beams when other vehicles are detected. Our system uses a B&W micro-camera mounted in the windshield area and looking at forward of the vehicle. Digital image processing techniques are applied to analyze light sources and to detect vehicles in the images. The algorithm is efficient and able to run in real-time. Some experimental results and conclusions are presented.**

I. Introduction

Modern automotive vehicles include a variety of different lamps to provide illumination under different operating conditions. Headlamps are typically controlled to alternately generate low beams and high beams. Low beams provide less illumination and are used at night to illuminate the forward path when other vehicles are present. High beams provide significantly more light and are use to illuminate the vehicle's forward path when other vehicles are not present. Daylight running lights have also begun to experience widespread acceptance.

There are various countries with regulations to control the amount of glare experienced by drivers due to preceding vehicles (other vehicles traveling in the same direction) and incoming vehicles (vehicles traveling in the opposite direction). These laws obligate to the vehicle manufacturers to build vehicles that comply with these regulations. For example, the Department of Transportation (DOT) in USA regulates the light emissions of vehicle high beam headlamps. In accordance with the DOT regulation limits, vehicle high beam headlamp emissions provide an intensity of 40,000 cd at 0^o, 10,000 cd at 3^o, 3250 cd at 6^o, 1500 cd at 9^o and 750 cd at 12^o. A scheme for understanding this problem is illustrated in Figure 1 [1]. In order to avoid an illuminance of 0.1 foot-candles (fc) incident on another vehicle at these angles, the vehicle high beams head-lamps should be dimmed within 700 feet (213 m) of another vehicle at 0^o, within 350 feet (107 m) of another vehicle at a horizontal position of 3^o and 200 feet (61 m) of another vehicle at a horizontal position of 6^o.

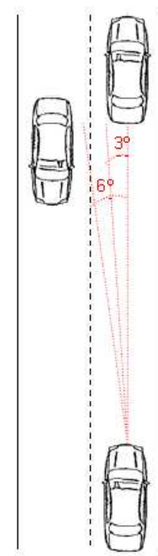


Fig. 1. Scheme of the dimming vehicle high beam headlamps problem

In order to prevent drivers of other vehicles from being subjected to excessive glare levels an automatic control of the vehicle headlamps can be done. For a preceding vehicle, the distance by which the controlled vehicle's headlamps must be dimmed, can be less that for an oncoming vehicle since glare form behind is usually less disruptive than oncoming glare. In the last few years many researchers have studied the effects of oncoming headlight glare [2]. An automatic headlamp dimmer system must sense both the head lights of the oncoming vehicles as well as the tail lights of preceding vehicles. Then, it has to distinguish between nuisance light sources, such as reflections of road signs or road reflectors, streetlights, etc, from light sources that require headlight control to avoid an undesirable performance.

Several automatic headlamp dimmer control systems have been proposed in the literature but at the moment none of them are commercialized. Currently the two more important systems are:

- Vehicle lamp control developed by Gentex Corporation. It is a system and method of automatically controlling vehicle headlamps including an image sensor and a controller to generate headlamp control signals [3].
- Adaptive Headlight Control (AHC) developed by Mobileye. To perform AHC Mobileye uses an image grabber and detailed analysis of light sources appearing in the image. According to its Web page Mobileye's AHC will be in serial development for a 2008 production for Siemens VDO [4].

Under night time driving conditions the more confident visual information for detecting vehicles are their head lights and tail lights. Some researchers have been working on the development of systems for nighttime vehicle detection and they are based mainly in the detection of head lights and tail lights [5].

Our work proposes an effective automatic control of the vehicle headlamps based on the detection of head lights and tail lights under night time road conditions. The main stages of the algorithm are explained in section II. Experimental results can be found in section III. Conclusions and future works are presented in section IV.

II. Algorithm

Our method comprises the following steps: The input images are obtained from the vision system using a B&W camera which is mounted behind the windscreen inside the camera-assisted car. These input frames show nighttime road enviroment in front of the car. As can be seen in Figure 2, typical nighttime road conditions are characterized by a dark background and bright objects corresponding to head lights, tail lights and nuisance light sources (reflections of road signs or road reflectors, streetlights, etc). Firstly, an adaptive thresholding must be applied to detect bright blobs in the image, which are corresponded with vehicles' lights. Then, the segmented blobs are clustered, based on geometric characteristics of the blobs, in order to distinguish vehicles of other nuisance light sources. Each cluster is tracked in a sequence, using a Kalman Filter, obtaining a multi-frame clustering. After that, tracked objects are classified in signs (main nuisance light source due to the reflections of the own vehicle's light over the road traffic signs) or vehicles, using a Support Vector Machine (SVM). Finally, a decision between the low/high beams turned on is taken.

Fig. 2. Typical nighttime road enviroment

A. Bright Objects Segmentation

In this step of the algorithm, B&W images are thresholded using an adaptive threshold in order to detect image bright objects and to measure some geometric parameters over them. Some important aspects must be considered for choosing a correct threshold value such as: road illumination conditions, vehicle's lights appearance, nuisance light sources and camera parameters.

Figure 3 depicts 3D intensity shape of a standard vehicle's head light. It has a Gaussian shape where the centre pixels belongs to the light source with values above 250. The edge pixels belong to the background with values below 50. As it can be seen, there is a high range in order to fix a threshold for light detection. Normally, nuisance light sources use to appear in the image with values below 200 (see Figure 4(b)). The problem is that there are some reflections of road signs that present similar intensity values as the vehicle's light, as we depitct in Figure 4(a). In these cases it is imposible to differentiate them using a thresholding method.

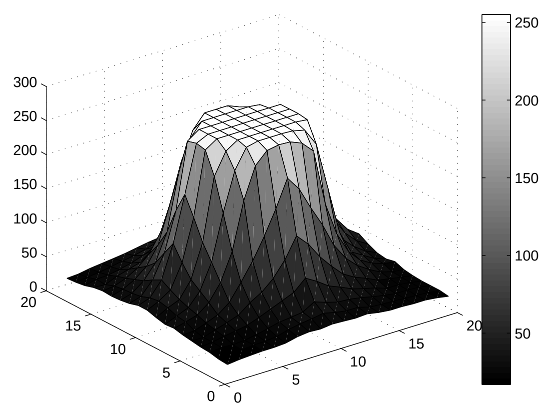


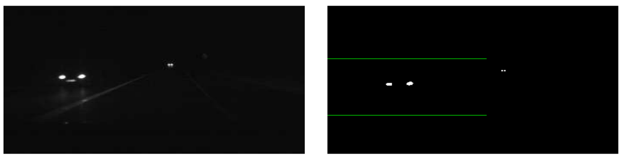
Fig. 3. Shape of vehicle's head light

Another problem is that head and tail lights have different intensity values in the B&W image Actually, intensity for tail lights is lower than for head lights and sometimes below most of the nuisance artifacts in the image. This is the reason because tail lights detection is more difficult than head ones. Figure 5(b) shows how bright objects are extracted from the original image. The green lines that appear in Figure 5(b) define the area of

(a) Sign light vs Vehicle's head light (b) Nuisance light vs Vehicle's tail light

Fig. 4. Grey scale difference between road sign, nuisance light, tail lights and head lights

analysis in the image.



(a) Original image (b) Thresholded image

Fig. 5. Bright objects segmentation

B. Clustering Process

The goal of this process is to cluster the detected blobs in the previous step. As long as a cluster in a frame is matched with the same cluster in the next frame, this is considered as an object, and must be evaluated to determine if this object is considered a vehicle or not.

The clustering and matching process starts by finding the closest object of the previous frame to each blob in the current frame. If the closest object exists, the blob is associated to that object. In the case that the closest object had already an associated blob, proximity between the two blobs is evaluated, and if it is suitable that both blobs belong to the same vehicle, the blob is added to the object's blobs list. This may happen with the two lights of a car as it approaches. Then objects are tracked using a Kalman Filter [6].

Each object has a live time. This time counts the number of frames in which it has been matched. Objects must be matched during a minimum number of frames in order to be considered as valid.

An important issue of the clustering process is to classify objects between preceding or oncoming vehicles. If ever an object is detected to be at a distance twice farther than any other distance at what it has been before, the object is classified as *preceding*, which means that the object is moving at the same direction of the camera assisted car. For the rest of cases the object is classified as *oncoming*, which means that the object is moving at the opposite direction.

C. Distance Estimation

In order to estimate the distance between the camera assisted car and the detected vehicles using monocular vision, a perspective camera model is applied [7], as it can be seen in Figure 6. Origin of the vehicle coordinate system is located at the central point of the camera lens. The X_V and Y_V coordinates of the vehicle coordinate system are parallel to the image plane and the Z_V axis is perpendicular to the plane formed by the X_V and Y_V axes. A vehicle at a look-ahead distance Z from the camera will be projected into the image plane at a vertical and horizontal coordinates (u,v) respectively. Vertical and horizontal mapping models can be carried out but in this application the most important is the vertical one. The vertical model considers that the road is flat and it uses the following parameters:

- I: Image
- Z: look-ahead distance for planar ground (m)
- $hCAM$: elevation of the camera above the ground (m)
- $Light_{HEIGHTY}$: elevation of the vehicle's light above the ground (m)
- θ_{CAM}: camera pitch angle relative to vehicle pitch axis (rad)
- θ_Z: incident angle of the precedent vehicle's light in the camera relative to vehicle pitch axis (rad)
- v: vertical image coordinate (pixels)
- $HEIGHT$: vertical size of the CCD (pixels)
- F_v: vertical focal length (pixels)

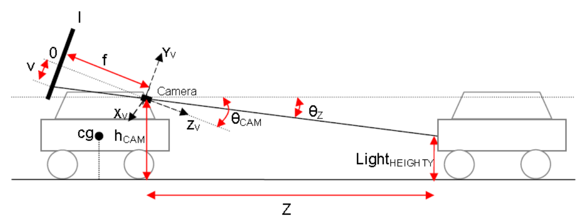


Fig. 6. Vertical road and mapping geometry

According to Figure 6, the vertical mapping geometry is mainly determined by the camera elevation h_{CAM} and vehicle's lights elevation $Light_{HEIGHTY}$ above the local ground plane as well as the pitch angle (θ_{CAM}). The longitudinal axis of the vehicle is assumed to be always tangential to the road at the vehicle centre of gravity (cg).

To each image scan line at v, there corresponds a pitch angle relative to the local tangential plane of:

$$\theta_Z = \theta_{CAM} + atan\left(\frac{v}{F_v}\right) \tag{1}$$

From this, the planar look-ahead distance corresponding to v, is obtained as:

$$Z = \frac{h_{CAM} - Light_{HEIGHTY}}{tan\left(\theta_Z\right)} \tag{2}$$

And finally, after applying a coordinate change, the equation for computing the look-ahead distance Z becomes:

$$Z = \frac{h_{CAM} - Light_{HEIGHTY}}{tan\left(\theta_{CAM} + atan\left(\frac{2 \cdot v - HEIGHT}{F_v}\right)\right)} \tag{3}$$

Even though this distance estimation is reasonably good in almost all the scenarios, there are situations as uneven roads where the horizontal mapping geometry must be considered, as we depict in Figure 7. For this purpose a correction of the distance Z is proposed in which the projection in the horizontal coordinate of the image (u) is introduced:

$$Z_{AUX} = \frac{Z \cdot (2u - WIDTH)}{F_u} \tag{4}$$

where:

- u: horizontal image coordinate (pixels)
- $WIDTH$: horizontal size of the CCD (pixels)
- F_u: horizontal focal length (pixels)

And finally the real distance (Z_R) can be obtained from the last two distances applying the following equation:

$$Z_R = \sqrt{Z_{AUX}^2 + Z^2} \tag{5}$$

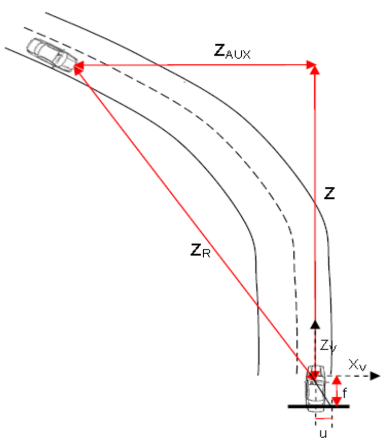


Fig. 7. Horizontal road and mapping geometry correction

The parameter $Light_{HEIGHTY}$ is defined as the elevation of the vehicle's light (head lights or tail lights) above the road. Since we are working with only one camera at night and estimating 3D distances very far, it is not possible to calculate this from the image analysis. Then, this parameter is computed off-line in a previous setup. As there are high differences between the elevation of the head and tail lights in vehicles, two different values were assigned to this parameter as a function of the kind of light. These values represent the average elevation of analyzed vehicles in the setup process. Besides, classification between preceding or oncoming vehicles is carried out in the clustering stage of the algorithm. Depending on this classification, one of the next two different values will be used:

- Head lights: $Light_{HEIGHTY}$=0.6 m
- Tail lights: $Light_{HEIGHTY}$=0.8 m

However, this distance is only an approximation, since some sources of error can affect this estimated distance, such as: elevation of the vehicle's light, road unevenness, object's centroid, etc.

D. Black Hat Transformation

The top-hat transformation is a powerful operator which permits the detection of contrasted objects on non-uniform background [8]. There are two different types of top-hat transformations: white hat and black hat. The white hat transformation is defined as the residue between the original image and its opening. The black hat transformation is defined as the residue between the closing and the original image. The operations white and black hat transformations are defined as follows respectively:

$$\mathbf{WH_T}\left(\mathbf{x},\mathbf{y}\right) = (f - f \circ B) \tag{6}$$

$$\mathbf{BH_T}\left(\mathbf{x},\mathbf{y}\right) = (f \bullet B - f) \tag{7}$$

In the equations 6 and 7 $f(x, y)$ is a grey scale image and B is the structuring element. Both operators, white and black hat can be used in order to modify the contrast of the image or enhancing contrast in some regions of the image. Normally, in grey scale images, the local contrast is ruled by two kinds of features: bright and dark features. The white hat image contains local peaks of the intensity and the black hat image contains local valleys of the intensity. As we can stand out the effect of the halo (local valleys of intensity) of head lights or tail lights, the black hat transformation was chosen for this purpose. In fact, the halo is one of the most important parameters to distinguish between road signs and vehicles. This effect is more important for head lights since the intensity of these lights is higher than for tail lights. In Figure 8, the halo effect for a vehicle can be seen.

(a) Original image (b) Black hat image

Fig. 8. Halo effect for vehicles

As can be seen in Figure 9, this effect is not enough significant for road signs.

(a) Original image (b) Black hat image

Fig. 9. Halo effect for road signs

Once the transformation is done, an indicative parameter of the lights' halo called *hat* is computed as the average intensity of a defined rectangle including the object.

E. Classification Using Support Vector Machines

One of the most important problems of the system is to distinguish between vehicle's lights and reflections of traffic signs (main nuisance light source). In this step, the detected bright objects are classified as signs or vehicles depending on some parameters using Support Vector Machines (SVMs)[9]. Two aspects are essential in the deployment of SVMs classifiers: the training strategy and the classifier structure. As SVMs are supervised learning methods used for classification, it is necessary to obtain a model under supervised training (*training mode*), and once the model is obtained, it can be used in real applications (*test mode*).

An input vector was defined for the classifier. This vector is composed of different parameters which are computed per object and define the state vector for the SVM. The parameters of the vector are:

- Area in pixels
- Coordinate v of the object's centroid
- Hat Value
- Rectangularity
- Aspect Ratio
- Length of the object's contour
- Circularity

The output of the SVM d, is simply the signed distance of the test instance from the separating hyperplane. This output indicates wether the analyzed object corresponds to a vehicle or not and can be used as a threshold for separating nuisance light sources and vehicles.

The classification algorithm uses this result and classifies the objects as signs or vehicles depending on its output distance from the separating hyperplane. The classification between vehicles and nuisance lights it is more difficult at far distances. This problem can be seen in Figure 10 where one vehicle located close to the horizon line in the image (at a distance of approximately 200 m) is surrounded by several signs and the system classified each of the objects correctly (headlights in green and road signs in blue).

Fig. 10. Classification of objects at far distances

III. Experimental Results

The system was implemented on a Pentium IV 3 Ghz platform and the size of the recorded image sequences is 720 pixels by 480 pixels per frame. The computation time spent on processing one input frame depends on the complexity of the road scene (mainly in the number of blobs and objects to be processed). The frame rate of the system is in average close to 20 frames per second which is enough for real time demands. Exhaustive experimental tests (more than 7 hours of video sequences) under different night time roadscenes were done for analyzing the performance of the system.

A. Distance Estimation

One sequence was tested in which a vehicle was placed at a distance of 200 m in front of the camera-assisted car. Then, the vehicle approached from a distance of 200 m to a distance of 0 m with a constant speed of 30 Km/h. The purpose of the sequence was to detect and track the vehicle's head lights so as to evaluate the accuracy of the distance estimation. Figure 11 depicts a sample of the scenario for the distance estimation analysis. The results of this analysis can be seen in Figure 12.

Fig. 11. Detection of an oncoming vehicle

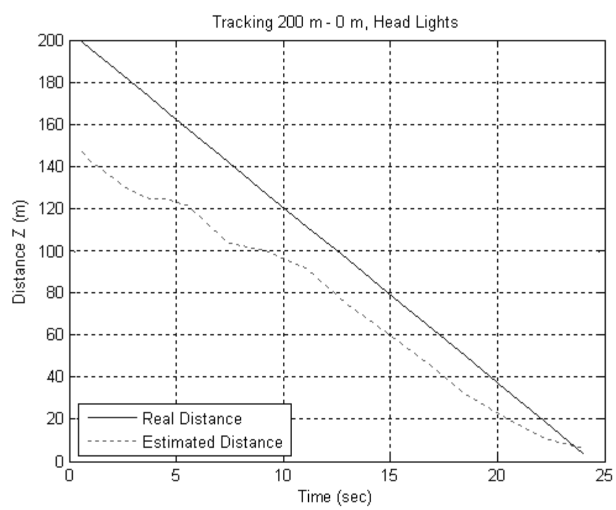


Fig. 12. Distance estimation 200 - 0 m. Head lights

B. Analysis of the Classifier

The SVM was trained using a representative database for learning and testing. For creating the training and test sets, the ratio between positive (vehicles) and negative (mainly reflections of traffic signs) must be set to an appropriate value in order not to produce misslearning or a high percentage of false positive detections (signs classified as vehicles) during on-line tests [9]. The quality of the classifier is measured by the probability of detection P_D(objects that are classified correctly) and the probability of false alarm P_{FA}(vehicles that are classified as signs and viceversa). These two indicators are shown together in Figure 13.

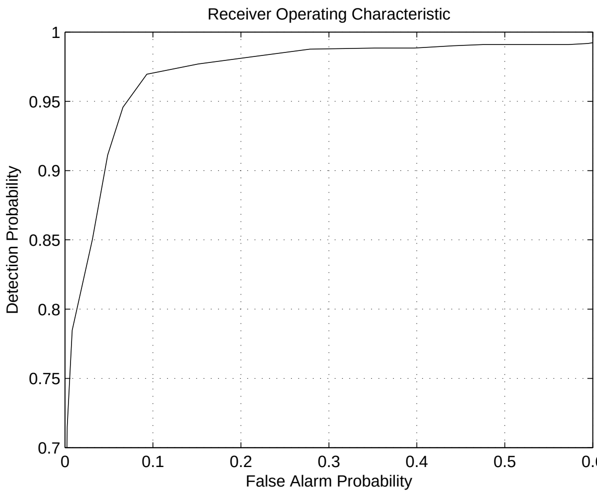


Fig. 13. Receiver operating characteristic

C. Head Lights Detection

The system can detect head lights for first time at distances between 300 m - 500 m, depending on road conditions. In some tests that were done some vehicles with high beams where detected even at 700 m, which is a very good performance, since it is very difficult to detect and classify objects at these distances.

All the head lights are detected, but the problem is when these head lights are detected. Normally, in good road conditions, the head lights are detected immediately but if road conditions change (due to road unevenness at far distances) some head lights can be detected later since the classifier depends on the vertical image coordinate. Figure 14 depicts a sample in which two objects are detected and classified correctly, one is a vehicle (at a distance of approximately 70 m) and the other is a sign.

Fig. 14. Head lights detection at 70 m

D. Tail Lights Detection

Tail lights are more difficult to be detected than head lights. This is because luminance of tail lights is lower than luminance of head lights. Besides, variety and diversity of tail lights is so huge that makes detection more difficult. This means that detection of tail lights depends too much on the vehicle type. In average the system can detect tail lights for first time in a range between 50 m - 80 m. Figure 15 depicts a sample in which tail lights of one vehicle were detected at a distance of 35 m.

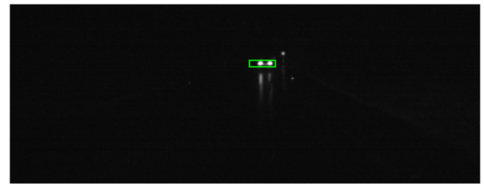


Fig. 15. Tail lights detection at 35 m

IV. Conclusions and Future Work

In this paper we have presented a night time detection computer system for driving assistance. On the one hand, the system performance is very good for head lights (distance of detection 300 m - 500 m) but on the other hand, the performance for tail lights (distance of detection 50 m - 80 m) must be increased.

The results are encouraging, and we plan to include several improvements to the current implementation. In the near future, a parameter indicative of the road vertical curvature will be included in the camera model in order to estimate this curvature at far distances.

Acknowledgment

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