Histogram Distance based Road Surface Detection on a Single Image

AYHAN KÜÇÜKMANİSA, OĞUZHAN URHAN
Electronics & Telecom. Eng. Dept. Embedded and Vision Systems Lab. (KULE)
Kocaeli University
Umuttepe Campus, 41380, İzmit-KocaeliTURKEY
{ayhan.kucukmanisa, urhano}@kocaeli.edu.tr - http://kule.kocaeli.edu.tr

Abstract: - In this work, a novel histogram comparison based road surface detection approach which can be used in advanced driving assistance systems (ADAS) is proposed. The proposed method employs a lane detection approach to decide vanishing line. After the vanishing line is obtained, only the region below this point is processed. At the next stage, center of gravity (CoG) values of 1×k sized regions selected from the road surface is computed. This CoG computation is done using RGB histogram signature of the selected regions. The CoG slice is employed to check candidate road surface points by comparing histograms via Quadratic-Chi histogram distance. Experimental results show that the proposed approach is capable of detection road surface efficiently.

Key-Words: - Road surface detection, Lane detection, Quadratic-Chi histogram distance, ADAS.

1 Introduction

During the last decade traffic safety is becoming vitally important with the increasing number of vehicles on the roads. The need for driver assistance systems that can support drivers about their flaws to ensure traffic safety is increasing day by day. These kind of supportive systems are called as Advanced Driving Assistance Systems (ADAS). Automated Parking System, Lane Departure Warning System (LDWS), Emergency Braking System (EBS), Adaptive Cruise Control (ACC) are considered as the most important ADAS. Although road region information can be employed for different purposes, it is important to obtain this region successfully for ADAS. Recently, many vision based approaches have been proposed in the literature for road surface detection. Some of these approaches presented in [1] to [3] employ stereo imaging sensor whereas most of them as in [4] to [6] utilize only single imaging sensor. The mostly used techniques in road surface detection are machine learning [1], density maps or stereo data [2,3], textural [4] and pixel distribution [5,6]. Since it is required to analyze two input image in the stereo based methods and training and classification stages that used in machine learning based methods, computational load is the main problem of these approaches. The selection of right texture that used as a prior knowledge directly affects success of textural based methods.

The proposed method in this work consists of three stages. At the first step, lane detection is used to determine vanishing line to reduce computational load and improve road detection performance. At the next step candidate road surface features are obtained using Quadratic-Chi histogram distance matching and Center of Gravity (CoG). Finally, candidate road surface features are eliminated and the final road area is detected using proposed morphology approach.

2 Proposed Method

The proposed approach aims to detect road surface using a single input image that is captured by a forward looking camera. The block diagram of the proposed method is shown in Fig. 1.

2.1 Preprocessing

It is aimed to determine vanishing line using detected lane markings and get possible road area segments at preprocessing step of proposed method.

2.1.1 Lane markings enhancement

The structures of lane markings might be corrupted for reasons such as reflections on the roads, erosion of markings by time, shadow and weather conditions. In order to reduce these negative effects at the lane marking detection, firstly a lane filter given in (1) as presented in [7] is used. This filtering is performed on V (value) channel of HSV color space representation of input image. The filtering result is shown in Fig. 2.

$$y_i = 2x_i - (x_{i-T} + x_{i+T}) - | x_{i-T} - x_{i+T} | \quad (1)$$

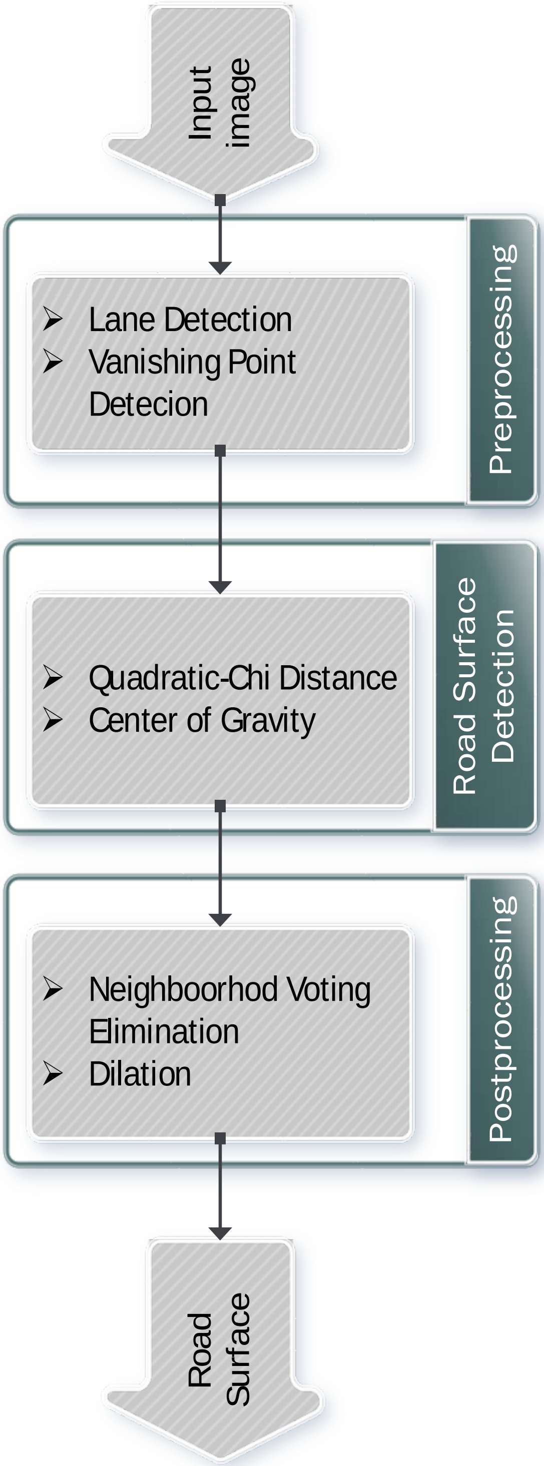


Fig. 1. The flowchart of proposed method.

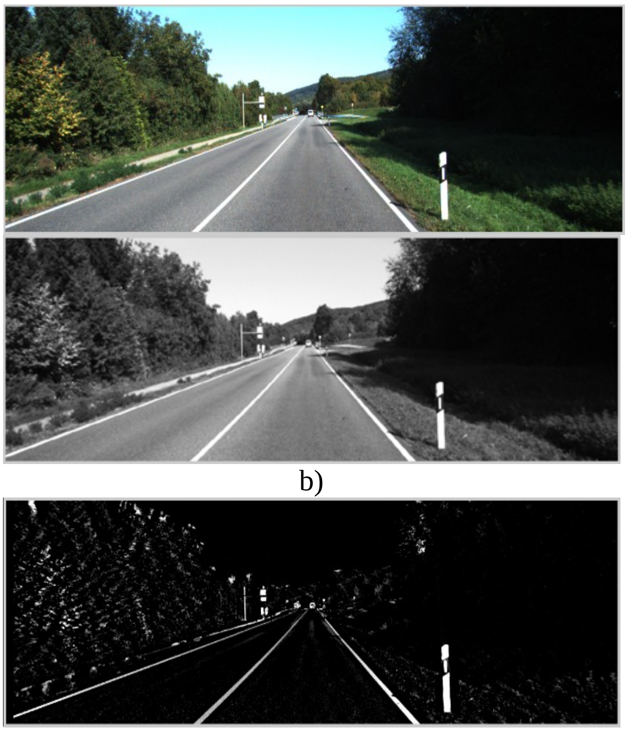


Fig. 2. Lane markings filter a) Original image b) HSV color space V channel c) Filtering result

2.1.2 Line detection

After the filtering, binary image is constructed comparing filtered image against to a with threshold value which is obtained by making use of Otsu method. Fig. 3 shows binary version of the Fig. 2 (a) after the thresholding

Fig. 3. Binary image

These pre-processes improves line detection performance for different road and lighting conditions. Next, Hough transform [9] is used to detect all lines in the binary image. The detected lines are shown in Fig. 4.

Fig. 4. Detected lines using Hough transform

2.1.3 Lane markings detection

At the previous step, all lines detected using Hough transform. However, using all detected lines may cause false detections in vanishing point decision step. Thus, in order to improve road surface detection performance, only the line that belongs to lane markings need to be used. Hence, lane marking lines should be detected at this point.

For this purpose, the detected lines are separated into two groups according to their angle values, initially. The line angles which are not between predefined values are eliminated. Finally, a single line from both right and left line group are obtained using median filter according to their middle point along the vertical position. The lane marking detection results obtained at the stage are shown in Fig. 5.

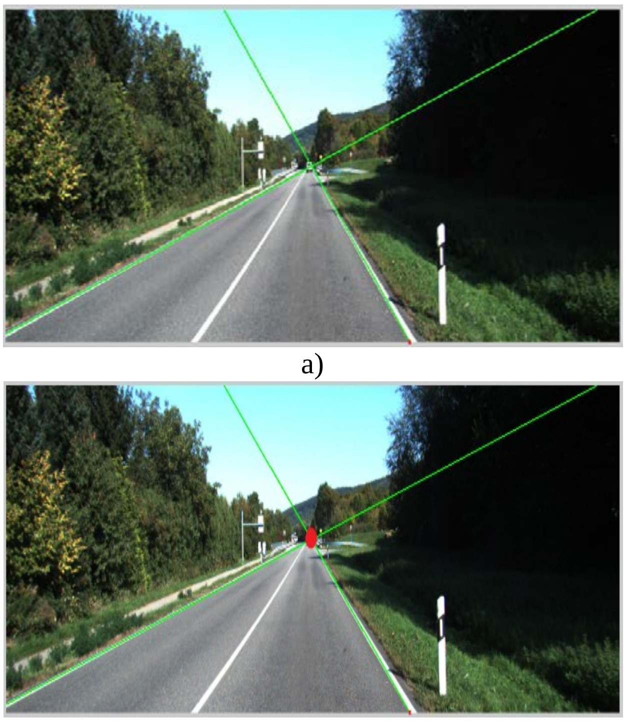
Fig. 5. Detected Lane markings

2.1.4 Vanishing point detection

The vanishing point decision is important because it reduces computational load and false detection rate of road surface. In the scope of this work, intersections of lane markings projections along the image are used to find vanishing point. The intersection of lane markings that shown in Fig. 6(a) and detected vanishing point according to their intersection is shown in Fig. 6(b). The vanishing line is the horizontal line passing over horizontal point of the vanishing point and parallel to the ground plane.. Because the area above the vanishing line does not contain any road area information, all next processes of proposed method will be performed on the area below the vanishing line.

2.2 Road Surface Detection

There are many differences with road surface area compared to other areas in the captured scene with camera. These differences are analyzed and distinctive features are determined. First, it is seen that using HSV color space in road surface detection with histogram matching method gives better results compared to other color spaces such as RGB and CIE Lab. Therefore, the input image is transformed into HSV color space and it is used as input together with the RGB color space for all steps of road surface detection algorithm.



a)

b)

Fig. 6. Detection of vanishing point a) Intersection point of lane markings b) Vanishing point

HSV color histogram and CoG values of RGB histogram signature of 1×k segments on the area below the vanishing line of input image, which is called *I*, is analyzed. It is seen that the histogram values of the road area have lower contrast compared to the non-road area, and road area has higher and stable CoG values. Therefore, it can be used as a second criterion for road detection.

2.1.1 Road surface estimation

In order to obtain road area successfully along the image using histogram and CoG values, little part of road must be known for comparison of areas with these values. It is known that the area between lane markings is a part of road area. At the previous step vanishing point is found by the help of lane markings. The vertical line passing through the vanishing point should be the road region. The samples that taken along this line gives the road area information. Fig. 7 shows this road area with red dashed line.

Input image I is separated into three parts in order to reduce illumination and shadows effects through the detection process. Therefore, 1×k sized samples are taken with a "diamond" like pattern on road sampling line for each part. These samples are taken from all HSV and RGB image channels and averaged to obtain a general road area sample for each part.

Fig. 7 : Road area sampling line

There parts of road and diamond like pattern that used in sampling are shown in Fig. 8. This sampling process is carried out on the HSV color image and RGB color image of input image, separately.

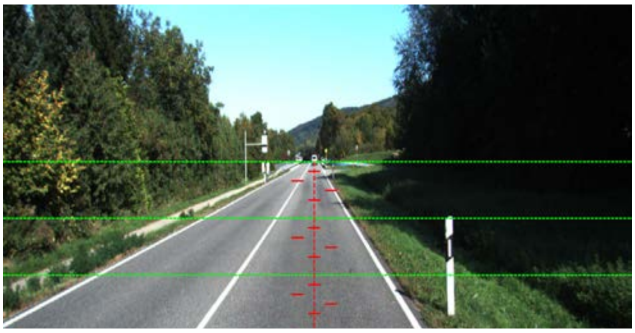
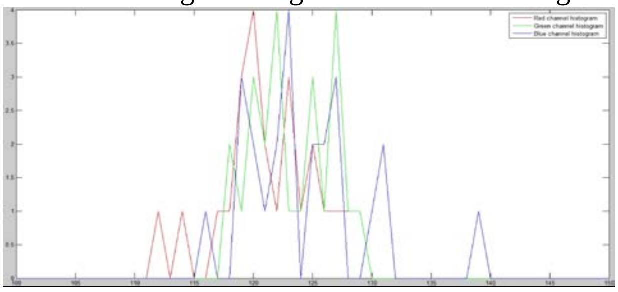


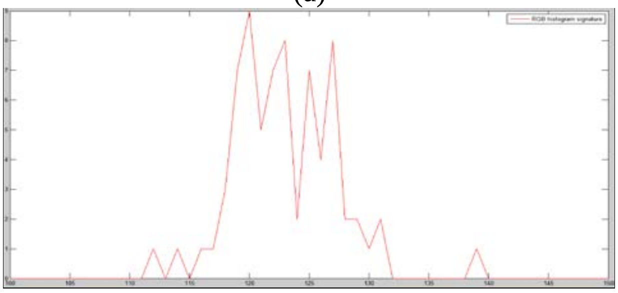
Fig. 8 : Road area sampling

2.1.1 Road surface detection

Histogram on HSV image and CoG value on RGB image are analyzed at the road surface detection step. All histogram distance and CoG value calculations are performed with 1×k sized segments which are centered by every pixel and they are compared with road samples. It should be noted that analyzing process is performed for each road part separately with their road samples. The pixels to be compared on image are chosen with a sampling ratio of N to reduce computational load. First, histogram distance map is created using Quadratic-Chi distance [10] with HSV image of I. Second, 1×k sized segment histogram of each channel of RGB image is computed. Then these histograms are summed to create a histogram signature. Fig. 9 shows a sample 1×k sized segment histogram of RBG channels and computed histogram signature. Then CoG value is computed using the histogram signature. Histogram distance map and CoG map is calculated along the image and are shown in Fig. 10.



(a)



(b)

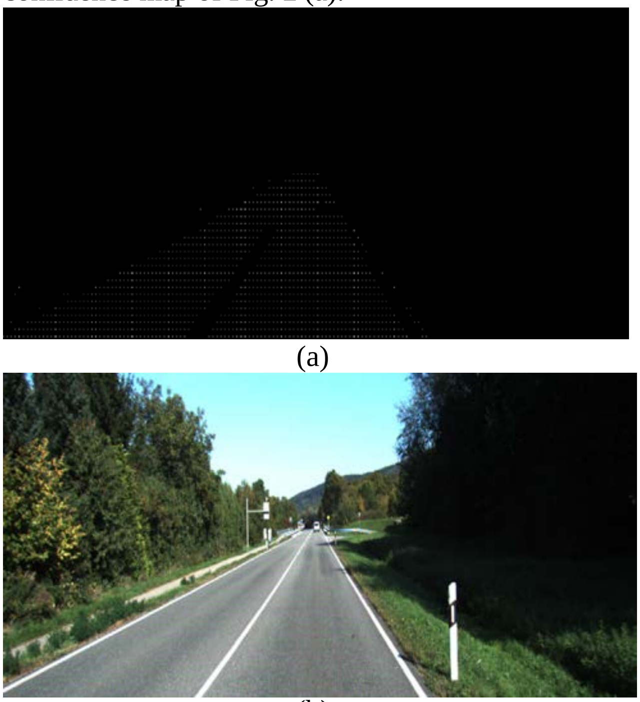
Fig 9. RGB histogram signature (a) Histograms for all channel (b) Histogram signature

(a)

(b)

Fig. 10 : Histogram distance map and CoG map (a) Histogram distance map (b) CoG map

Road candidate area which is also called as confidence map is constructed according to two criteria. A pixel which has a lower histogram distance than a predetermined value and at the same time has a COG value between defined ranges is marked on the confidence map. Fig. 11 shows the confidence map of Fig. 2 (a).



(a)

(b)

Fig. 11 : Confidence map (a) Confidence map (b) Confidence map visualization on the input image.

2.3 Post-processing

The confidence map which will be used for final road decision step might have some outliers. These outliers are eliminated using a neighborhood voting algorithm shown in Algorithm 1 in order to improve detection result. In the Algorithm 1 *interval* value is the *N*. This algorithm controls 8 neighbor pixel locations of a marked pixel with distance of *N* and finds number of marked pixels. If this number of marked pixels is lower than five (the majority of controlled points) this pixel location is eliminated.

Then final road surface area will be detected using dilation morphology operation on the confidence map. The dilation kernel size is determined by the value of *N*. The final road surface detection result is shown in Fig. 12.

Fig. 12 : Proposed road surface detection method result

Algorithm 1 Neighborhood voting elimination

```
for i = 1 : height of image
vote = 0;
  for j = 1: width of image

     if (input_image (i, j) != 0)
          for k = -interval :  interval
               for l = -interval: interval
                    if(image(i + k, j + l) != 0)
                         vote = vote + 1;
                    end
               end
          end
     end

  end

    if (vote > 5)
       output_image (i, j) = 1;
    else
       output_image(i, j) = 0;
    end

end
```

3 Experimental Results

Proposed method is evaluated on KITTI road dataset [11]. Fig. 13 shows visual results of proposed method on the several KITTI dataset images. Performance assessment of road detection methods is performed by comparing road detection result and ground truth data which is provided by the KITTI dataset. The performance evaluation metrics that used in this work are Precision, Recall, MaxF (maximum F-measure), Accuracy, Average Precision (AP), false positive rate (FPR), false negative rate (FNR) [11]. These metrics are calculated as

$$Precision = \frac{TP}{(TP + FP)} \tag{2}$$

$$Recall = \frac{TP}{(TP + FN)} \tag{3}$$

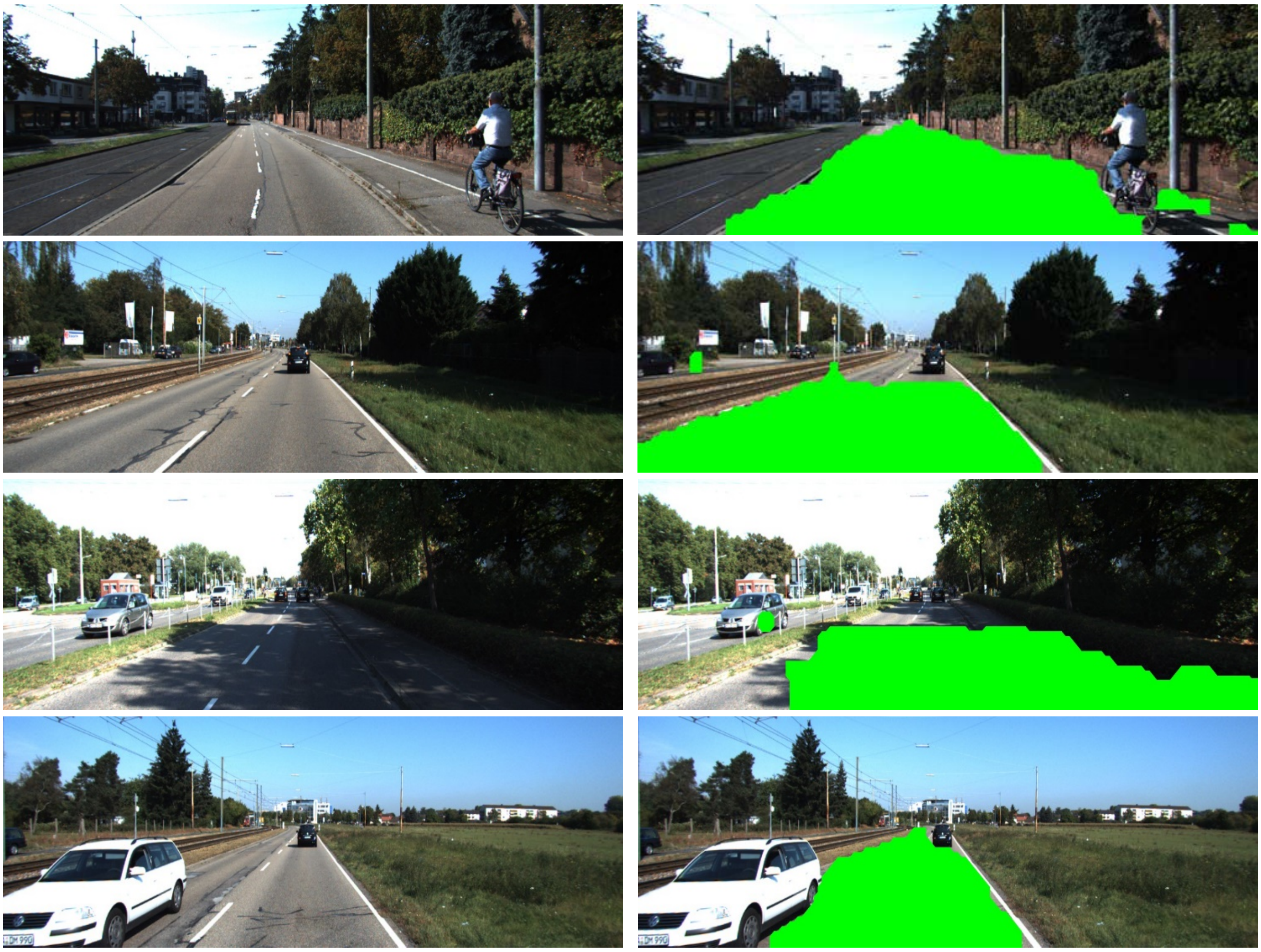
$$F - measure = (1+\beta^2)\frac{Precision \cdot Recall}{\beta^2 \cdot (Precision + Recall)} \tag{4}$$

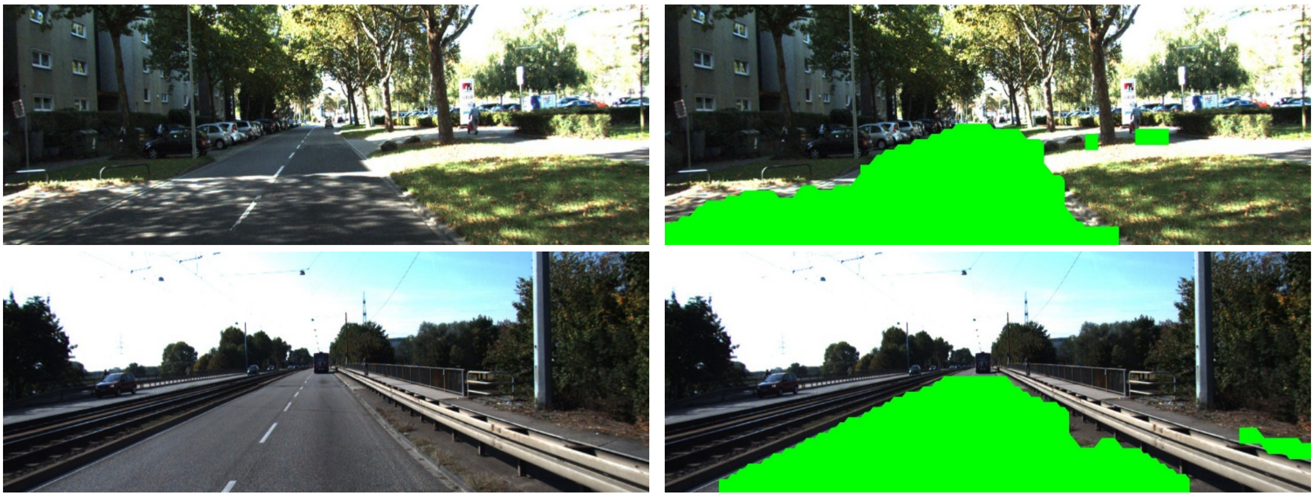
$$Accuracy = \frac{TP + TN}{(TP + FN + FP + TN)} \tag{5}$$

$$FNR = \frac{FN}{(TP + FN)} \tag{6}$$

$$FPR = \frac{FP}{(FP + TN)} \tag{7}$$

The proposed method is implemented in MATLAB on a PC with 2.3 GHz Quad core CPU. Table I shows objective evaluation results in terms of given metrics of methods presented by Alvarez *et al* [12], Brust *et al* [13], Xiao *et al* [14], Wang *et al* [15], Vitor *et al* [16] and proposed approach with UM_ROAD images category of KITTI dataset. This table also contains run time of methods with their implementation environments. As seen from this table, the proposed approach provides good results and it has lowest FPR comparing with the other methods. Additionally, it is appropriate for real-time applications on embedded platforms with its processing speed.





(a) (b)

Fig. 13 : Road surface detection results (a) Original images (b) Road surface detection results

Table 1 : Evaluation results

Methods	MaxF	AP	Precision	Recall	FPR	FNR	Runtime	Enviroment
Alvarez *et al (2013)* [12]	73,69	76,68	69,18	78,83	16,00	21,17	2 s	1 core 2.5 Ghz (C / C++)
Brust *et al (2015)* [13]	76,28	79,29	72,44	80,55	13,96	19,45	20 s	8 cores 2.5 Ghz (C / C++)
Xiao *et al (2016)* [14]	76,43	83,24	75,53	77,35	11,42	22,65	0,2 s	1 core 2.5 Ghz (C / C++)
Wang *et al (2014)* [15]	78,90	66,06	69,53	91,9	18,21	8,81	2 s	2 cores 2.5 Ghz (Matlab)
Vitor *et al (2014)* [16]	83,68	72,79	82,01	85,42	8,54	14,58	2,5 min	8 cores 3.0 Ghz (C/C++)
Proposed Method	76,76	62,34	72,54	81,50	6,08	18,50	2 s	4 cores 2.3 Ghz (Matlab)

4 Conclusion

In this paper a novel road surface detection method using a single image is presented. The main target of the proposed method is robust road detection with low computational load. The proposed approach has a preprocessing step based on lane detection. This estimation of road area improves road surface detection performance significantly. The Quadratic-Chi histogram distance matching method firstly used in this work. The experimental results show that the proposed approach based on Quadratic-Chi histogram distance and CoG is able to determine road surface in various conditions at significantly good accuracy compared to existing method with its low computational load. The proposed approach is suitable for embedded platform with its low computational load.

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