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A Robust Approach for Road Detection with Shadow Detection Removal Technique

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Abstract: Road detection plays an important role in autonomous driving system. One of the greatest challenges for vision-based road detection is the presence of shadows and other vehicles. It's particularly challenging to detect unstructured road when it has both shadowed and non-shadowed area. Shadows can cause a significant problem in road detection since shadow boundaries may be incorrectly recognized or simply hinder the road detection process leading to a higher false rate detection. Therefore, shadow detection and removal is a crucial task in many computer vision applications. To tackle those issues, this study introduced an effective road recognition system using an image processing method to eliminate or reduce considerably the presence of strong shadows for unstructured road detection. The method's main novelties are the use of a simple and effective shadow detection and removal algorithm using bilateral filter combined with a model-based classifier. Shadows were detected using normalized difference index and subsequent thresholding based on Otsu's thresholding method. Furthermore, after the image-preprocessing step used for shadow removal, illumination invariant of road was estimated and a road probability map was calculated to determine whether or not each pixel belongs to road surface. Extensive experiments were carried out and the results showed that this method effectively detect unstructured road areas while being robust to strong shadows and illumination variations.

Key words: Road detection, image segmentation, shadow detection

INTRODUCTION

Road detection is an important aspect of autonomous vehicle navigation system. For those autonomous vehicles to properly navigate on roads they must first be detected and the proper road and non-road area must be located for generating paths while avoiding any obstacles.

Shadow detection and removal has also become an important research area in computer vision and image processing. This study focuses on vision-based road detection that is, detecting the road surface ahead of the experimental vehicle using an onboard camera. In order to render the algorithm robust to the presence of illumination or strong shadows, an image preprocessing technique is first performed to eliminate the shadow. The presence of shadows can reduce a great deal the successful rate of road detection and extraction, therefore it is necessary to eliminate the shadow then restore the image before performing the task of road detection in an unstructured urban area. While most shadow detection methods need multiple images for camera calibration, this study provides a simple method based on properties of color information and gradient information to extract shadows from a single image.

Several road detection systems have also been developed so far to address the topic of unstructured road segmentation (Bernuy *et al*., 2011; Kong *et al*., 2010; Oh *et al*., 2012; Hsu *et al*., 2012; Choi *et al*., 2012). Those methods are mainly based on road model, road features and the combination of the fore mentioned both methods. The method based on road features uses texture information between the road region and the non-road region. However, this kind of methods while having the advantage of being insensitive to road shapes, are very sensitive to illumination, strong shadows and are really time consuming. The detection systems based on road model usually detect road edges using gradient operators (Chen *et al*., 2011). Those systems detect road edges quickly but have a stronger response to the change of road surface feature and shadow edges.

A simple and efficient algorithm for unstructured road detection using an improved shadow removal method was proposed here. The study addresses the problem of the presence of illumination or strong shadows and is structured in two main parts: The first part which is shadow detection and removal and the second part which describes the overall road segmentation process while avoiding the use of road shape feature as part of the algorithm. Furthermore, a simple shadow detection and removal method (Singh *et al*., 2012) has been used as part of the road detection process to avoid the difficulties with noisy or cluttered road edges sometimes also caused by the presence of strong shadows. Prior to shadow removal

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Fig. 1(a-y): Some examples of unstructured road images under different conditions

process it first has to be detected. The shadow is first detected using Otsu's tresholding method in the Hue-Saturation-Value (HSV) color space then it's removed by using the mean and variance values of the buffer area which is the non-shadow area around each shadow.

The proposed approach will exploit the properties of shadows in luminance and chromacity and will therefore be applied in HSV color space. Figure 1 shows some example of unstructured road images obtained under different conditions.

MATERIALS AND METHODS

Image preprocessing: This step is very important for road detection system. Not only can it help reduce computational speed, but it can also greatly improve the recognition rate of the road extraction process ahead of the vehicle. This is achieved by eliminating features like the presence of strong shadows that might hinder the results.

Shadow detection: Firstly, shadows need to be detected prior to removing them; therefore shadow detection accuracy is crucial for a better shadow removal process. One of the first steps toward removing shadow in color images involves using the luminance and chromacity properties of shadows (Jyothisree and Dharan, 2013). The shadow detection process is performed using Otsu's tresholding algorithm in the HSV color space. HSV color space is used here because it is somehow sensitive to the brightness level of the image while it well describes the feature information of the shadow (Surkutlawar and Kulkarni, 2013). HSV color space is based on Hue (H), Saturation (S) and brightness Value (V) in which Hue can be distinguished from Saturation and brightness Value. Since, the input image containing shadows is in the RGB color space, a conversion from RGB to HSV space is therefore necessary. One of the reasons to process the image in the HSV space is that it's invariant to shadow. That is, it conveys the color characteristics of the image feature regardless of variations in scene illumination condition and what's more, shadow detection methods based on HSV color space are more accurate than in the RBG color space. This assumption is based on the simple idea that shadows change the brightness of the background but don't really affect the chrominance and saturation in HSV color space. The relation between RGB space and HSV space is as follow:

$$V = \frac{1}{3}(R+G+B) \tag{1}$$

$$S = 1 - \frac{3\min(R,G,B)}{R+G+B} \tag{2}$$

$$H = \begin{cases} \theta & \text{if } B \le G \\ 360^0 - \theta & \text{if } B \succ G \end{cases} \tag{3}$$

Where:

$$\phi = \cos^{-1}\left\{\frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right\} \tag{4}$$

Firstly, after converting the image from RGB space to HSV space, the intensity component (V) and the hue component (H) are obtained. Both H and V components are used in extracting the shadowed area in color images. Secondly, the ratio image (H+1)/(V+1) is obtained by applying the spectral ratio technique. It's used to enhance the hue property of shadows that is, the grey value of the shadow region is larger than non-shadowed region. Thirdly, Otsu segmentation method is applied over the histogram of the ratio image to determine the segmentation threshold for the ratio image. The Otsu's method finds an optimal threshold T which maximizes:

$$V(T) = \frac{(\bar{\mu}.w(T) - \mu(T))^2}{w(T).\mu(T)} \tag{5}$$

Where:

$$w(T) = \sum_{i=0}^{T} p_i;\ \mu(T) = \sum_{i=T+1}^{255} p_i;\ \bar{\mu} = \sum_{i=0}^{255} ip_i$$

and p_i is the probability of pixels with gray level i in the image.

After this step, the image is then segmented and the candidate shadow region image is obtained. The segmented image is firstly filtered by median filter for noise removal and then processed by morphological erosion and dilation techniques to get the shadow region. The image obtained after the tresholding will be a binary image where all shadow pixels are set to 1 and all non-shadow pixels are set to 0. Figure 2 shows both the original road images (upper row) in which the shadow has to be detected and the resulted binary images (lower row) with the shadow area detected using the proposed method.

Shadow removal: Once the shadow detection has been performed, the image is divided into two parts, a shadowed region and a non-shadowed region. Let's denote I_s the binary image obtained earlier. In this

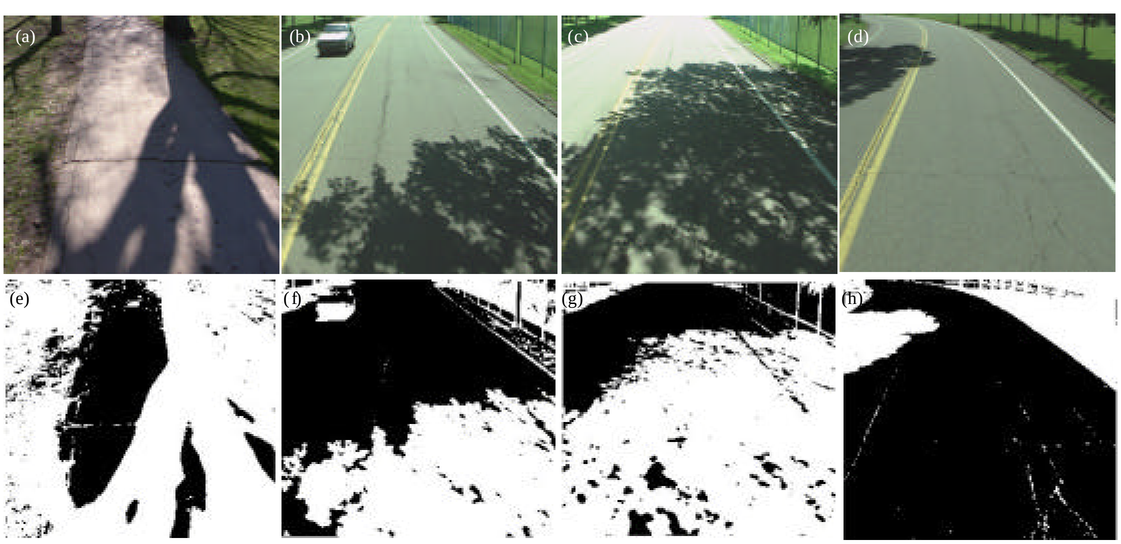

Fig. 2(a-h): Upper row (a-d) Input sample images and lower row: (e-h) Binary images showing the detected shadow region (white) study, we'll use the buffer area method developed in (Singh *et al*., 2012) for shadow removal. The buffer area is the area around the shadow and is used to compensate the shadow using the mean and variances of the shadow region. It's estimated using morphological operations on I_s. Firstly, shadows need to be classified based on the concept of connected components present on the binary image I_s. Each connected components corresponding to a shadow and its elements are set to 1 while set to 0 otherwise. The following procedure determines all connected components in the binary image and terminates when $I_k = I_{k-1}$:

$$I_k = (I_{k-1} \oplus B) \cap I_s \quad k = 1, 2, 3, ... \tag{6}$$

where, B is a suitable structuring element.

In the equation above, I_k contains all connected components of I_s and this process will create m sets of connected components representing m different shadows in the image.

Secondly, the buffer area of each shadow is computed using image subtraction operation and morphological dilation operation as follows:

$$I_{dilated,\, n} = (I_{n-1} \oplus B_{square}) \tag{7}$$

$$I_{buff,\, n} = (I_{dilated,\, n} - 1) \tag{8}$$

where, B_{square} is a square structuring element and $I_{buff,\, n}$ provides the location of the non-shadow points n = 1, 2, 3,..., m. These operations will expand the shadow boundaries. Finally, the shadow removal image is obtained as follow:

$$I_n'(i, j) = \mu_{buff,n} + \frac{I_n(i, j) - \mu_n}{\sigma_{buff,n}} \sigma_n \tag{9}$$

where, $I'_n(i, j)$ is the compensated value of the shadow pixel; $\mu_{buff,\, n}$ and $\sigma_{buff,\, n}$ are the mean and variance of the pixels of image I at location $I_{buff,n}$. Therefore, a shadow free image is obtained (Fig. 3) in which the road detection algorithm can be directly applied to.

Road detection algorithm: In this section, a road detection algorithm is devised for detecting unstructured roads which may have no lane markings, degraded edges or strong shadow conditions. It's also important to note that the road detection system is invariant to road shape. Several methods have been developed for unstructured road detection, they can mainly be classified into three groups (Wang *et al*., 2011): One based on road features, another based on road model and the third one is the combination of the fore two methods. In this study, after converting the original image back to RGB color space, color segmentation module based on Bayesian classifier is used where the probability distributions of the road and non-road pixels are approximated by histograms in a RGB space (Bernuy *et al*., 2011). The classifier includes three stages which are the likelihood estimation, the filtering and decision. The resulting image is a binary image that

Fig. 3(a-h): Results of the shadow removal algorithm. First row: (a-d) Road images containing shadow. Second row: (e-h) Shadow free images obtained using the proposed shadow removal method (the resultant images are either shadowed free or in some case the impact of shadow has been highly reduced) defines which pixel is part of the road and which one is not. The road histogram is determined using the information of a fixed region of the image while the non-road histogram is determined according to the classifier output (Prochazka, 2013).

Road histogram update: The road histogram is updated using a fixed set of pixels for each input image and the feedback from the road detection module. In order to do so, a temporal histogram of the pixels is obtained from the training area. Therefore, the road histogram is updated as:

$$H_r[r, g, b] = \alpha H_r[r, g, b]+(1+\alpha)H_t[r, g, b] \quad (10)$$

where, H_r is the road histogram, H_r is the temporal histogram of the training area and α is the weight of the memory of the road histogram

Classification using the bayesian theory: To classify the pixels (create a likelihood image), Bayes' theorem is used together with the Gaussian color models from the image. Bayesian classifier is used for color segmentation where the probability distributions of the road and non-road pixels are approximated by road histograms. The classifier includes three stages: Likelihood estimation, the filtering and decision.

Likelihood-based classification: According to Bayesian decision theory, a classifier decision can be taken by comparing the quotient of both road and non-road likelihood with a decision threshold:

$$H_r \approx \{P(\text{Color}|\text{Road})\} \quad (11)$$

$$H_n \approx \{P(\text{Color}|\text{Non-road})\} \quad (12)$$

where, H_r and H_n, respectively represent the road and non-road histograms, are approximations of the probabilities of finding a RGB pixel in a road and non-road area. The new image is therefore constructed by calculating the quotient of H_r and H_n for each pixel of the input image I_m as follow:

$$S[i] = \frac{H_r[I_m(i)]}{H_n[I_m(i)]} \quad (13)$$

Filtering and decision: This step uses the correlation between the probability quotient for a given pixel position. Temporal filtering is therefore applied to the probability quotient image to approximate this effect:

$$S_m[i] = \beta.S_m[i]+(1-\beta).S[i] \quad (14)$$

Given the fact that the probability that a pixel is part of the road depends not only on its color but also the color of its surrounding pixels, a median filter will thus be applied to the probability image to approximate this effect.

Finally, the final decision is taken by applying a decision threshold T:

$$B[i] = \begin{cases} 1 & S_m[i] \geq T \\ 0 & S_m[i] \prec T \end{cases} \quad (15)$$

RESULTS AND DISCUSSION

The road segmentation system has been tested in a variety of off-road scenarios under different illumination. The above method was tested in MATLAB R2001b. Figure 2 above shows shadowed RBG road images and their corresponding binary image showing shadows. The shadows detected are shown in white color. The effectiveness and robustness of this part of the algorithm can be seen from the fact that road surfaces are not detected as shadows. Figure 3 also shows some shadow free road images while Fig. 4 shows the resulting road segmentation images. It can be seen that this method has good robustness to the impact of shadow on the road due to the above shadow removal method. The results also show the effectiveness of the proposed algorithm in de-shadowing and detecting unstructured roads.

General performance evaluation: Here, detection rate and precision are used as the performance measures to evaluate the performance of the proposed road detection system. Therefore, in order to test the general performance of the proposed algorithm, rules defined in Alvarez *et al.* (2010) are used in this study. Those rules are defined in Table 1. The performance of the proposed algorithm is also outlined in Table 2. The system has been

Table 1: Rules and performance measures for road detection where $\hat{g}$ represents quality, DA the detection accuracy and DR the detection rate. All of which are defined using the entries of the contingency table. TN, FN, FP and TP, respectively stand for true negative, false negative, false positive and true positive

	Ground truth			
Contingency table	Non road	Road	Pixel wise	Definition
Non road	TN	FN	Quality	$\hat{g} = \frac{TP}{TP+FP+FN}$
Road	FP	TP	Detection rate	$DR = \frac{TP}{TP+FP}$
			Detection accuracy	$DA = \frac{TP}{TP+FN}$

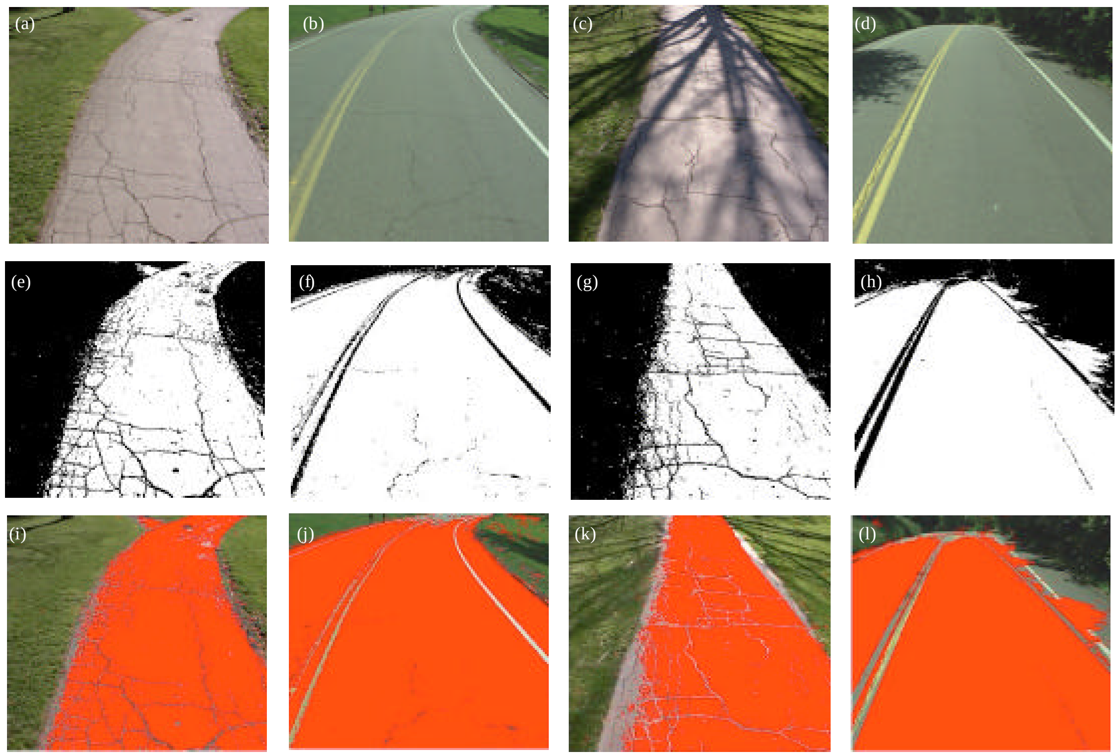

Fig. 4(a-l): First rows: (a-d) Four road sample images. Second rows: (e-h) Binary road segmentation images (obtained after applying the shadow detection removal technique followed by road segmentation algorithm). Third row (f-l) are the segmented road regions (in red)

Table 2: Performance of the proposed algorithm compared with algorithms presented by Alvarez *et al.* (2010) using a leave-one-out cross validation method from which three error measures are computed: Quality $\hat{g}$ detection accuracy DA and detection rate DR

Variables	$\hat{g}$	DA	DR
Algorithm 1	0.76±0.34	0.92±0.07	0.82±0.19
Algorithm 2	0.84±0.23	0.87±0.30	0.90±0.22
Proposed method	0.91±0.04	0.92±0.32	0.96±0.01

tested in a variety of scenarios like highway and urban expressway on straight and curved roads under different illumination. No calibration was needed for the experiment. Images sampled from the camera are in gray scale with a size of 640×480. Sample images provided in [cmu] (http://vasc.ri.cmu.edu/idb/html/road/may30_90/) are also used for the experiment.

Quantitative evaluations are provided using three pixel wise measures namely quality $\hat{g}$, detection rate DR and detection accuracy DA.

Low precision means that many background pixels are classified as road while low recall indicates failure to detect road surface. Equally weighting detection rate and detection accuracy, effectiveness F is defined as follow:

$$F = \frac{2PR}{P + R} \quad (16)$$

Effectiveness represents the trade off using weighted harmonic mean between detection rate and detection accuracy.

CONCLUSION

In this study, a robust and efficient way for unstructured road detection based on a simple yet effective shadow detection and removal algorithm has been introduced. First, the input image is converted to HSV space to detect shadows. Secondly, after the shadows are detected, they are removed by using the mean and variance value of the buffer area around each shadow. The said buffer area is estimated with the morphological operators. Finally, a real-time visual-based road segmentation method based on the use of adaptive color histograms has also been proposed. The results show the robustness and effectiveness of the proposed method, it also shows that this system is a good approach to road detection for autonomous vehicle. Further studies will include other research fields such as pedestrian tracking, vehicle detection, road sign detection and so on to improve the completeness of the system; this can be a good approach for fully autonomous vehicle navigation system.

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