Improved Shadow Removal for Unstructured Road Detection

Ngouh Njikam Ahmed Salim, Xu Cheng, Degui Xiao
College of Information Science and Engineering, Hunan University, Changsha, P.R.China

Abstract - *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 since the presence of shadows can cause hindrance and shape distortion of objects which may result in false detection of road. Shadows can also 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. To tackle those issues, this paper introduces an effective road recognition system using an image processing method to eliminate or reduce considerably the presence of strong shadows for unstructured road detection. Our 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 are detected using normalized difference index and subsequent thresholding based on Otsu's thresholding method. After the image-preprocessing step used for shadow removal, illumination invariant of road is estimated and a road probability map is calculated to determine whether or not each pixel belongs to road surface. Extensive experiments are carried out and the results show that our method effectively detect unstructured road areas while being robust to strong shadows and illumination variations. It's also important to note that the proposed algorithm does not depend on temporal restrictions and is invariant to road shape.*

Keywords: *Shadow detection, thresholding, road segmentation*

1 Introduction

Road detection is an important aspect of autonomous vehicle navigation system. For those autonomous vehicles to properly navigate on road, the roads 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 paper 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 our 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. Several road detection systems have been developed so far to address the topic of unstructured road segmentation [1], [2], [3], [4], [5]. 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 [6]. 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 [7]. 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 is proposed in this paper. The paper 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 our algorithm. What's more, as a novelty, we propose the use of a simple shadow detection and removal method [8] as part of our 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 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 removed by using the mean and variance values of the non-shadow area around each shadow (buffer area). The proposed approach will exploit the properties of shadows in luminance and chromacity and will be applied in HSV color space.

2 Image preprocessing

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

Fig.1. Unstructured Road images under different conditions [13].

2.1 Shadow detection

Firstly, we need to detect shadows 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. The shadow detection process is performed using Otsu's tresholding algorithm in the HSV color space. HSV color space is somehow very sensitive to the brightness level of the image and it well describes the feature information of the shadow [9]. 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 [10] and what's more, shadow detection methods based on HSV color space are more accurate than in the RBG color space. The relation between RGB space and HSV space is as follow:

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

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

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

Where

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

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. The ratio image enhances the hue property of shadows with low luminance, that is, the grey value of the shadow region is larger than non-shadowed region. Thirdly, we apply the Otsu segmentation method 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

$$V(T) = \frac{(\bar{\mu}.w(T) - \mu(T))^2}{w(T).\mu(T)} \tag{4}$$

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, 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.

2.2 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 paper we'll use the buffer area method developed in [8] 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,

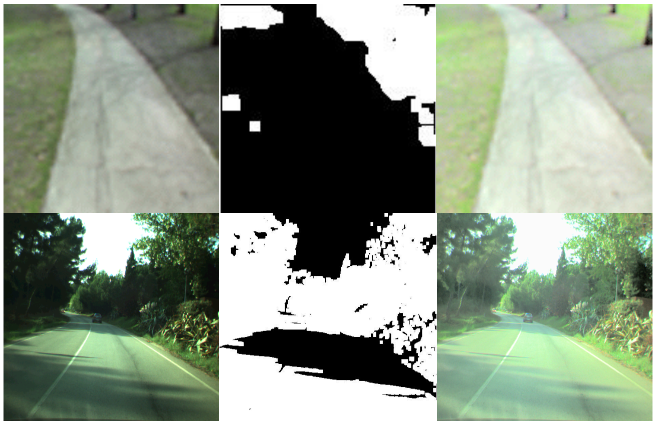

Fig.1 From left to right: input image, binary image showing shadows and shadow free image

shadows need to be classified based on the concept of connected components present on the binary image I_s. Each connected components correspond 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 $I_k = I_{k-1}$:

$$I_k = (I_{k-1} \oplus B) \cap I_s \quad k = 1,2,3... \qquad (5)$$

Where B is a suitable structuring element.

In the equation above, I_k contains all connected components of I_k 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:

$$I_{dilated,\,\mathrm{n}} = (I_{n-1} \oplus B_{square}) \qquad (6)$$

$$I_{buff,\,n} = (I_{dilated,\,n} - I_n) \qquad (7)$$

Where B_{square} is a square structuring element and $I_{buff,\,n}$ provides the location of the non-shadow points $n = 1,2,...,m$. These operations will expand the shadow boundaries.

Finally, the shadow removal image is obtained as follow:

$$I'_n(i,j) = \mu_{buff,n} + \frac{I_n(i,j) - \mu_n}{\sigma_{buff,n}} \sigma_n \quad n = 1,2,...,m \quad (8)$$

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 locations $I_{buff,\,n}$

3 Road detection algorithm

In this section, a road detection algorithm is devised for detecting unstructured roads which may have no lane markings on the road surface, degraded edges or road surfaces or strong shadow conditions which is solved by using the algorithm developed in the first section of this paper. It's also important to note that our 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 [11]: one based on road features, another based on road model and the third one is the combination of the fore two methods. In this paper, after converting the original image back to RGB color space, we'll use color segmentation module based on Bayesian classifier where the probability distributions of the road and non-road pixels are approximated by histograms in a RGB space [1]. The classifier includes three stages which are the likelihood estimation, the filtering and decision. The resulting image is a binary image that defines which pixels are part of the road and which one are not. The road histogram is determined using the information of a fixed region of the image while the non-road histogram according to the classifier output.

3.1 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:

$$H_r[r,g,b] = \alpha . H_r[r,g,b] + (1-\alpha). H_t[r,g,b] \qquad (9)$$

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

3.2 Classification using the bayesian theory

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.

$$H_r \approx \{P(Color|Road)\} \qquad (10)$$

$$H_n \approx \{P(Color|Non-road)\} \qquad (11)$$

Where H_r and H_n which respectively represent the road and non-road histograms, are approximations of the probabilities of finding a RGB pixel in a road and non-road respectively.

The new image is therefore constructed by calculating the quotient of H_r and H_n for each pixel of the input image as follow:

$$S[i] = \frac{H_r[I_m(i)]}{H_n[I_m(i)]} \qquad (12)$$

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:

$$S_m[i] = \beta . S_m[i] + (1-\beta) . S[i] \qquad (13)$$

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:

$$B[i] = \begin{cases} 1 & S_m[i] \geq T \\ 0 & S_m[i] \prec T \end{cases} \qquad (14)$$

4 Test results

Our 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 1 above shows shadowed RBG road images and their corresponding binary image showing shadows. The shadows detected are shown in white color. The accuracy of shadow detection can be seen from the fact that roads are not detected as shadows. Figure 2 also shows shadow free road images and the resulting road segmentation images. It can be seen that our method has good robustness to the impact of shadow on the road due to the above shadow removal method. The results show the effectiveness of the proposed algorithm in de-shadowing and detecting unstructured roads.

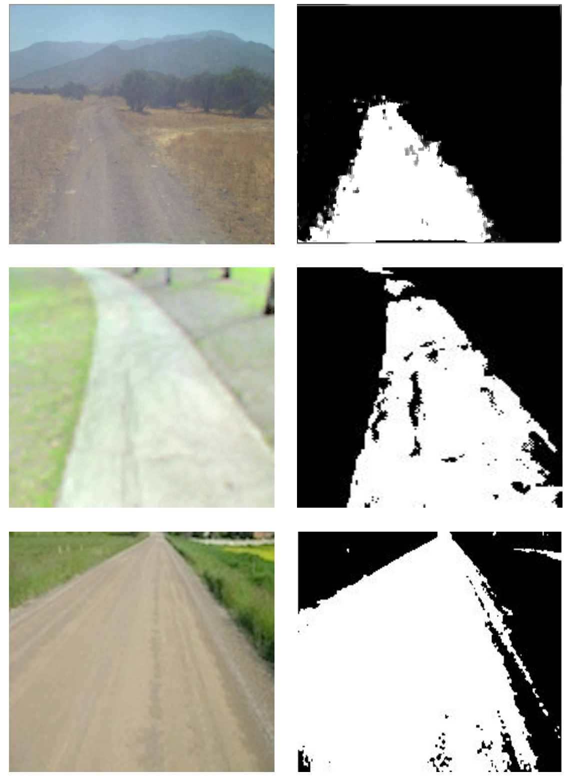

Fig.2. Shadow free images and their corresponding segmentation output.

Performance evaluation

In this section, we use recall and precision as the performance measures to evaluate the performance of the proposed road detection system. Quantitative evaluation are provided using three pixelwise measures namely precision, recall and effectiveness. Precison and recall are defined as:

$$recall = \frac{N_{success}}{N_{success} + N_{\mathrm{missing}}} \times 100\% \qquad (12)$$

$$precision = \frac{N_{success}}{N_{success} + N_{false}} \times 100\% \qquad (13)$$

Where $N_{success}$ represents the number of successfully detected road from the detection process, N_{missing} stands for the number of undetected road, and N_{false} represents the number of false alarms. The sum $N_{success} + N_{missing}$ is the total number of automatically generated ground truth data in the entire image sequences.

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

$$F = \frac{2PR}{P+R} \tag{14}$$

Effectiveness represents the trade off using weighted harmonic mean between precision and recall.

5 Concluding remarks

In this paper, we have introduced a novel and efficient way for unstructured road detection based on a simple yet effective shadow detection and removal algorithm. 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, we also proposed a real-time visual-based road segmentation method based on the use of adaptive color histograms. 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 our system., this can be a good approach for autonomous vehicle navigation system.

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