MVA2005 IAPR Conference on Machine VIsion Applications, May 16-18, 2005 Tsukuba Science City, Japan
15-3

Shadow Compensation in Color Images for Unstructured Road Segmentation

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Abstract

Road-following by mobile robots under varying outdoor illumination demands special care to be taken in road segmentation to handle color changes in sunny or shadow parts. This paper addresses the technical feasibility of an automatic color evaluation method for fast segmentation of roads with unknown geometrical shapes. Instead of color segmentation in 2D or 3D color space, we use automatic color projection to shorten the total processing speed.

1 Introduction

In a "follow–road" mission in order to use visual feedback for robot position control, the location of the road must be detected in the input image. This involves segmenting the image into road and non–road regions even in presence of shadows on the road surface (Fig.1) and locating the road which corresponds to robot direction.

One global approach is use of 3D representation of the surrounding field by stereo vision [11]. Systems that employ grey level images like [7, 16, 13, 14, 15, 6] either ignore the segmentation problem in shadow and highlights on the road surface, or use the edge properties of structured roads. Therefore, such methods cannot be used for degraded forest roads. Also in [12] it is shown that fusion of too many image features like texture and color does not improve the result of road segmentation necessarily. Automatic calculation of feature weights is a problem in such methods.

The Carnegie Mellon University in Pittsburgh, USA, have conducted excellent researches on autonomous outdoor vehicle navigation using color image processing and range data, such as RALPH, ALVINN or RANGER [2, 9]. The research was based on color clustering in 3D color space which can be considered as a general solution to color–based road segmentation. SCARF and UNSCARF [4, 5] are two remarkable examples of this method. However, in both examples the geometry properties of the road is an important factor.

(a) (b)

Figure 1: Unstructured roads with strong shadows (a) test image by CMU (b) The road in our test field.

To avoid the time consumption of clustering in 3D color space, many researches tried to reduce the number of data dimensions. Turk et al. [3] discussed that asphalt roads can be separated by a threshold in R/B plane, based on this fact that in a color image pavements look more blue than surrounding dirt or vegetations. Also Lin et al. [10] proposed asphalt road segmentation in S/I (Saturation/Intensity) plane, indicating that asphalt saturation is lower than surroundings regions. Such methods are applicable only to asphalt paved roads. Fernandez et al. [1] proposed a method for segmentation of forest dirt roads based on converting the input RGB image to H/I (Hue/Intensity) plane with 128 color (hue) and 64 gray levels.

2 Brightness Invariants

Our purpose of color analysis is to reject shadow and highlights in the road segmentation algorithm by using one single parameter. To speak in the language of light physics, each sensor cell in a given image point receives a band of λ, the total received color (C) is written in integral form:

$$C = \int_0^\infty I(\lambda)\rho(\lambda)S(\lambda)d\lambda \tag{1}$$

where λ (in [nm]) is the wavelength of the light emitted by a point in the environment ($\lambda \in$\{infrared$\sim$ultraviolet\}). The sensor effect $S(\lambda)$ itself is a combination of CCD sensitivity $c(\lambda)$ and the output amplifier scaling factor s_λ:

$$S(\lambda) = s_\lambda c(\lambda) \tag{2}$$

Since the CCD sensor sensitivity $c(\lambda)$ is usually unknown, it is approximated by a delta function $\delta(\lambda)$. By replacing

$$\int_0^\infty S(\lambda)d\lambda = s_\lambda \int_0^\infty \delta(\lambda)d\lambda = s_\lambda \tag{3}$$

it will simplify to:

$$C = s_\lambda I(\lambda)\rho(\lambda). \tag{4}$$

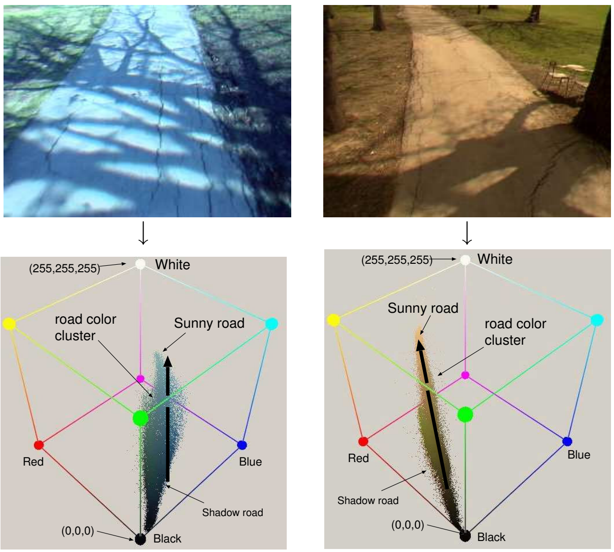
As a result, the color component – say R – in sunny and shadow regions can be written as:

$$R_{\mathrm{s}} = s_{\mathrm{r}} I_{\mathrm{s}}(r)\rho(r) \tag{5}$$

$$R_{\mathrm{sh}} = s_{\mathrm{r}} I_{\mathrm{sh}}(r)\rho(r) \tag{6}$$

where s_{r} stands for sensor's output amplifier factor for the red signal, I_{s} is brightness of both highlight (direct reflection) and ambient light (the indirect reflection), I_{sh} is the ambient light and $\rho(red)$ is the reflection function of object in red light. Without loss of generality, the same equations can be hold for G an B components.

An empirical analysis of colors in RGB cube (as shown in Figure 2) shows that the pixel distributions can be represented simply by slope and interception diagonal axis of color clusters.



(a) (b)

Figure 2: Effects of sunlight on the road color (a) a change in brightness (b) a change in brightness and color.

The comparison between sunny and shadow parts yields us to the resault that color pixels are either shifted in brightness:

$$R_{\mathrm{s}} = s_{\mathrm{r}}(I_{\mathrm{sh}}(r) + b)\rho(r) \tag{7}$$

(where b is shift of brightness), or shifted in color saturation:

$$R_{\mathrm{s}} = s_{\mathrm{r}}(m I_{\mathrm{sh}}(r))\rho(r) \tag{8}$$

where m is the scale factor. Based on statistical results, there have been two types of color features for elimination of brigtness effect from color signals:

2.1 Subtraction–based brightness–invariants

In this case the easiest way to remove brightness information to form a pure color channel is to subtract it. Examples of this approach are ohta's I_2, E and or S in YES color system. In fact, any subtraction like $R-B$, $G-B$, $R-G$ in 2D or

$$S^{*} = \max(R,G,B) - \min(R,G,B) \tag{9}$$

in 3D or other combinations of this type will generate a new parameter which is not sensitive to brightness changes. For asphalt roads bounded by dirt regions Turk in [3] suggested $R-B$ parameter. But to considering the three dimentional nature of color, the following parameter is proposed:

$$r_1 r_2 r_3 \left\{ \begin{array}{l} r_1 = \max\{G,B\} - R \\ r_2 = \max\{R,B\} - G \\ r_3 = \max\{R,G\} - B \end{array} \right. \tag{10}$$

2.2 Division–based brightness–invariants

Another way to achieve invariant parameters is to normalize the RGB values to the intensity factor. This can be done by division of color signals. Examples of this type of parameters are normalized–RGB (rgb), saturation calculated by:

$$S^{**} = \frac{\max\{\mathrm{R,G,B}\} - \min\{\mathrm{R,G,B}\}}{\max\{\mathrm{R,G,B}\}} \tag{11}$$

or the new introduced colors like $c_1c_2c_3$

$$c_1c_2c_3 \left\{ \begin{array}{l} c_1 = \arctan\left(\frac{R}{\max\{G,B\}}\right) \\ c_2 = \arctan\left(\frac{G}{\max\{R,B\}}\right) \\ c_3 = \arctan\left(\frac{B}{\max\{G,R\}}\right) \end{array} \right. \tag{12}$$

and $l_1l_2l_3$:

$$l_1l_2l_3 \left\{ \begin{array}{l} l_1 = \frac{(R-G)^2}{(R-G)^2+(R-B)^2+(G-B)^2} \\ l_2 = \frac{(R-B)^2}{(R-G)^2+(R-B)^2+(G-B)^2} \\ l_3 = \frac{(G-B)^2}{(R-G)^2+(R-B)^2+(G-B)^2} \end{array} \right. \tag{13}$$

which are suggested by Gever and discussed in [8]. Yet we propose another brightness–invariant model can be obtained by calculation:

$$r'_1r'_2r'_3 \left\{ \begin{array}{l} r'_1 = \frac{\max\{G,B\}-R}{\max(R,G,B)} \\ r'_2 = \frac{\max\{R,B\}-G}{\max(R,G,B)} \\ r'_3 = \frac{\max\{R,G\}-B}{\max(R,G,B)} \end{array} \right. \tag{14}$$

It is shown that in some forest road scenes, segmentation by r'_3 yields to better results in comparison to other brightness invariant parameters.

3 Road Segmentation

Assume that a road can be represented by mean value μ_{c} of an unknown color, where subscript c indicates the road. We desire the road segmentation be performed by computation of Euclidean distance so that for any given image pixel x, the distance defined by:

$$d = |x - \mu_{\mathrm{c}}| \tag{15}$$

shows the similarity of that pixel to the road. Clearly calculation of distance by Eq.(15) is far faster than clustering techniques that use multiple color clusters.

Given a color feature f we would like to know if it can be used in Eq.(15) for road segmentation or not. This is done by dividing the image into road and non–road regions. For the first frame, this task is done by operator but in the next frames it is performed automatically by the program. The road (h_{r}) and non–road (h_{nr}) histograms of feature f is then used to define how f fits for segmentation of road region, as explained in following paragraphs:

The zone z is the minimum region in the histogram centered on μ_{r}, where more than z percent of road pixels are located in it. For example when $z = 90$, then z includes 90% of total number of road pixels in the histogram. Mathematically it can be expressed by:

$$\frac{\sum_{\mu_{\mathrm{r}}-d_z}^{\mu_{\mathrm{r}}+d_z} h_{\mathrm{r}}}{N_{\mathrm{r}}} \times 100 > z \quad \text{(in percent)} \tag{16}$$

where h_{r} is the road histogram, N_{r} is the total number of road pixels and d_z indicates the distance from μ_{r} as shown in Fig.3.

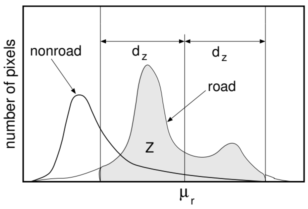


Figure 3: The definition of zone z in of road and non–road histogram. For a given z, the feature f is evaluated by Eq.(17).

For any given z, a factor κ calculated by:

$$\kappa = (1.0 - \frac{\sum_{i=\mu_{\mathrm{r}}-d_z}^{\mu_{\mathrm{r}}+d_z} h_{\mathrm{nr}}}{N_{\mathrm{nr}}}) \times 100 \tag{17}$$

is used for evaluation of the feature f, where N_{nr} is the total number of non–road pixels. The feature with higher value of κ can then be selected for road segmentation.

The method of feature evaluation explained above in Eq.(17) was applied on many road scenes including a road image set provided by CMU used for their NAVLAB tests [2, 4, 5]. We have examined this evaluation process on some of them as shown in Fig.4.

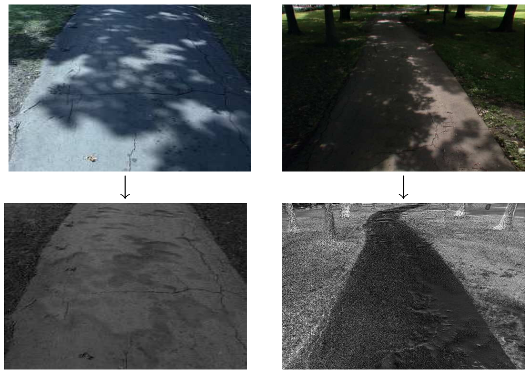


Figure 4: Results of feature selection for road segmentation in different test roads. Upper images are input and lower images are the output of selected color channel with highest value of κ calculated by Eq.(17).

Figure 5: The robot while self–navigation in a real forest field.

4 Implementation

The road extraction by automatic color selection explained in previous section was used for navigation of a prototype 4 wheel robot. The robot was missioned through a forest road which is shown in Fig.5.

The color parameter evaluation of this particular road scene is summaraized in Fig.6.

Once the image is calculated by selected color feature, road segmentation is then performed by region growing. Finally the road model is estimated by line regression across the line edges. Based on this evaluation, some images are shown in Fig.7. The 4'th row of images in Fig.7 shows a failure result. This is because, the colors are saturated and values are beyond the sensing range of the camera.

5 Conclusion

When there are no tools for prediction of color changes in shadow or highlights on the road surface, clustering in 2D or 3D color space is probably the most general solution. However, our experiments on several road scenes show that in most cases it is possible to find out a single dimensional image feature for road segmentation, without any need for color clustering.

The feature is selected by an evaluation process, which evaluates different features before navigation, and uses that feature for road extraction while navigation. Once the feature is selected, the road segmentation is then performed simply by calculation of Euclidean distance of each pixel from mean value of the road sample.

Two new color sets called $r_1r_2r_3$ and $r_1'r_2'r_3'$ were introduced and it was shown that in some cases, the segmentation by these features yields to better results than other conventional parameters.

We can conclude that there is no singular feature which can be used for all situations. A difficult example is a colorless scene (like snow roads) with no information about geometrical shape of the road. In absence of prior knowledge about geometrical shape of the road exists, correct extraction of the road region will be very complicated.

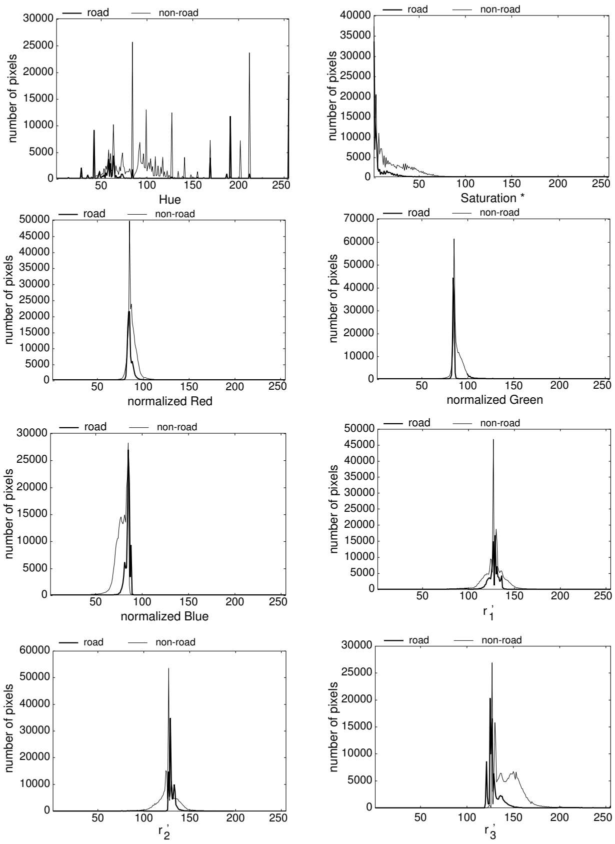


Figure 6: Histogram analysis of the road scene in Fig.5. r_3' has the highest value of κ calculated by Eq.(17).

Figure 7: Results of color selection for road segmentation in our test field. Darker regions have similar values to the road color.

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