ADAPTIVE FUZZY COLOUR SEGMENTATION ON RGB RATIO SPACE FOR ROAD DETECTION

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Abstract: In this paper, the RGB ratio is defined according to a reference colour such that the image can be transformed from a conventional colour space to the RGB ratio space. Different to distance measurement, a road colour segment is determined by an area in RGB ratio space enclosed by the estimated boundaries. Adaptive fuzzy logic, which fuzzy membership functions are defined according to estimated boundaries, is introduced to implement clustering rules. Low computation cost of the proposed segmentation method shows the feasibility to real time application. Experimental results for road detection demonstrate the robustness to intensity variation of the proposed approach.

1 INTRODUCTION

Colour segmentation is an essential issue to vision applications, such as object detection and vision navigation etc (Bosch et al., 2007; Lin, 2007). The process of colour segmentation consists of colour representation, colour feature extraction, similarity measurement and classification. In colour representation, the RGB (Red, Green and Blue) model, which expresses colour as a mixture of red, green and blue three colour components, is often used to depict colour information of an image (Weng et al., 2007; Bascle et al., 2007). By a transformation, the secondary colours, which are CMY (Cyan, Magenta and Yellow) or RG-GB-BR, can be obtained and used as an alternative colour model (Wang et al., 2007). The HSI model, which transforms RGB into Hue, Saturation and Intensity, is also a popular colour model at present, and good performance are shown in many works (Kim et al., 2008; Kim et al., 2007; Wangenheim et al., 2007). HSV (Value) and HSL (Luminance) are very similar to the HSI model due to the applied transformation formulas. Using the HSI colour model, a specific colour is able to be recognized regardless of variation of saturation and intensity. CIE Luv, CIE Lab and YCbCr (Wang and Huang, 2006; He et al., 2007) are colour spaces which represent colour by its intensity (L and Y) and chromaticity (uv, ab and CbCr). In this paper, we propose a novel colour model called the RGB ratio model, which is based on a fact that a change of intensity of a reference colour will lead to a change of RGB colour components, but their ratio to the reference colour will be linear to the intensity change (Benedek and Sziranyi, 2007; Mikic et al., 2000). With this property, a specific colour can be recognized despite an intensity variation. Moreover, information of three colour components (RGB) is reserved to describe the chromaticity by the proposed RGB ratio space. Therefore, inheriting the characteristics of HSI and RGB models, the RGB ratio has advantages on object recognition under intensity variations.

There exist many state-of-art and complex techniques for colour segmentation which are excellent at partitioning an input image. For example, the global colour statistics can be represented by a set of overlapping regions and modeled by a mixture of Gaussians (GMM), and a local mixture model is described by Markov Random Fields (MRFs) (Kato, 2008). By optimizing parameters of the global and local model, maximum likelihood is estimated and then a pixel can be classified. Although marvelous segmented results are revealed, a large number of iterations are necessary to determine optimal parameters. As a result, the computation time of an image with 256×256 resolution costs 16 seconds (Tai et al., 2007).

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Hill manipulation of colour histogram is another commonly used approach to achieve colour segmentation. A three dimensional histogram can be obtained by accumulating three colour components of pixels. Then dominant hill detection and minor hill dismantling are used to estimate clustering index (Aghbari and Al-Haj, 2006). The idea of 'Histon' , which is an encrustation of histogram such that the elements in the histon are the set of all the pixels that can be classified as possibly belonging to the same segment, was introduced for colour segmentation by Murshrif and Ray (2008). The total computation time of a 179×122 image requires 2.41 seconds.

Neural networks (Bascle et al., 2007) are used as clustering kernel for colour segmentation recently, where components of the RGB space and the intensity are used as inputs and three calibrated colour components are considered as outputs of the modified multi-layer perceptron (MLP). After the training procedure, a good segmentation performance is achieved. Furthermore, the look-up tables (LUT) of the modified MLP can be applied for real-time applications such that the execution time for a 320×240 image is 0.00375 second. However, a huge amount of database is required to be created. If an input image is very different from database, the network should be re-trained to improve the result. The fuzzy C-means theory is applied as the clustering method (Kuo et al., 2008), and similarity measurement is based on Euclidean distance (Luis-Garcia et al., 2008). Bosch et al. (2007) recognize grass, sky, snow and road using fuzzy logic with predefined classes, where the average processing time for image size of 180×120 to 250×250 requires 60 seconds.

The use of template image is another fast segmentation method. For instance, image database of eye is established beforehand. Skin colour is obtained from a colour conversion matrix with colour of the sclera. Consequently, fixed thresholds of HSV space are introduced to detect skin area in an input image (Do et al. 2007). However, the use of template image is restricted to specific object, and may require a large image database.

In this paper, we propose an adaptive fuzzy decision kernel to achieve a quality segmented result. Firstly, the linearity between RGB ratio and intensity is estimated by linear progressive method and parameter estimation. Secondly, an upper and a lower boundary are obtained statistically for each colour ratio. These boundaries are used to define fuzzy membership functions of colour ratio clusters, which dynamically vary corresponding to intensity changes. It makes the fuzzy decision more adaptive and more effective.

This paper is organized as follows: The proposed RGB ratio space to represent colour characteristic is defined in Section 2. Linear progressive method and parameter estimation, which are adopted to estimate linearity between RGB ratios and intensity, are described in Section 3. Upper and lower boundaries are also obtained in Section 3 to describe fuzzy membership functions, which can be used to achieve segmentation of an input image. The proposed segmentation method is applied for road detection in Section 4. The results and comparisons are demonstrated to show its feasibility. Conclusions are given in Section 5.

2 RGB RATIO SPACE

Road detection is a typical application of colour segmentation. In this study, the central bottom area of an image defined by $(2N+1)\times(2N+1)$ pixels should belong to the road. From projective geometry, this area is closest to the camera system. If this area is not part of the road, the navigation system should give a stop or turning command instead of evaluating the reference road colour value. By calculating average values of RGB components of the $(2N+1)\times(2N+1)$ pixels, the reference road colour is defined as

$$Ref_j = \frac{\sum_{m=-N}^{N}\sum_{n=-N}^{N} f_j(\frac{w}{2}+m,(h-N)+n)}{(2N+1)^2} \tag{1}$$

where $j = R,G,B$, $f_j(x,y)$ is the colour component of a pixel which coordinates is (x,y) in the initial image, and $w\times h$ is the image resolution.

Based on the existence of the linear relation between RGB ratio $f_{r_{RGB}}$ and intensity f_I , we define the linear relation as the following.

$$f_{r_j} = P_j \times f_I + Q_j,\ j = R,G,B \tag{2}$$

Parameters P_j and Q_j in equation (2) is not available straightforwardly because the pixel set of the road is under determined. Therefore, a sample set of the road $\mathbf{C} = \left\{ f_{HSI}\left(x_1,y_1\right), f_{HSI}\left(x_2,y_2\right),\cdots, f_{HSI}\left(x_k,y_k\right)\right\}$

defined in the HSI space as described in (3) is introduced to estimate P_j and Q_j.

$$\mathbf{C} = \left\{ \; \left| f_i(x,y) - Ref_i \right| \le \lambda_i \; \middle| \; f_{HSI}(x,y) \right\} \tag{3}$$

where $i = H,S,I$, $\lambda_H = 20°$, $\lambda_S = 0.1$ and $\lambda_I = 0.1$ are the appropriate thresholds defined in the HSI space (Gonzalez and Woods, 2002). Therefore, the RGB ratio value of the sample set $\mathbf{C}$ can be obtained as

$$f_{r_j}(x_k, y_k) = \frac{f_j(x_k, y_k)}{Ref_j}, \; j = R,G,B \tag{4}$$

3 SEGMENTATION METHOD

3.1 Road Model Construction

With the sample set $\mathbf{C}$, parameters P_j and Q_j can be determined using linear estimation (Yates and Goodman, 2005) as follows.

$$P_j = \frac{\sum_{i=1}^{k}\left(f_{r_j}(x_i,y_i) - \mu_{r_j}\right)\left(f_I(x_i,y_i) - \mu_I\right)}{\sum_{i=1}^{k}\left(f_{r_j}(x_i,y_i) - \mu_{r_j}\right)^2} \tag{5}$$

$$Q_j = \mu_{r_j} - P_j \times \mu_I \tag{6}$$

where $j = R,G,B$, μ_{r_j} is the mean colour ratio value and μ_I is the mean intensity of $\mathbf{C}$. Although P_j and Q_j are obtained based on the sample set $\mathbf{C}$, the maximum/minimum intensity value ($L_{\max} / L_{\min}$) of the actual road set are required to fully describe the road model. A searching procedure is applied as follows.

Step 1 : Let $z_{\max} = l_{\max}$ and $z_{\min} = l_{\min}$ where $l_{\max}$ and $l_{\min}$ are the maximum and minimum intensity values of the sample set $\mathbf{C}$, respectively.

Step 2 : Let searching range $z_1 \in [z_{\max}, z_{\max} + \delta]$ and $z_2 \in [z_{\min} - \delta, z_{\min}]$

Step 3 : With

condition 1 : $\left| f_{r_j}(x,y) - \left(P_j \times z_1 + Q_j\right) \right| \le \varepsilon$

condition 2 : $\left| f_{r_j}(x,y) - \left(P_j \times z_2 + Q_j\right) \right| \le \varepsilon$

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If the number of pixels which
  satisfy condition 1 / condition 2
  is zero
  Lmax=zmax / Lmin=zmin and stop.
else
   set zmax=zmax+δ / zmin=zmin−δ
   if zmax ≥ 1 / zmin ≤ 0
    set Lmax=1 / Lmin=0 and stop.
   else
    redo step 3.
```

$f_{r_{RGB}}(x,y)$ is the image represented by RGB ratio, $\delta = 0.05$ and $\varepsilon = 0.05$.

With $L_{\max}$ and $L_{\min}$, the boundary of the road colour set can be described as follows. The line $\overline{AB}$ in Fig. 1 is estimated from the sample set $\mathbf{C}$ in one of the colour ratio planes. $A(L_{\min}, r_{jA})$ and $B(L_{\max}, r_{jB})$ are the extreme points on $\overline{AB}$, which is obtained from the searching procedure. The arc $\overset{\frown}{AEB}$, which represents the upper boundary of the road colour set, can be defined by a circle center $O(I_O, r_{jO})$ and radius R determined as follows .

$$R = \frac{D^2 + K^2}{2D} \tag{7}$$

$$\begin{aligned} I_O &= I_M \pm \sqrt{\frac{R^2 - K^2}{1 + S^2}} \\ r_{jO} &= r_{jM} - S\left(I_M - I_O\right) \end{aligned} \tag{8}$$

Where $K = \overline{AM} = \overline{BM}$, $S = \dfrac{L_{\min} - L_{\max}}{r_{jB} - r_{jA}}$ and $D = \overline{EM} = \alpha \times e$. e is the mean squared colour ratio error of the sample set $\mathbf{C}$, and α is a gain corresponding to model strictness, α = 2 in this study.

From (7) and (8), equations of the upper boundary $\overset{\frown}{AEB}$ and the lower boundary $\overset{\frown}{AFB}$, as shown in Fig. 2, can be represented as (9) and (10) .

$$\overset{\frown}{AEB}: \begin{cases} r_j = r_{jO} + \sqrt{R^2 - \left(I - I_O\right)^2} \\ I_O = I_M + \sqrt{\dfrac{R^2 - K^2}{1 + S^2}} \end{cases} \tag{9}$$

$$\widehat{AFB}: \begin{cases} r_j = r_{jO} - \sqrt{R^2 - \left(I - I_O\right)^2} \\ I_O = I_M - \sqrt{\dfrac{R^2 - K^2}{1 + S^2}} \end{cases} \tag{10}$$

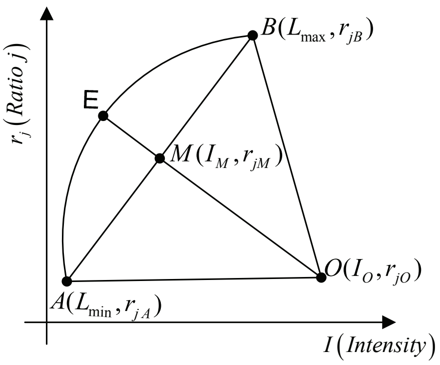


Figure 1: Determination of the upper road colour set boundary.

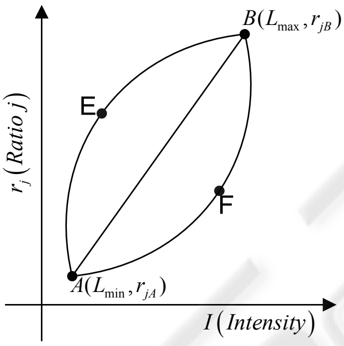


Figure 2: The upper and the lower boundary of the road colour set.

3.2 Adaptive Fuzzy Road Detection

For robustness and flexibility, fuzzy logic is used as the decision maker of the proposed segmentation method, where the membership functions are adaptively defined according to the road set obtained in section 3.1. In this paper, three RGB ratios and the corresponding intensity are four inputs of the fuzzy decision system. Fig. 3(a-c) show three membership functions for input ratios, where the Lower/Upper represent the sets which colour ratio is smaller/greater than the lower/upper boundary of the road colour set. The upper boundary (UB) and the lower boundary (LB) are obtained by (9) and (10), respectively. $d = \beta \times e$ and β is a gain for the sensitivity of the fuzzy system. In this way, membership functions for each input are adaptively defined according to the intensity value. The membership functions of the two outputs, Dissimilar and Similar, are shown in Fig. 3(d). Fuzzy decision table is shown in Table 1, and max-min-composition method (Zimmermann, 1991) is used as the defuzzification method. Quality road detection results using the proposed adaptive fuzzy decision are demonstrated in the next section.

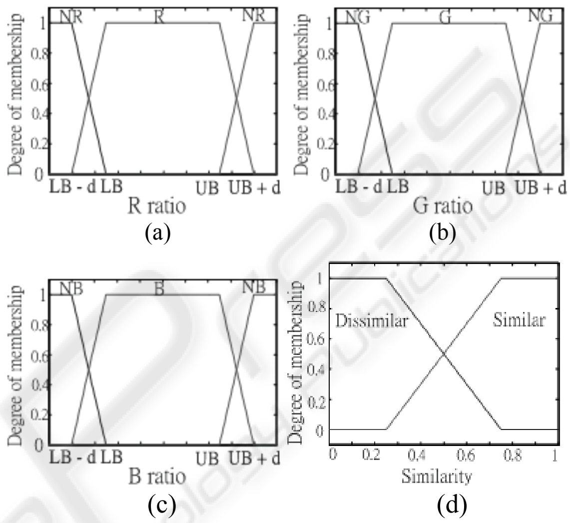


Figure 3: Fuzzy membership functions.

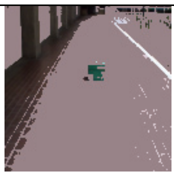
Table 1: Fuzzy decision table.

R ratio	G ratio	B ratio	Segmentation
NR	NG	NB	Dissimilar
NR	NG	B	Dissimilar
NR	G	NB	Dissimilar
NR	G	B	Dissimilar
R	NG	NB	Dissimilar
R	NG	B	Dissimilar
R	G	NB	Dissimilar
R	G	B	Similar

4 EXPERIMENTAL RESULTS AND DISCUSSIONS

For road detection studies, experimental images on brick pavement are taken by the SONY EVI-D70 camera. Original image size is 640×480 and is resized to 128×128 for real-time performance. All algorithms are applied in VC++ with Pentium-4 3.0GHz CPU and 1GB memory. To evaluate the performance of the road detection using the proposed colour segmentation method, the detection rate, TPR, FPR and FNR, introduced by Do et al. (2007) is applied as follows.

Table 2: Comparison of segmented results of brick pavement.

Result	TPR (%)	FPR (%)	FNR (%)
 RGB with optimal Euclidean distance 0.5	84.09	18.29	15.91
 HSI with optima Euclidean distance 0.7	64.56	10.57	35.21
 RGB ratio with $\beta = 2$ adaptive fuzzy	98.14	3.65	1.86

First of all, we define the exact road region as true ground (TG), while all pixels are classified as road by the proposed method are defined as detected ground (DG). True positives (TP) are correctly detected road pixels, false negatives (FN) are incorrectly dropped road pixels, and false positives (FP) are false road pixels outside the exact road region. The true positive rate (TPR), which is TP/TG, is the proportion of true positives to true ground, the false negative rate (FNR), which is FN/TG, is the proportion of false negatives to true ground, and the false positive rate (FPR), which is FP/DG, is the proportion of false positives to detected ground.

Road detected results using the proposed method on brick pavement are shown in Table 2. Detected results using the RGB model and the HSI model with Euclidean distance measurement are compared with the proposed approach. From Table 2, the TPR of the proposed method is much higher than the other two methods and the FPR is less than 5%. It was revealed that the colour is difficult to be recognized for its intensity close to 0 or 1 (Plataniotis and Venestsanopoulos, 2000). Therefore, an intensity adjustment is applied to avoid the achromatic case and to improve detected results, as shown in Table 3. From the detection rate listed in Table 2 and 3, the TPR of adjusted images using the proposed method is increased by 0.8% and the FPR is dramatically decreased by 2.65%. Segmented results demonstrated in Table 2 and 3 show the superiority and the successfulness of the proposed method.

Table 3: Comparison of segmented results with intensity adjustment of brick pavement.

Result	TPR (%)	FPR (%)	FNR (%)
 RGB with optimal Euclidean distance 0.4	90.25	18.85	9.75
 HSI with optima Euclidean distance 0.7	64.52	11.00	35.14
 RGB ratio with $\beta = 2$ adaptive fuzzy	98.94	1.00	1.06

5 CONCLUSIONS

This paper proposes the RGB ratio space to construct the road model. The linear relation for the road model between colour ratios and the intensity is estimated by a detected road reference value. Adaptive fuzzy decision is also introduced as the clustering method to detect the road in a more robust and effective manner. The use of adaptive membership functions according to the intensity for each colour ratio achieves satisfactory performance for the road detection. Experimental results demonstrate the feasibility of the proposed approach.

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