Integration of Feature Distributions for Colour Texture Segmentation

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Abstract

This paper proposes a new framework for colour texture segmentation and determines the contribution of colour and texture. The distributions of colour and texture features provides the discrimination between different colour textured regions in an image. The proposed method was tested using different mosaic and natural images. From the results, it is evident that the incorporation of colour information enhanced the colour texture segmentation and the developed framework is effective.

1. Introduction

Texture and colour are the two important innate features that can be employed to detect the colour texture variations in an image. Segmentation was based on grey scale images until recently, when the concern changed to the joint representation of texture and colour for colour texture segmentation. The main objective of this paper is to develop a framework for colour texture segmentation and to determine the use of colour information in the colour texture segmentation process.

In this paper, the colour and texture features were extracted separately and combined for colour texture segmentation. The grey scale algorithms were employed in the luminance plane with colour information as an extra cue. The developed colour texture segmentation method integrates colour and texture by using their feature distributions. Chen *et al.* [1] proposed a method using the distributions of colour and local edge patterns which is used to derive a homogeneity measure for colour texture segmentation. Jain and Healey [4] introduced a method for colour texture classification based on unichrome features computed from the three spectral bands independently and opponent colour features that utilise the spatial correlation between spectral bands. Drimbarean and Whelan [2] examined the contribution of colour information to the overall classification performance by extracting texture features and colour features. It was found that the inclusion of colour increases the classification results without significantly complicating the feature extraction algorithms. Pietiekainen *et al.* [8] presented a colour texture classification based on separate processing of colour and pattern information. From the classification results it was concluded that colour and texture have complementary roles.

In this study, Local Binary Pattern (LBP) [5] is used as the texture feature extraction technique. The LBP operator alone cannot properly detect large scale textural structures that exists in real world applications. In addition, LBP is not invariant to rotation. The limitation of LBP in the segmentation procedure was overcome by combining the colour features. Colour features were derived based on *k*-means algorithm which clusters the input image by organising the data into *k* different clusters. The distributions of LBP and the distributions of colour clustered labels were combined for colour texture segmentation. This unification of colour and texture increases the efficiency of colour texture segmentation. Any of the available feature extraction techniques can be used in this framework.

2. Feature Distributions

LBP is invariant against any monotonic grey scale transformation. This provides robust pattern related information and knowledge about the spatial structure of the local image texture. LBP is combined with the contrast of the texture which is a measure of local variations present in an image for the texture description. The distributions of LBP and contrast $(256 * 8)$ were used for texture description.

This study uses the unsupervised clustering technique based on the *k*-means algorithm to cluster the colour features. The *k*-means algorithm [3] is the simplest and most popular among the iterative clustering algorithms. The k-means algorithm organises the objects into an efficient representa-

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tion that characterises the population being sampled. The number of clusters is generally image dependent so the initial guess is 10 clusters, this number is sufficient to capture all the relevant clusters. The distribution of the colour clusters is used for colour description.

Modified Kolmogorov Smirnov (M-KS) A non-parametric test M-KS statistic was used for comparing LBP/C with colour clustered labels. This tests the hypothesis that two empirical feature distributions have been generated from the same population. M-KS has the desirable property that it is invariant to arbitrary monotonic feature transformations. The M-KS statistic is defined as the sum of the absolute value of the discrepancies between the normalised cumulative distributions.

$$D(s,m) = \sum_i \left| \frac{F_s(i)}{n_s} - \frac{F_m(i)}{n_m} \right| \quad (1)$$

where $F_s(i)$ and $F_m(i)$ represents the sample cumulative distribution functions; n_s and n_m represents the number of pixels in the sample regions. Since M-KS is normalised, it is advantageous over other statistical measures such as: G statistic and the Chi square statistic.

3. Segmentation Method

The unsupervised colour texture segmentation method involves three steps: hierarchical splitting, agglomerative merging and the boundary refinement.

Hierarchical Splitting The hierarchical splitting recursively splits the input image into four subblocks. The six pairwise M-KS values between the LBP/C of the 4 subblocks were calculated. The uniformity of the region was tested by a decision factor

$$R = \frac{MKS_{max}}{MKS_{min}} > X \quad (2)$$

where X is a threshold value, MKS_{max} and MKS_{min} represents the highest and the lowest M-KS values.

Agglomerative Merging An agglomerative merging procedure was applied on the image which has been split into blocks of roughly uniform textures. This procedure merges similar adjacent regions until a stopping rule is satisfied. The pair of adjacent segments which has the smallest Merger Importance (MI) value were merged. The MI value between two regions is calculated as followed,

$$MI = w_1 \times MKS_1 + w_2 \times MKS_2 \quad (3)$$

where w_1 and w_2 represents corresponding weights for LBP histogram and colour clustered histogram and MKS_1 and MKS_2 are the M-KS statistic for texture and colour histograms respectively. The weights are automatically detected using an uniformity factor defined as the maximum ratio between the pixel count contained in each bin in the colour histogram and the pixel count contained in the whole region under investigation. This uniformity factor assess the distribution or the scatter-ness of the colour histogram.

$$k = \max_i \left\{ \frac{L[i]}{N_p} \right\} \quad (4)$$

where k represents the uniformity factor for the sample regions. The uniformity factor is calculated for sample and model regions and these values are used to determine the two weights. In this regard, if the difference between k_1 and k_2 is less than 0.1, then the colour distribution associated with the sample and model region have a similar uniformity factor and the weights are calculated as follows: $w_2 = (k_1 + k_2)/2$ and $w_1 = 1 - w_2$. This indicates that colour influences more than texture, hence colour statistic is given more importance. On the other hand, if the difference between uniformity factor is high, both the texture and the colour are given equal weights $(w_1 = w_2 = 0.5)$. After each iteration, the smallest merging importance value is evaluated and the algorithm halts when this value is higher than a threshold value.

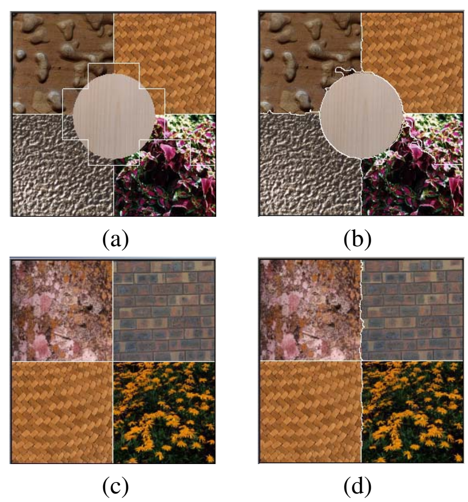

Figure 1. (a), (c) Segmentation before boundary refinement, (b), (d) Segmentation after boundary refinement

Boundary Refinement The agglomerative merging procedure resulted in blocky segmented image. A new bound-

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ary refinement algorithm was developed and used for the improvement at the boundaries between various regions. A pixel is regarded as a boundary point if it is on the boundary of at least two distinct regions, i.e., its region label is different from at least one of its four neighbours. For an examined point *P*, a discrete square with a dimension *d* around the pixel was placed and the colour histogram for this region was computed. The corresponding colour histograms for the different neighbouring points were calculated. The homogeneity of the square region and the *i*th neighbouring region, *i*=1,2,...*l*...*n* region was computed. The pixel is reclassified if the MI value between adjacent regions and the region around the pixel under consideration is lower than the merge threshold. This procedure is iterative and proceeds until no pixels are relabelled. Reassigning pixels in this way improves the accuracy of the segmentation process. Figure 1 shows the segmentation result before and after boundary refinement.

4. Experimental Results

The experimental evaluation of the proposed method was based on 46 images from VisTex [9] image database consisting of mosaics and natural images. The mosaics were constructed using a random selection of different textures from the VisTex texture image database. In addition, 2 mosaic images used by Petrou *et al.* [7] and 2 natural images used by Panjwani *et al.* [6] were also used for the experiments.

Weights		
Colour (w_2)	Texture (w_1)	ē (%)
1.0	0.0	4.84
0.6	0.4	4.53
0.2	0.8	11.71
0.0	1.0	26.71
automatic selection	automatic selection	< 1.0

Table 1. Average segmentation error (%) based on the colour and the texture weights

Tests were carried out to demonstrate the importance of the colour and texture descriptors for colour texture segmentation. Table 1 illustrates the segmentation error based on colour and texture features. The weights in the merging stage were replaced with different values ranging from 0.0 to 1.0. The mean error rate for different colour and texture weights were calculated. The error rates in Table 1 shows that up to a weight of 0.6 for colour the segmentation error is minimal beyond which the error increased significantly. The errors at the colour weights 0.2 and 0.0 was found to be substantial. From Table 1 it is apparent that colour weights 0.6 and texture weights 0.4 resulted in a good segmentation with minimum error. In addition, the automatic selection of colour and texture weights provided a good result with minimum segmentation error. The following conclusions can be drawn from these experimental results. Texture alone or colour alone cannot provide a good segmentation. The proper inclusion of both colour and texture is necessary for a more accurate colour texture segmentation.

The results in Figure 2 shows that the error in segmentation based on colour alone or texture alone is higher compared to the segmentation based on colour and texture. In addition, the results depicted in Figure 2 illustrate that the incorporation of colour with texture increases the accuracy of colour texture segmentation.

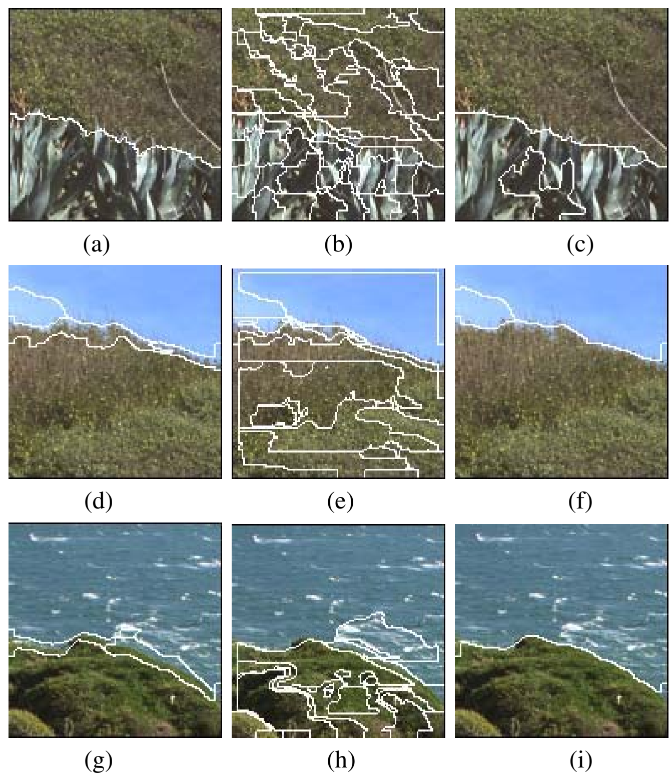

Figure 2. (a), (d), (g) Segmentation based on colour, (b), (e), (h) Segmentation based on texture, (c), (f), (i) Segmentation based on colour and texture

The boundaries obtained after the merging stage and the boundary refinement stage were presented in Figure 3 and Figure 4. These images shows the detected boundary embedded over the original image. Figure 3-M1 illustrates a

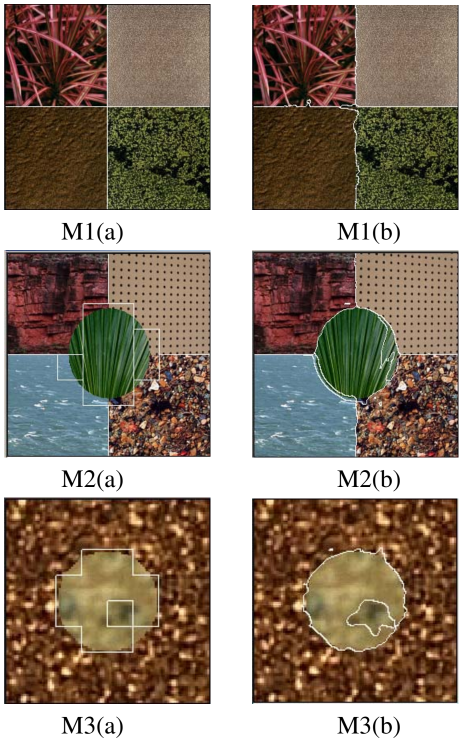

Figure 3. Colour texture segmentation of mosaic images. (a) represents segmented image and (b) represents boundary refined image.

proper segmentation result. Figure 3-M2 and M3 shows segmentation of small regions due to the difference in the colour.

Figure 4-N1 represents the segmented beach image. The segmentation method merged the small features within the bird as a single region. Figure 4-N2 shows the segmented image of the rocks and sea. It can be noted that the region representing the clouds and the sky is considered as a single region. In addition, the regions on the rock and sea were merged together as a single region. It is evident from the segmented results that it is not possible to differentiate regions with similar colour and different textures.

5. Conclusions

A new framework was developed for colour texture segmentation which integrates the colour and the texture features. The distribution of colour features and the distribution of the texture features were used for colour texture discrimination. The distribution of the derived features encompasses both the structural pattern and the colour of the image. The method was applied to various mosaic and nat-

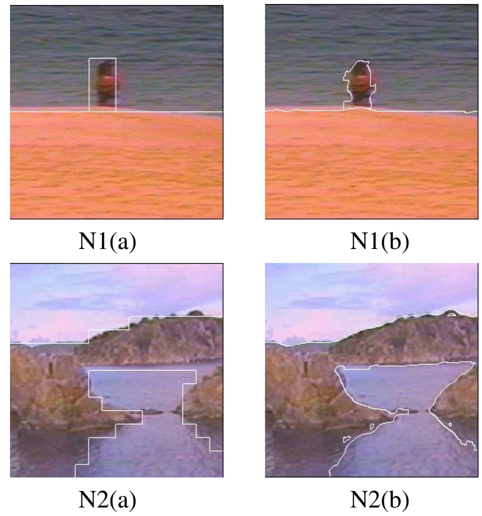

Figure 4. Colour texture segmentation of natural images

ural images and the importance of colour in colour texture segmentation was demonstrated.

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