Research article

A generic framework for colour texture segmentation

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Abstract

Purpose – The purpose of this paper is to propose a generic framework based on the colour and the texture features for colour-textured image segmentation. The framework can be applied to any real-world applications for appropriate interpretation.

Design/methodology/approach – The framework derives the contributions of colour and texture in image segmentation. Local binary pattern and an unsupervised *k*-means clustering are used to cluster pixels in the chrominance plane. An unsupervised segmentation method is adopted. A quantitative estimation of colour and texture performance in segmentation is presented. The proposed method is tested using different mosaic and natural images and other image database used in computer vision. The framework is applied to three different applications namely, Irish script on screen images, skin cancer images and sediment profile imagery to demonstrate the robustness of the framework.

Findings – The inclusion of colour and texture as distributions of regions provided a good discrimination of the colour and the texture. The results indicate that the incorporation of colour information enhanced the texture analysis techniques and the methodology proved effective and efficient.

Originality/value – The novelty lies in the development of a generic framework using both colour and texture features for image segmentation and the different applications from various fields.

Keywords Image processing, Adaptive system theory, Colours technology, Cluster analysis, Smoothing methods

Paper type Research paper

1. Introduction

Segmentation of images is important and useful for many applications from image processing perspective. The segmentation of natural images is a complex problem due to the irregular boundaries of the objects in the scene, which have different objects with varying colour and textures. Therefore, colour and texture are intrinsic features that can play a vital role in the segmentation of an image. The objective of this paper is to investigate the use of colour features in image segmentation and to construct a framework for colour texture segmentation. Absence of a universally accepted model for colour texture segmentation and the existence of a number of applications for colour texture segmentation are the motivating factor for this study. Various issues that affect the colour texture segmentation are addressed in this work in order to achieve a simple, effective and efficient framework for colour texture segmentation.

Segmentation is a computationally intensive task as there is a dependency between the image resolution and the speed of processing. The speed of segmentation also depends on feature extraction from texture and colour planes and the segmentation process. Hence, the speed of processing is an important consideration throughout the development of colour texture segmentation algorithm in this study. This resulted in the selection of simple techniques, such as the local binary pattern (LBP) to extract texture features and unsupervised *k*-means colour clustering to extract colour features, without affecting segmentation accuracy.

In general, the analysis of natural images has proved to be extremely hard. Texture and colour in natural image are often non-uniform due to the change in scale, orientation or other visual distortions (Ojala and Pietikainen, 1999). The natural image does not have well defined boundaries. As a result, segmentation errors arise while defining the boundaries between two non-homogeneous regions. It is also affected by uneven illumination conditions. The methods for texture segmentation developed have only occasionally evolved in the real-world applications (Maenpaa, 2003). The selection of appropriate method to incorporate the chromatic information into texture analysis plays a vital role for colour texture segmentation. The three spectral band method is simple which extends the standard texture analysis techniques such as co-occurrence, LBP, discrete cosine transform, Gabor filters, etc. to colour images and the result is obtained in each colour plane individually (Caelli and Reye, 1993; Panjwani and Healey, 1995) presented an unsupervised texture segmentation algorithm based on Markov random field models for colour textures. Their models characterised a texture in terms of spatial interaction between spectral bands. Jain and Healey (1998) introduced a method based on unichrome features computed from the three spectral bands independently and opponent features that utilised the spatial correlation between spectral bands using Gabor filters. They concluded that the

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opponent colour features significantly improved the classification accuracy over simply using unichrome features. Grey scale algorithms are applied to the intensity plane and the colour information is used as additional information (Maenpaa *et al.*, 2002; Drimbarean and Whelan, 2001) examined the contribution of colour information to the overall classification performance by using the above approach. The approach divides the colour signal into luminance and chrominance components, the information from both intensity and colour planes were extracted separately and merged together for colour texture processing.

Chen *et al.* (2005) proposed an approach for segmentation which combines knowledge of human perception with an understanding of signal characteristics in order to segment natural scenes into perceptually/semantically uniform regions. The approach is based on two types of spatially adaptive low-level features. The first describes the local colour composition in terms of spatially adaptive dominant colours, and the second describes the spatial characteristics of the greyscale component of the texture. Ilea and Whelan (2008) developed an unsupervised image segmentation method (referred to as CTex) that is based on the adaptive inclusion of colour and texture in the process of data partition. A burn colour image segmentation and classification system based on colour and texture feature information was proposed by Acha *et al.* (2005) and Weng *et al.* (2007) used weighted distributions of colour index histogram and LBP to measure the similarity of adjacent texture regions during the segmentation process. A multichannel segmentation algorithm is proposed which uses both grey-level intensity and texture-based features for region extraction. The intensity-based segmentation is obtained using the modified pyramid-based region extraction algorithm. The texture-based segmentation is obtained by a bi-level shifted-window processing algorithm that uses new generalized co-occurrence matrices. The results of individual segmentations obtained from different channels, representing the complete set of colour and texture information, are analyzed using heuristic merging rules to obtain the final colour and texture-based segmentation (Dhawan and Sicsu, 1992).

The literature review indicates that many processing techniques were developed for specific segmentation application, but there is no robust technique to give a general framework for colour texture segmentation. This research work focuses on the development of a novel methodology for robust colour texture segmentation that can be applied to various images.

2. Colour texture segmentation techniques

The colour texture segmentation method proposed in this paper combines texture and colour information's that makes the segmentation robust and efficient for different types of images. The colour texture segmentation procedure is described in the following sections.

2.1 Selection of colour space

To process colour images, the first task is to select a suitable quantitative representation of colour, i.e. to select a suitable colour space (Sangwine and Horne, 1998). A number of colour spaces exists (Schanda, 2007), but they have different advantages in representing colour; therefore it is necessary to select the colour space according to the requirement of the task. In this work, RGB, HSI, YIQ, CIE-XYZ, CIE-LAB and CIE-LUV colour spaces were used in the three spectral band segmentation method (Drimbarean and Whelan, 2001). To serve as a prerequisite, the performance of different colour planes was tested using this method. The segmentation method based on the unified approach of texture and colour processing focused on RGB, HSI and YIQ colour spaces, although the method is applicable to any colour space. In order to extract features from colour and intensity plane separately, HSI and YIQ colour spaces were selected. In addition, both YIQ and HSI colour space emulate the human visual system. Hence, YIQ and HSI colour spaces were chosen for this study. The intensity information is extracted from I and Y-planes in HSI and YIQ spaces, respectively. Similarly, the colour information is extracted from the two-chrominance planes (Schanda, 2007). In order to compare with the basic standard colour spaces, the method adopted for segmentation is also applied to RGB colour space. YIQ is a linear and HSI nonlinear transformation of RGB cube. The nonlinear relations used to convert RGB space to HSI space are explained in Whelan and Molloy (2000). The YIQ space can be computed as a linear function of the RGB values. Detailed explanation about the colour spaces can be found in Whelan and Molloy (2000).

2.2 Texture feature extraction technique

Local binary pattern

The LBP is one of the feature extraction techniques that provide pattern related information. LBP is invariant to any monotonic greyscale transformation and is based on two level version of the texture spectrum method developed by Wang and He (1990). The knowledge about the spatial structure of local image textures can be obtained from this method. Ojala *et al.* (1996) developed this LBP technique for greyscale images and carried out the texture classification based on feature distributions of different texture measures and found that the method performed well for Brodatz (1968) textures. A textured image is decomposed into a set of small textural units. A texture unit (TU) is represented by eight elements, each of which has one possible value (0, 1) obtained from the neighborhood of 3×3 pixels. The neighborhood in the original image is represented by $V = \{V_0, V_1, \ldots, V_8\}$. The occurrence distribution of TU is called the texture spectrum. LBP is described with $2^8 = 256$ possible TU. The $\mathrm{TU} = \{E_1, E_2, \ldots, E_8\}$ is obtained by applying the threshold operation using the following rule:

$$E_i = \begin{cases} 0 & V_i < V_0 \\ 1 & V_i \geq V_0 \end{cases} \tag{1}$$

where V_0 is the center pixel. LBP is represented by the equation:

$$\mathrm{LBP} = \sum_{i=1}^{8} E_i \times 2^{i-1}. \tag{2}$$

Since one texture measure is inadequate to describe the grey scale variations of the local texture, LBP is combined with the contrast of the texture (C), which is a measure of local variations present in the image. The contrast of the texture is obtained as the difference between the average grey levels of pixels with value 1 and pixels with value 0 contained in the TU. The distribution of the LBP/C of the image represents the texture spectrum with a 2D histogram of size $256 \times b$, where b is the number of bins for contrast measure. As suggested by Ojala *et al.* (1996), eight bins were used for contrast measure (also, the experiments in the present study confirmed that best segmentation has been achieved when eight bins have been used to sample the contrast measure). This 2D histogram is used as a texture discriminating feature in this work.

The above-mentioned method is explained with an example:

$$\mathrm{LBP} = 2 + 4 + 8 + 32 + 128 = 174 \tag{3}$$

$$C = \frac{8+6+7+8+9}{5} - \frac{2+3+1}{3} = 5.6. \tag{4}$$

The original 3×3 neighborhood, as shown in Figure 1(a) (represented by V), is thresholded by the value of the center pixel to obtain Figure 1(b) (represented by E_i). The value of the pixels in the thresholded neighborhood was multiplied by the binomial weights given to the corresponding pixels as shown in Figure 1(c) to obtain the TU, Figure 1(d). The values of the eight pixels were added to get the LBP value, equation (3), of the TU. Equation (4) represents the calculation of the contrast measure. This technique is computationally simple and efficient.

2.3 Pre-processing technique

Adaptive smoothing

Various smoothing techniques are used for different purposes in computer vision. In general, smoothing algorithms are classified into two categories, linear and nonlinear. In linear smoothing, local operators are uniformly applied to an image to form the output intensity of a pixel from a weighted summation of input intensities of its neighboring pixels. The main disadvantage of linear smoothing is that the boundary between different regions is blurred after smoothing. On the other hand, the nonlinear smoothing preserves important features and also removes noise. Adaptive smoothing is a nonlinear smoothing technique, which adapts pixel intensities to the local attributes of an image on the basis of discontinuity measures. The feature preserving adaptive smoothing algorithm proposed by Chen (2000), where the local and contextual discontinuity measures are jointly used is implemented in this study. The advantage is that the parameters in the given adaptive smoothing algorithm critically determine the smoothing process. This procedure is used to prevent over segmentation. The effects of the parameters are discussed with a detailed explanation on the adaptive smoothing and the implementation of the algorithm in Chen (2000).

The use of adaptive smoothing is illustrated with two example images in Figure 2. This is used as a preprocessing procedure to eliminate noise and to increase the cluster continuity. Figure 2(a) and (f) shows the original image. Figure 2(b) and (g) represents the smoothed and the clustered image. Figure 2(c) and (h) shows the merged image and Figure 2(d) and (i) shows the boundary-refined image without smoothing. Figure 2(e) and (j) shows the boundary-refined result of the same image with adaptive smoothing. A comparison of the results with and without smoothing demonstrates the effect of the adaptive smoothing. Without smoothing, the segmentation is erroneous and the green grass is wrongly segmented, Figure 2(d). With the smoothing algorithm, the noise is removed which improves the segmentation in the boundaries between two different grass regions, as shown in Figure 2(e). Figure 2(i) shows that the segmentation without smoothing could not identify the boundaries properly. Figure 2(j) shows the smoothing algorithm correctly recognizes the boundaries which are evident from the clustered image by the thin blue line between the sky and the plants, and in addition a small region of the plant was also segmented. This demonstrates that the adaptive smoothing is mainly useful for the images with irregular boundaries such as natural images which prevents over-segmentation and helps to obtain a precise segmentation at the boundaries.

Figure 1 Steps in the calculation of LBP and C value

2	8	6
7	5	3
8	1	9

(a)

0	1	1
1		0
1	0	1

(b)

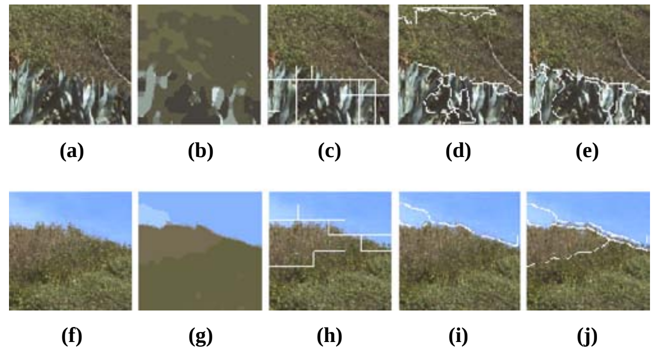
1	2	4
8		16
32	64	128

(c)

0	2	4
8		0
32	0	128

(d)

Figure 2 The influence of adaptive smoothing



2.4 Colour feature extraction technique

k-means colour clustering

Colour is the other discriminating feature used in this work. In order to extract the colour information, the image areas with similar properties will be identified. For this purpose, an unsupervised k-means clustering technique (Duda and Hart, 1973) is employed.

Colour clustering is the process of grouping finite set of similar objects into subsets. The objects are organized into an efficient representation that characterizes the population being sampled. This technique was adopted to determine the colour clustered distributions. Initially, the partition can be formed by specifying a set of k-seed points. Seed points are the first k-patterns chosen randomly from the pattern matrix. A set of k-patterns, well separated from each other, were obtained by taking the centroid of the data as the first seed point and selecting successive seed points at a distance away from the seed points already chosen. The initial clustering was formed by assigning each pattern to the nearest seed point which forms k-clusters. The centroid of the clusters forms the initial cluster centers. In the second step, assign each pattern to the centroid closest to the cluster. Calculate the new cluster centers as the centroids of the clusters. Repeat the second step until all the points have their cluster memberships defined.

The main problem with the standard clustering algorithms is the difficulty to estimate the number of clusters in the image. The number of clusters is the input parameter for the *k*-means algorithm and the value of this parameter is dependent on the complexity of the image. Determination of the optimal number of clusters would be a very difficult task as this parameter is image dependent. In order to address this issue, the number of clusters is set to an initial value of 10, sufficiently large to assure that all-important regions in the image with similar colour characteristics are clustered. The proper way to handle this is to experiment with different values for *k*. For the images used in this study and the applications, the initial value of 10 is found to produce best results. In principle, the best value exhibits the smallest intra-cluster distances and largest inter-cluster distances. Figure 3 shows an example of the *k*-means clustering adopted.

As a follow-up to *k*-means clustering, the refinement of the initial clusters is based on the merging of clusters that have similar properties. In this regard, two adjacent clusters are merged if the difference between their center values is less than a preset threshold value. This process is iterative and repeated until no more merges occur, allowing the algorithm to recover poor initial partitions and select a suitable number of clusters. A detailed explanation of different algorithms for clustering data can be found in Jain and Dubes (1988). Before the application of the *k*-means algorithm, the input image is subjected to adaptive smoothing to reduce the noise and to increase the cluster continuity.

2.5 Similarity measure

Modified Kolmogorov Smirnov

The hypothesis that the two empirical feature distributions have been generated from the same population is tested using the non-parametric test. Colour and texture description vary considerably over an image due to the inherent variation in surface appearance and also due to the changes in illumination, shading, etc. Hence, the appearance of the region is best described by the distribution of features, rather than individual feature vector. Histograms are used as non-parametric estimators of empirical feature distributions (Puzicha *et al.*, 1999). A nonparametric test Modified Kolmogorov Smirnov (MKS) statistic is used to compare LBP/C with colour clustered labels. This tests the hypothesis that two empirical feature distributions have been generated from the same population. MKS has a desirable property that it is invariant to arbitrary monotonic feature transformations. The MKS statistic is defined as the sum of the absolute value of the discrepancies between the normalized cumulative distributions (i.e. the number of pixels contained in each bin is divided by the total number of pixels contained in the distribution):

$$D(s,m) = \sum_{i=0}^{n} \left| \frac{F_s(i)}{n_s} - \frac{F_m(i)}{n_m} \right| \quad (5)$$

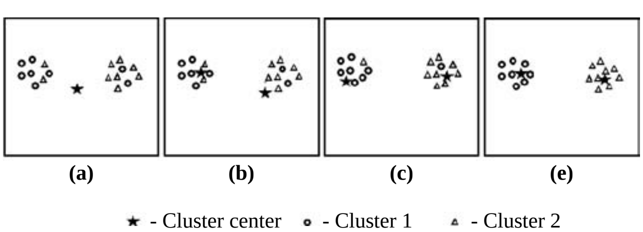
where:

$F_s(i)$ 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 MKS is normalized, it is advantageous over other statistical measures such as: G-statistic and the χ^2-statistic.

Figure 3 Steps in *k*-means clustering

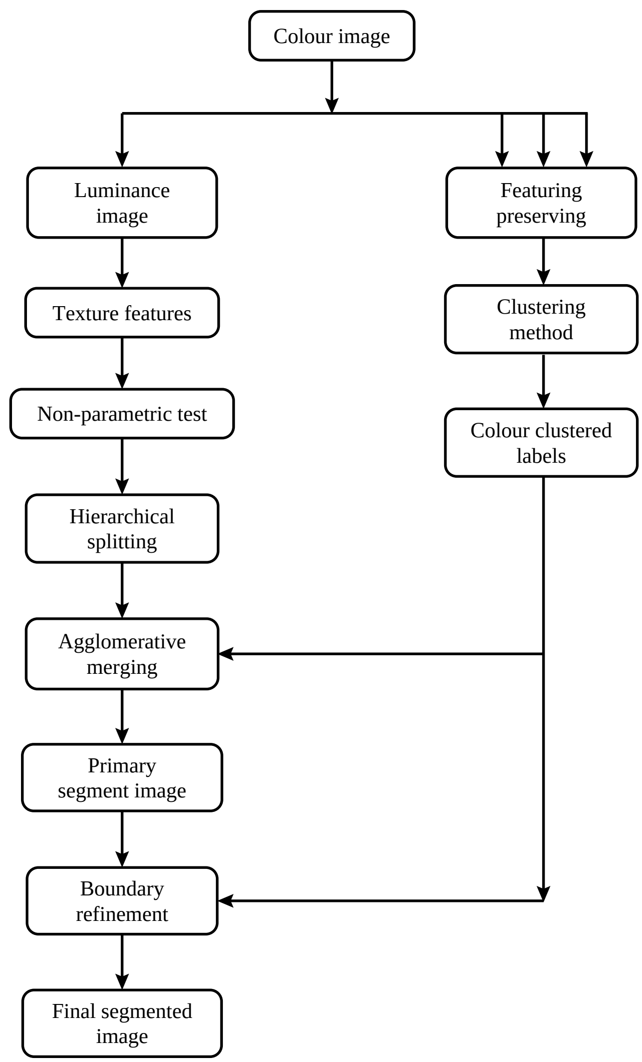


Notes: (a) Represents the original image with the different patterns and the centroid of the image data; (b) illustrates the cluster membership after the first iteration; (c) shows the cluster membership after the second iteration; (d) represents the final clustered image

3. Segmentation method

The segmentation method includes various tasks that are illustrated in the flowchart, Figure 4, and described in the following sections:

Figure 4 Flowchart representing various tasks in the proposed image segmentation methodology



1 Hierarchical splitting:

- The hierarchical splitting phase tests the uniformity of the region. Initially, the features are identified by means of feature extraction techniques, in which image information is reduced to a small set of descriptive features. The LBP and the contrast (C) features are extracted from the luminance plane, i.e. from the average of the three planes in RGB, from *Y*-plane in YIQ or from *I*-plane in HSI colour space.
- The distribution of the texture features are used for texture discrimination.
- An MKS non-parametric statistical test is used as a similarity measure to discriminate the texture distributions.
- A hierarchical splitting method is used to split the image based on the texture descriptors using the similarity measure.

This phase results in a split image using the texture features that is used for agglomerative merging in the next phase.

2 Agglomerative merging. The second phase has four steps:

- An adaptive smoothing is performed to preserve the features and to obtain a good segmentation along the boundaries. This technique removes noise and prevents over segmentation.
- An unsupervised *k*-means clustering algorithm is performed on the image to classify the patterns into their respective classes and to obtain the distribution of the colour clustered labels.
- Distribution of the texture features and the distribution of the colour clustered labels are used to describe the texture and the colour, respectively. The distributions of colour and the textures were used to derive the merger importance (MI) value between two adjacent regions. The MI value was calculated using the MKS statistic. Weights are included to both texture and colour features in the histogram and are computed using the histograms of the clustered labels.
- An agglomerative merging procedure based on the merging criteria determines the similarity between two different regions using MKS statistic, producing the segmented image.

3 Boundary refinement. The final step is to refine the boundaries of the image. A boundary refinement algorithm enhances the segmented result to obtain the final segmented image.

3.1 Hierarchical splitting

The segmentation method followed is based on a split and merge computational model (Ojala and Pietikainen, 1999). The first step involves recursively splitting the image hierarchically into four sub-blocks using only the LBP/C data. The similarity measure between the resulting four sub-blocks is computed using the MKS statistic. The uniformity of the region is evaluated by a decision factor as follows:

$$R = \frac{\mathrm{MKS}_{\max}}{\mathrm{MKS}_{\min}} > X \tag{6}$$

where $\mathrm{MKS}_{\max}$ and $\mathrm{MKS}_{\min}$ are the highest and lowest MKS values, respectively, that results after calculating the pair-wise MKS values of the four sub-blocks, X is a split threshold value. The splitting process continues until the stopping rule is satisfied or the block size is smaller than a predefined value (for this implementation the minimum block size has been set to 16×16). During the splitting procedure for each block, the LBP/C distribution is computed.

The choice of X is based on testing different values. Preferably, X should be small to allow more split. The threshold value X was experimentally set at 1.2 for mosaic images and 1.1 for natural images as these values produced best results for the images considered in this study. An error occurs when a block defined by uniform texture is split into four blocks. In that situation, the merging procedure can easily compensate for the over split. On the other hand, if several textures are considered as uniform then the error recovery is not possible. Figure 5 shows an example for hierarchical splitting of the image.

3.2 Agglomerative merging

The agglomerative merging procedure combines adjacent regions that have similar characteristics. It calculates the MI between any adjacent regions in the split image and the regions with the smallest MI value are merged. The MI value is calculated as follows:

$$\mathrm{MI} = w_1 \times \mathrm{MKS}_1 + w_2 \times \mathrm{MKS}_2 \tag{7}$$

where w_1 and w_2 represent the corresponding weights for LBP/C histogram and colour histogram, respectively, and the MKS_1 and MKS_2 are the MKS statistics for texture (LBP/C) and colour histograms in the two adjacent regions. The adjacent regions are also referred to as the sample and model regions. The weights are automatically detected using a uniformity factor (k_j) defined as the maximum of the ratio between colour clustered histogram and number of pixels in the two regions under consideration, the sample and the model regions:

$$k_j = \max\left\{\frac{\mathrm{Clust}_j[i]}{N_p}\right\} \tag{8}$$

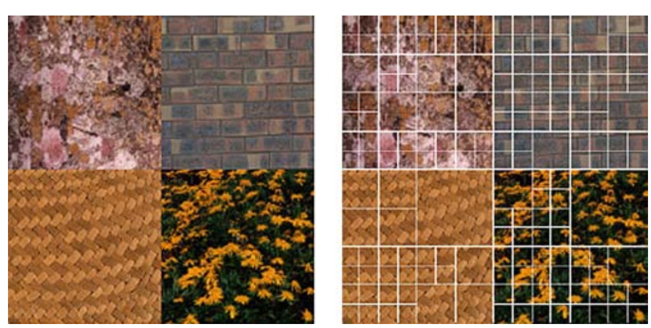
where k_j represents the uniformity factor for the sample and the model regions, respectively, where Clust defines the colour histogram of the region j, i is the histogram index and Np represents the number of pixels in the region j that is evaluated. If the difference between k_1 and k_2 is less than 0.1, i.e. both the sample and the model weights are more or less the same, then:

$$w_2 = \frac{k_1 + k_2}{2} \tag{9}$$

and:

$$w_1 = 1 - w_2. \tag{10}$$

Figure 5 A typical example for splitting based on the uniformity criterion



(a) (b)

This indicates that colour influences more than texture, hence colour statistic is given more importance. On the other hand, if the difference between *k*s is high, both the texture and the colour are given equal weights. The automatic selection of colour and texture weights provides a good result with minimum segmentation error (Brodatz, 1968). This agglomerative merging method is repeated iteratively until a simple stopping rule is satisfied:

$$\mathrm{Min}(\mathrm{MI}) > Y \tag{11}$$

where:

Min (MI) represents the minimum MI value.
Y is the threshold value.

If the minimal (MI) value between all adjacent regions is higher than a threshold value, then the merging procedure is halted. This resulted in blocky-segmented image. Figure 6 shows an example for the merging procedure. The threshold Y is 0.9 for mosaic images and 1.0 for natural images.

A boundary refinement algorithm is used to eliminate these blocky segments, as described in the following section.

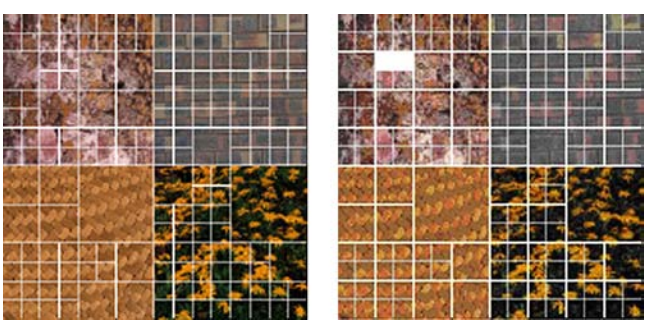
3.3 Boundary refinement

The boundary refinement algorithm is developed based on the work in Ojala and Pietikainen (1999), 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 neighbors. For an examined point P, a discrete square with a dimension d around the pixel is placed and the colour histogram for this region is computed. The corresponding colour histograms for the different neighboring points are calculated. The homogeneity of the square region and the ith neighboring region, $i = 1, 2, \ldots, l, \ldots, n$ region is 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 relabeled. Reassigning pixels this way improves the accuracy of the segmentation procedure (Figure 7).

4. Experimental results and discussion

The experimental validation of the proposed method is based on VisTex (2000) texture image database from MIT Media

Figure 6



(a) (b)

Notes: (a) Image from splitting; (b) merged regions with Min (MI)

Figure 7

(a) (b)

Notes: (a) Represents the result after agglomerative merging stage; (b) represents the results after boundary refinement stage

Lab. The database consists of 19 different natural objects: brick, bark, buildings, clouds, fabric, flowers, food, grass, leaves, metal, paintings, sand, stone, terrain, tile, water, wood and miscellaneous. The images were taken from many sources including examples from real world photography. All images are stored as raw portable pixmap (ppm) files.

The database has two main components: reference textures, texture scenes.

In this research work, the images were first converted to bitmap format of 24-bit colour depth and true colour RGB representation. The experimental validation is carried out on 50 images consisting of mosaics and natural scenes. The mosaic of colour texture images of size 256×256 were constructed using a random selection of four different textures of size 128×128 from the reference texture database. The non-uniform textures inside a block such as clouds and the sky, flowers with the stem and textures with variations due to the dark and light colours were also considered in the colour texture analysis. Images with two textures and four blocks and images with five textures, i.e. four blocks and a circle in the middle were also constructed. Some real world scenes of size 128×128 were randomly selected from texture scenes for the test database. Two mosaic images, used by Mirmehdi and Petrou (1998) and two natural images used by Panjwani and Healey (1995) were also considered for the experiments.

The proposed method has been implemented on a personal computer with Intel Pentium III processor with 256 MB RAM and 1.6 GHz speed. The operating system used is Microsoft Windows 2000. The program was developed using Microsoft Visual C++6.0 using Microsoft Foundation Class tool. The Windows bitmap file format is used for image input/output.

The average processing time for 256×256 images is as followed: adaptive smoothing – 73.45 s; unsupervised colour clustering – 14.611 s; splitting and merging – 1.442 and 1.6286 s, respectively. The time taken to perform boundary refinement depends on the segmented result from the merging stage and also depends on the number of iteration it takes to complete the process.

Various set of tests were performed to analyze the effectiveness of the approaches and also to test the effect of colour spaces. A set of three values each for split threshold and merge threshold was considered to determine the minimum segmentation error. The split threshold was tested for 1.1, 1.2 and 1.3 and merge threshold was tested for 0.8, 0.9 and 1.0. The best value for the split and merge thresholds were found to be 1.2 and 0.9, respectively. The parameters used for the natural images differed from that of the mosaic images. For natural images the split threshold value is 1.1 and the merge threshold value is 1.0. Based on the segmentation results the number of bins for contrast is quantized to 8 bins. Similar results were obtained with 16 bins as reported by Ojala and Pietikainen (1999).

The overall performance of the segmentation is shown in Table I. On comparing the results, the relative merits of different colour spaces are found to be non-conclusive. No significant difference was observed between the segmentation results using the three colour spaces. This suggests that none of the colour space is superior as all the three colour spaces performed equally well. This is in accordance with the review made in Drimbarean and Whelan (2001).

A test was carried out to demonstrate the importance of the colour and the texture descriptors for colour texture segmentation. Table II illustrates the segmentation error based on the colour and texture features. The error rate for each image is computed at the end of the merging stage to compare the weights. The weights in the homogeneity measure were replaced with different values ranging from 0.0 to 1.0. The mean error rate for different colour and texture weights are calculated as followed:

$$e = \frac{\text{number of pixels incorrectly segmented in the image}}{\text{total number of pixels in the segmented image}} \times 100. \tag{12}$$

The error rates in Table II 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 of 0.2 and 0.8 were found to be substantial. From Table II, it is apparent that colour weight of 0.6 and texture weight of 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. This is in agreement with the findings by Chen and Chen (2002). The following conclusions can be drawn from these results: Texture alone or colour alone cannot provide good image segmentation. Proper inclusion of both colour and texture is necessary for good colour texture segmentation. In few cases, the exclusion of texture weights provides a reasonable segmentation, but the exclusion of colour weights resulted in poor segmentation.

Table I The performance of different colour spaces

Technique	LBP (%)
RGB	95
YIQ	96.6
HIS	95

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

Colour (w_2)	Texture (w_1)	e (%)
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

Figure 8 shows the detected border embedded over the original image. The detected border represented by the white line is drawn to distinguish the regions based on the colour and texture similarities that indicate a homogenous region. Colour texture segmentation results shown in these figures used LBP/C with colour clustering features. The usefulness of the proposed colour texture segmentation method is demonstrated by successfully detecting meaningful regions in images. In addition, few aspects of the results which are considered to be important were emphasized.

The result in Figure 8(a) after boundary refinement shows the accuracy with which segmentation is performed. Though the result is not equivalent to the ground truth (considering the ground truth in a macro scale which represents four quadrants), as per the human knowledge this segmentation is perfect. Figure 8(b) shows segmentation with a small block inside the circle which is properly segmented and refined in the final process. The segmentation in Figure 8(c) shows the colour texture segmentation based on the colour texture variations. In few cases, such as Figure 8(d) the error recovery after merging is possible during the boundary refinement.

The performance of the proposed method for colour texture segmentation was tested over a set of ten real images of which sample images are shown in Figure 9. Natural images have rich source of colour and textures. Segmentation of natural images is more complex, since defining the boundaries between various regions are difficult. Figure 9(a) and (c) shows the original image. As stated before, the segmentation merged the small features within the bird as a single region in Figure 9(b). Figure 9(c) shows the segmented image of the rocks and sea. The clouds in the region are considered as a single region. In addition, the regions on the rock and sea are merged together as a single region. In few cases different textures with similar colour are identified as same region. This is due to influence of the colour where the algorithm is unable to differentiate as that of the human beings.

Figure 10(a) and (b) shows the image after the merging stage and the boundary refinement stage, respectively. In the merging stage, the boat is not segmented properly, after the boundary refinement stage the boat is separated from the sea and merged with the group of buildings because of the small difference in the colour. Figure 10(c) and (d) shows the merged image and the final segmented image. The result shows that rock and the river are segmented properly. The segmentation of the natural images is acceptable. The framework works robustly and detected the abnormalities accurately.

This research work emphasizes that the colour is an important feature and it forms the major part in colour textured image segmentation. Colour not only improves the segmentation results but also is useful in error recovery as well. In colour texture segmentation, colour or texture alone does not provide enough information for proper segmentation. Also, individual characteristics such as colour or texture do not best describe the colour texture analysis. Hence, the combination of colour and texture is essential to properly discriminate the colour textured regions in an image.

The proposed colour texture image segmentation method is robust for any application including natural images compared

Figure 8 Segmented mosaic images after boundary refinement

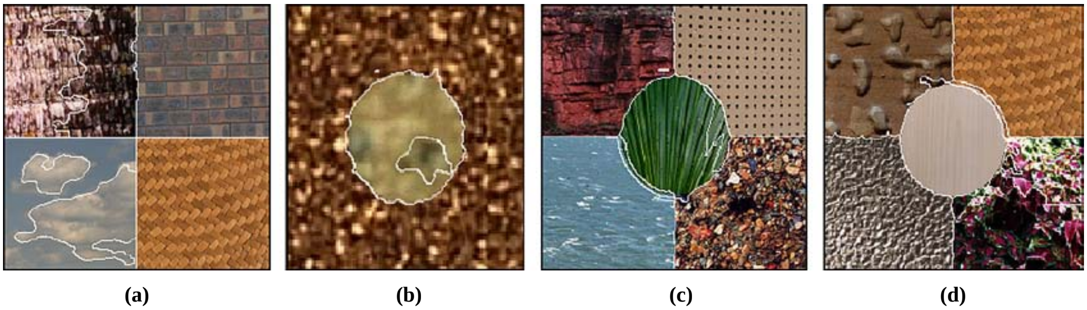


Figure 9 Segmentation of natural images – I

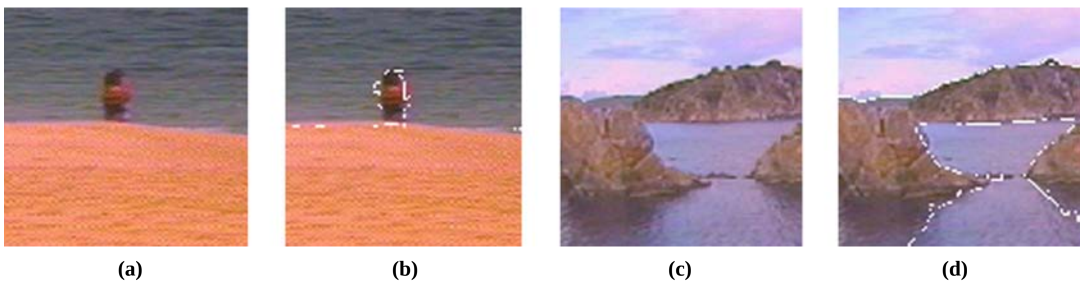
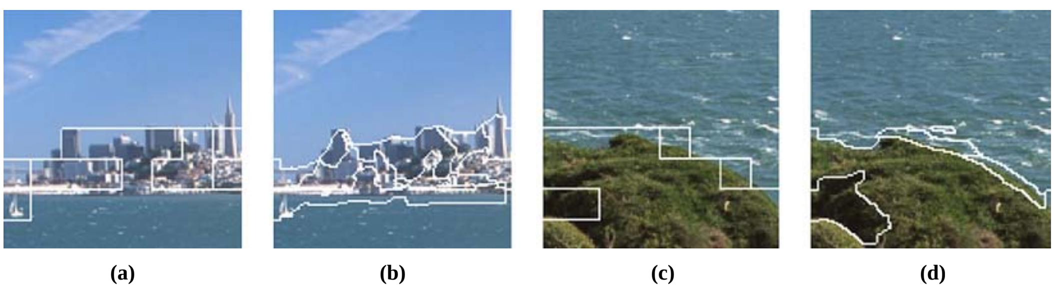


Figure 10 Segmentation of natural images – II



Notes: (a), (c) represents the result after agglomerative merging stage; (b), (d) represents the result after boundary refinement stage)

to other methods. Say for example, the method proposed by Chen and Chen (2002) which uses colour distributions and local edge pattern distributions segmenting the semantic regions such as the whole sky without discriminating the clouds or distinctive objects within a region (Figures 13-16 in Chen and Chen (2002)). The proposed method produced similar results to that of Mirmehdi and Petrou (1998) to obtain colour texture segmentation for mosaic images.

The proposed colour texture segmentation method has many advantages including:

- prior knowledge about the number of types of textures is not required;
- the error recovery after merging is possible during the boundary refinement; and
- the use of adaptive smoothing for segmentation play an imperative role for the preservation of features and the removal of noise in the image.

The future framework for colour texture segmentation may be incorporated with automatic selection of the split and merge threshold parameters. The proposed technique can be extended to handle complex images and other applications such as segmentation or ground classification of aerial images and medical images.

5. Applications to colour texture segmentation and evaluation

The developed framework can be applied to a number of applications. Three of the applications were selected and presented in this paper. The applications include: Irish script on screen images (ISOS) images, skin cancer images and the sediment profile imagery (SPI). All the three applications use different images taken from different cameras and varying environment. The results show the robustness of the proposed colour texture segmentation method.

The following section presents the segmented results and the salient features of the segmentation.

5.1 Irish script on screen images

The ISOS images are digital images of ancient Irish manuscripts. The sample images were taken from Irish manuscripts online – ISOS (see: www.isos.dcu.ie/). The storage of letters, papers or other documents in ordinary stationery-grade folders or plastic sleeves invites certain deterioration even when kept in sealed containers. A historic document which would otherwise appreciate greatly as a prime investment is debased in value. In addition, the corrosive effects of modern environment and time are a threat to document preservation. The objective of ISOS is to create digital images of Irish manuscripts, and to make these images available together with relevant commentary, accessible on a web site. The purpose of such a web site is to provide an electronic resource which will:

- provide exposure on the internet for a vital part of cultural heritage;
- place these primary materials at the disposal of scholars and students; and
- contribute to the conservation of these valuable books and documents by creating images of high-resolution detail which, generally speaking, will reduce the need to handle the artifacts themselves.

Segmentation of the old document images helps to determine the amount of damage in the document, caused by the different factors. This encompasses decomposing a document into its various corrupted components. This provides information on the amount of care to be taken to preserve the document from further damage.

Figure 11(a) shows the correct identification of the stained regions on the script images. A small portion of the green region is identified. Figure 11(b) shows the segmentation of the soiled region and the unsoiled region. Figure 11(c) shows the discoloured and the blemished regions. In addition, one large coloured region was identified precisely. Colour plays a vital role in the developed framework which is evident from the presented results. Though the small scripts were not segmented separately, the damaged region and the different colours in the script were identified properly. The quantification of the segmentation of the ISOS images was based on the ground truth images. A boundary was drawn around the stained regions in the image and these regions were considered as the ground truth for quantification. The average segmentation error for four script images was found to be 2.6 percentages.

5.2 Skin cancer images

Skin cancer is the most prevalent form of human cancer that is generally caused by over exposure to sun. There are different types of skin cancer and some are likely to be fatal. Clinical features of pigmented lesions suggestive of skin cancer are known as the ABCD's of the skin cancer: asymmetry, border irregularity, colour variation, diameter greater than 6 mm. There are various image analysis techniques developed to measure these features. Measurement of image features for diagnosis of the skin cancer images requires the detection of the lesions and their localization in an image. It is essential to determine the lesion boundaries accurately so that the measurements such as maximum diameter, irregularity of the boundary, and colour characteristics can be accurately computed. As a first step in skin cancer identification, the lesion boundaries are delineated by various image segmentation techniques. In this research work, colour and texture information from an image is used for the segmentation of the lesion boundaries. The segmentation helps to diagnose the skin lesions in the early stages. The skin lesions have complex structure, colour as well as large variations in size.

Generally, the lesions have a high contrast with respect to healthy skin areas. The borders of lesions are not always well defined which makes the segmentation more complex. To analyze skin lesions, it is necessary to accurately locate and isolate the lesions. The efficient performance of the proposed colour texture segmentation method exactly recognized the boundaries in the skin lesions as shown below.

Colour is one of the significant features in the examination of a skin lesion. Typical examples of lesions show reddish, bluish, grey and black areas and spots. Figure 12(a) shows the segmentation of the skin lesion. The fine variation in the colour is identified and segmented accurately. Figure 12(b)-(d) shows the segmented results of the skin lesion. This segmentation clearly identifies the difference in colours in the skin lesion. The distribution of texture and colour features presents significant information; hence the segmentation based on the two features seems to be appropriate. This allows for the isolation of the lesion from healthy skin and extracts homogeneous coloured regions separately. The quantification of the skin lesion segmentation was based on visual results. The experimental results obtained proved to be encouraging and indicate that this method of colour texture segmentation is appropriate to be applied for detection of skin cancer images. Further evaluations on the segmentation can only be performed by an experienced dermatologist.

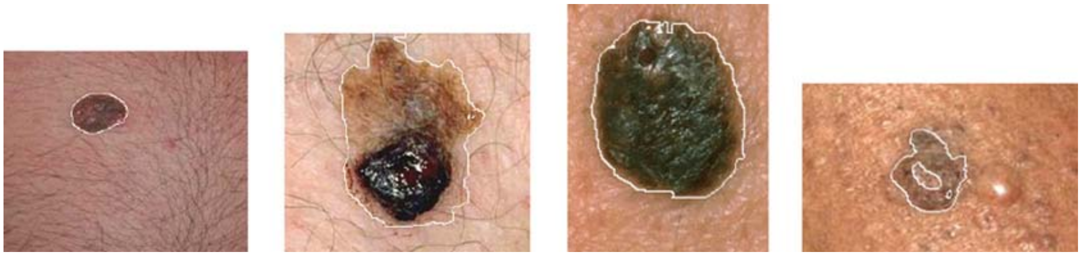
Figure 11 Segmented ISOS images

(a) (b) (c)

5.3 Sediment profile imagery

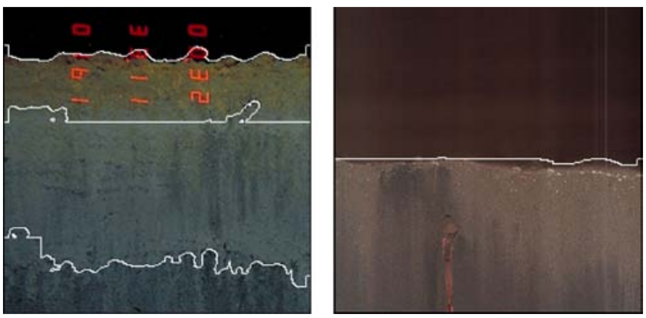
SPI is a remote sensing technique that is used to determine whether the marine sediments provide suitable habitat for bottom dwelling fauna. This is an innovative and cost efficient method of surveying and monitoring lake or marine aquatic environments. The traditional method of sample collection and subsequent laboratory analysis is time consuming and expensive and data return time is slow. SPI is based on single lens reflex camera photography and computer-based image analysis which greatly accelerates the time required to write reports and provide relevant data. The physical, chemical and biological features associated with organic enrichment of the underwater sediment are imaged and measured with the SPI system. The segmentation of the SPI images is the preliminary step in most pictorial pattern recognition and scene analysis problems. These images are hard to process due to the light absorption, changing image radiance and lack of well-defined features. The underwater images show

Figure 12 Segmentation of skin cancer images



(a) (b) (c) (d)

Figure 13 Segmentation of SPI images



(a) (b)

fluctuating oxygenation levels under different organic loading and hydrographic conditions.

Figure 13(a) shows an example of a sediment image under high organic loading stress in hypoxic conditions. This is an example of heavily impacted sediment. There is a clear difference in colour between the sediment surface layer and that lying under it. The colour texture segmentation clearly identifies different layers. Figure 13(b) shows the sediment image with burrowing marine worms. The opportunistic worms thrive in high organic loading conditions and their burrowing action can often reintroduce oxygen into depleted sediments. Owing to the thin feature difference in the organic sediment and the worm, the colour texture distribution could not identify the worm separately. But the sediments were segmented accurately. The results were compared with the results obtained by Ghita *et al.* (2003) and found to be similar. The segmented result indicates that the developed framework for colour texture segmentation is able to identify the different sediment layers in the image.

6. Conclusions

This paper investigates the use of colour features for colour texture segmentation and constructs a framework for colour texture segmentation. The segmentation method is based on the colour and the texture present in the colour textured image. The distribution of the derived features encompasses both the structural pattern and the colour of the image which is used in the framework. It was shown that the inclusion of the colour increases the segmentation performance. The results presented imply that the segmentation error is minimum for the colour weights. The colour texture analysis performed shows that colour alone or texture alone cannot provide a proper segmentation. The proper way of inclusion of colour and texture resulted in a better colour texture segmentation. The experiments outlined in this work illustrates that the use of colour improves the performance of texture analysis. The inclusion of colour in an appropriate way provides efficient and effective colour texture segmentation. Three applications were experimented using the methodology. The proposed colour texture segmentation method is able to identify different colour textured regions in the image and the results of the segmentation process are appropriate and visually acceptable. In all the three applications, colour is the dominant factor in the segmentation process.

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