INTEGRATION OF FEATURE DISTRIBUTIONS FOR COLOUR TEXTURE SEGMENTATION AND ITS APPLICATIONS

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Abstract

This paper proposes a framework for colour texture segmentation. The framework uses the colour and the texture distributions for discriminating the colour textured regions. The proposed colour texture segmentation method was tested in three different applications. The applications includes Irish Script on Screen (ISOS) images, skin cancer images and Sediment Profile Imagery (SPI). Image textures are used in combination with colour features for the segmentation of the colour textured regions in the document, to identify the diseased area in the skin cancer images and to segment underwater images. The inclusion of colour and texture as distributions of regions provide a good discrimination of the colour and the texture. The experimental results proved that the framework is effective and efficient.

Keywords: *Colour, Texture, ISOS Images, Skin Cancer Images, SPI Images*

1 Introduction

Colour and texture are important features in image segmentation. This paper developed a novel framework which considers the distributions of colour and the distributions of texture to discriminate the colour textured regions. Researchers have developed different frameworks for colour texture segmentation and most of them are designed for a specific application. Jolly *et al.*[8] proposed an algorithm for colour texture segmentation that was applied to update old cartographic aerial maps. Song *et al.* [6] proposed a method that uses colour and texture to detect defects in random colour textured images and in particular, granite images. Kyllonen *et al.* [5] described a wood surface inspection method that combines colour percentile features with texture features based on simple spatial operators.

An application independent colour texture method is proposed in this paper. The framework covers applications from different fields. Three different applications from three different areas were selected for testing the developed framework. The applications discussed in this paper are ISOS images for the segmentation of the color textured regions in the document, segmentation of skin cancer images to identify the diseased area and SPI images to segment the underwater images. The images evaluated in this paper are taken from different environments and the segmentation is found to be efficient.

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2 Framework for Colour Texture Segmentation

2.1 Steps in Colour Texture Segmentation

A novel framework was developed for combining texture and colour information for colour texture segmentation that makes the segmentation robust and efficient for different types of images. The steps are as follows,

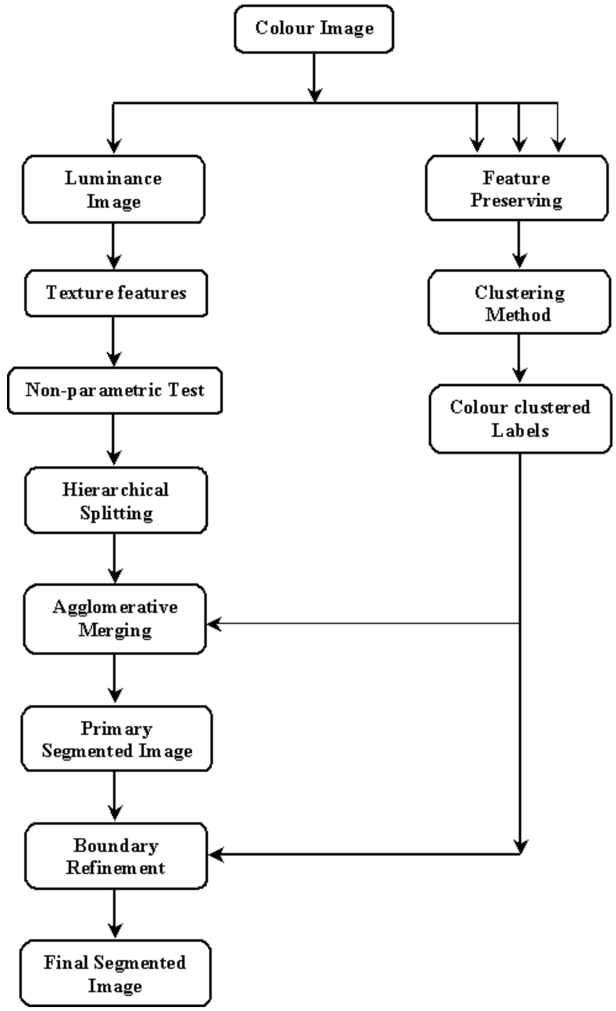


Figure 1: Framework for colour texture segmentation

- Initially the features were 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 features are extracted from the luminance plane.
- The distribution of the texture features are used for texture discrimination.
- A Modified-Kolmogorov Smirnov (M-KS) 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.
- 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 was used to derive the merger importance (MI) value between two adjacent regions. The MI value was calculated using the M-KS statistic. Two weights are computed to set the statistical relevance for texture and colour distributions.

- An agglomerative merging procedure based on the merging criteria determines the similarity between two different regions using M-KS statistic, producing the segmented image.

- 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.

2.2 Details of Colour Texture Segmentation

2.2.1 Feature Distributions

LBP 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.
The proposed method uses the unsupervised clustering technique based on the *k*-means algorithm to cluster the colour features. The *k*-means algorithm [1] is the simplest and most popular technique among the iterative clustering algorithms. The k-means algorithm organises the objects into an efficient representation that characterises the population being sampled. The number of clusters is generally image dependent so the initial value is set to 10 clusters, this number is sufficient to capture all the relevant clusters. The distribution of the colour clusters is used for colour description.

2.2.2 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 [10]. The M-KS statistic is defined as the sum of the absolute value of the discrepancies between the normalised cumulative distributions,

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

where $F_s(i)$ and $F_m(i)$ represent the sample cumulative distribution functions; n_s and n_m represent the number of pixels in the sample and model regions respectively. Since M-KS is normalised, it is advantageous over other statistical measures.

2.2.3 Segmentation Method

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

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

$$R = \frac{MKS_{max}}{MKS_{min}} > X \tag{2}$$

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,

$$MI = w_1 * MKS_1 + w_2 * MKS_2 \tag{3}$$

where w_1 and w_2 represent the weights for the LBP histogram and the colour clustered histogram respectively. MKS_1 and MKS_2 represents the M-KS statistic for texture and colour histograms respectively. The weights are automatically detected using an uniformity factor 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.

$$k_j = \max \left\{ \frac{CL_j[i]}{N_p} \right\} \tag{4}$$

where k_j represents the uniformity factor for the two sample regions. 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 $w_2 = (k_1 + k_2)/2$ 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 k_1 and k_2 is high, both the texture and the colour are given equal weights. Details about the colour and texture weights can be found in [9]. The developed method follow a simple stopping rule, $MinMI > Y$, where MinMI represents the minimum merger importance value. If this is greater than a threshold value then the merging procedure is halted.

Boundary Refinement The agglomerative merging procedure resulted in blocky segmented image. A new boundary refinement algorithm was developed and used for the improvement at the boundaries between various regions. A pixel is regarded as a boundary point if 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 significantly improves the accuracy of the segmentation process.

3 Applications and Evaluation

The developed framework can be applied to a number of different applications. Three out of a number of possible applications were selected and presented in this paper. The applications for colour texture segmentation include the segmentation of colour textured regions in Irish manuscript document, disease detection, and the segmentation of underwater images. Application database consists of the Irish Script On Screen (ISOS) images, skin cancer images and the Sediment Profile Imagery (SPI). The following sections presents the segmented results and the salient features of the segmentation.

3.1 Irish Script on Screen Images

The ISOS images are digital images of Irish manuscripts. The sample images were taken from old Irish manuscripts online - Irish Script On Screen (See: http://www.isos.dcu.ie/). About 5,000 early Irish language manuscripts survive and those appearing on this website form an important and distinctive part of Irish heritage. This includes the Book of Leinster, which is compiled in the second half of the 12th century. 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. Slowly but inexorably, paper degrades and discolors, and ink fades. High heat and humidity are also detrimental. Most papers contain acid which over time will cause the paper to weaken and become brittle. 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 is a threat to document preservation. The objective of ISOS is

(1) (2) (3) (4)

Figure 2: (1 - 4) represents segmented results of ISOS images after the boundary refinement stage

to create digital images of Irish manuscripts, and to make these images available together with relevant commentary, accessible on a website. The ISOS images are available in joint photographic experts group (jpeg) format. The ability to segment a document into functionally different parts has been an ongoing goal of segmentation of the document analysis research. Segmentation of the old document images helps to determine the amount of damage in the document, caused by the afore-mentioned 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. Four ISOS images were considered as the application database.

Figure 2-(1) illustrates the correct identification of the stained regions on the script images. A small portion of the green region is identified. Figure 2-(2) shows the tarnished region. Figure 2-(3) demonstrates the segmentation of the soiled region and the unsoiled region. In addition, one large coloured script was identified precisely. Figure 2-(4) categorises the discoloured and the blemished regions. 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 percentage.

3.2 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. Skin cancers can be classified into melanoma and non-melanoma. Melanoma is the most dangerous form of skin cancer. It can spread through the whole body and is usually fatal if it does. If detected early, the cure rate for melanoma is almost 100 percent. Late detection, when the melanoma is more than three millimeters deep, results in only a 59 percent survival rate. Melanoma's are much less common than non-melanoma's, but they

account for most of the mortality from skin cancers. Detection of malignant melanoma in its early stages considerably reduces morbidity and mortality [7]. People are considered more at risk if they have many moles, are fair skinned with blue eyes, tend to sunburn easily or have freckles [4]. The rate of melanoma cases worldwide is increasing faster than any other cancer, with an annualised rate of increase of six percent. Since 1973, the mortality for melanoma has increased by 50 percent.
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 6mm. 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 localisation 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

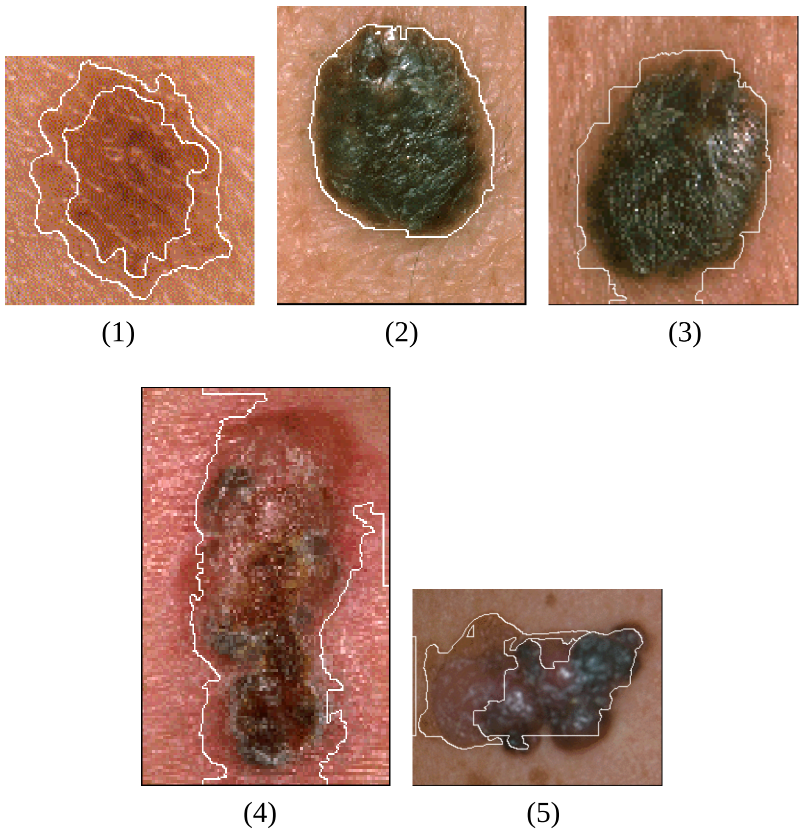


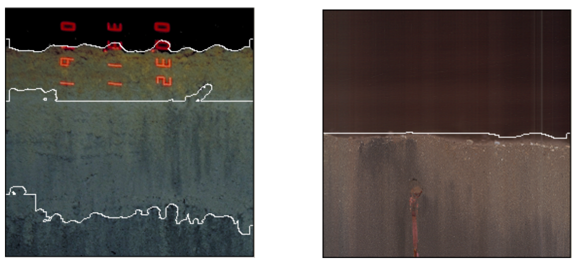
Figure 3: (1 - 5) represents segmented results of skin cancer images after the boundary refinement stage

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 cancer images obtained were in graphics interchange format (gif). Five skin cancer images considered for the application database were taken from the [3].
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 analyse skin lesions, it is necessary to accurately locate and isolate the lesions. The efficient performance of the proposed colour texture segmentation method exactly recognised the boundaries in the skin lesions as shown in Figure 3.
Colour is one of the significant feature in the examination of a skin lesion. Typical examples of lesions show reddish, bluish, grey and black areas and spots. Figure 3-(1), shows the segmentation of the skin lesion. The fine variation in the colour is identified and segmented accurately. Figure 3-(2), Figure 3-(3),

Figure 3-(4) and Figure 3-(5), illustrates 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.

3.3 Sediment Profile Imagery

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 (SLR) 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



(1) (2)

Figure 4: (1) and (2) represents segmented results of SPI images after the boundary refinement stage

the light absorption, changing image radiance and lack of well defined features. The underwater images shows fluctuating oxygenation levels under different organic loading and hydrographic conditions.
Figure 4-(1) shows an example of a sediment image under high organic loading stress in hypoxic conditions. This is an example of a 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 4-(2) represents 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. Due 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.* [2] 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.

4 Conclusion

The goal of this paper is to find the performance of the developed colour texture segmentation method in the script images, skin cancer images and underwater images. The proposed algorithm, was tested in three different applications, ISOS script images, skin cancer images and the underwater images. The algorithm was applied on the images and was found to produce proper segmentation results. All these applications use different images taken from different cameras and varying environment. In spite of these differences, 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 a determinant factor in the segmentation process.

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