# Investigation on the Discrete Cosine Transform and Chromaticity Features in Colour Texture Analysis

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*Abstract* — **This paper focusses on the segmentation of colour texture images. The foremost purpose of this approach is to investigate the role of colour information in the analysis of textures. Discrete Cosine Transform is a filtering approach used to extract features from the luminance plane. Each filter mask captures a particular property of the local texture structure. The distribution of chromaticity features with filter masks are used for colour texture description. An unsupervised texture segmentation method was adopted to achieve the segmented result. The performance of the method was evaluated using ROC curve analysis. The results specifies the importance of the incorporation of colour.**

*Keywords* — **Colour, Texture, Discrete Cosine Transform, Segmentation, Chromaticity features.**

## I Introduction

Colour and texture are two innate properties of an image and are very important attributes in image analysis. A colour texture can be regarded as a pattern described by the relationship between its chromatic and structural pixel distribution [1]. Although texture and colour are often dealt with seperately, this may not be a suitable approach as most textured images have a colour aspect and most coloured surfaces are textured. There are few standard methods that are widely used to incorporate the chromatic information into texture analysis. Among different methods the most common approach is to process each color band seperately [2]. Another method uses the spatial interaction between different spectral bands. This paper focuses on the processing of colour and texture information seperately, where the colour signal is divided into luminance and chrominance components and are used for colour texture segmentation. The Discrete Cosine Transform (DCT) developed by Ng *et al.* [3] was used to extract greyscale features from the intensity plane, followed by the extraction of colour features from the chrominance planes. For a comparative study DCT features are extracted from the three spectral bands. An unsupervised texture segmentation method developed by Ojala *et al.* [4] for greyscale textures, is used to segment the image where a novel data structure was proposed to implement the segmentation algorithm [5]. The contents of this paper is organised as follows: Section 2 depicts the related work in the field of colour texture analysis. Section 3, describes different colour spaces, feature extraction technique used and provides a detailed description of colour texture segmentation. Section 4 presents the experimental evaluation and Section 5 concludes with a summary.

## II Related Work

Panjwani and Healey [6] presented an unsupervised segmentation algorithm based on Markov Random Field models for colour textures. Their models characterises a texture in terms of spatial interaction within each colour plane and interaction between different colour planes. The effectiveness of the model and algorithm have been demonstrated on many colour images of natural scenes. Jain and Healey [7] introduced a method based on unichrome features computed from the three spectral bands independently and opponent features that utilise the spatial correlation between spectral bands using Gabor filters. Paschos [8] presented a visual monitoring system which incorporates colour and texture processing principles for image analysis. This system performs a scene segmentation based on colour and texture information. Several aerial images of wetland scenes have been used for testing the proposed method. Drimbarean and Whelan [1] examined the contribution of colour information to the overall classification performance. They extended the grey level algorithms to colour images and found that the inclusion of colour increases the classification results without significantly complicating the feature extraction algorithms. For their classification experiments the VisTex [9] database was used. Pietiekainen *et al.* [10] presented a colour texture classification based on separate processing of complementary colour and pattern information. The experiments in this classification method were conducted using VisTex database and Outex texture database [11]. From the classification results they concluded that colour and texture have complementary roles. Jolly and Gupta [12] described a new algorithm for combining colour and texture information for the segmentation of colour images. The algorithm uses maximum likelihood classification combined with a certainty based fusion criterion. This algorithm was demonstrated on mosaics of textures, outdoor scene images, and a number of aerial images and the segmentation results were able to combine the advantages of both the colour and texture segmentation processes. Chen *et al.* [13] proposed a new method for colour texture segmentation using feature distributions. They make use of the distributions of colour and local edge patterns to derive a homogeneity measure for color textured regions. VisTex images are used for the segmentation and they found excellent results for natural images. Though there exist many techniques for analysing colour and textures, only limited research work has been undertaken in the field of unified colour texture analysis.

## III Colour Texture Segmentation

Segmentation is the process of seperating mutually exclusive homogeneous regions of interest. There are numerous techniques for the extraction of texture features and various methods for segmentation. Skarbek *et al.* [14] classify segmentation as four categories: Pixel based segmentation, area based segmentation, edge based segmentation and physics based segmentation and provides a detailed survey of the methods. Predominantly, the methods are developed for greyscale textures. More recently, colour and texture features have been combined, this is referred to as colour texture analysis. This section explains the colour spaces used for the analysis, feature extraction technique, and the method adopted for colour texture segmentation.

### *a) Colour Spaces*

A colour space is a model for representing colours in terms of intensity values. A colour model is the geometric representation of colours in a three dimensional space. The RGB, additive colour space is the fundamental colour space in image processing. Different colour spaces are better for different applications. Hence, for an improved colour processing a more appropriate method is to utilise a different colour space, where the same information is represented in a way that corresponds better to the segmentation method. Some of the various colour spaces in scientific use are HSI, HSV, YIQ, CIE-XYZ, CIE-LAB, CIE-LUV etc. The advantage of the colour texture model described in this paper is that it can be applied to any colour space, although we will focus on YIQ and HSI colour spaces for the purpose of this paper. YIQ is a linear and HSI is nonlinear transformation of RGB cube. HSI representation of colour is close to the method of colour description used by humans [15]. The YIQ and HSI systems separate the colour information of an image from its intensity information. Grey level algorithms can be applied to the intensity plane and the texture information is extracted from the luminance plane i.e from Y plane in YIQ and I plane in HSI space. The colour information is extracted from the two chrominance planes.

### *b) Feature Extraction Technique*

The objective of feature extraction is to obtain information about the texture present in the image under analysis. A feature is a function of one or more measurements, computed so that it quantifies some significant characters of the object. The feature extraction process produces a set of features that, taken together comprise the feature vector. This drastically reduced the amount of information compared to the original image. The feature vector represents all the knowledge upon which the subsequent classification decisions could be based. DCT is a feature extraction technique suggested by Ng *et al.* [3]. Randen and Husoy [16] performed a comparative study based on the filtering approaches and found improved results using the DCT approach. Local linear properties can be extracted using well known transforms similar to DCT. Here a $3 \times 3$ DCT is used for texture feature extraction and the one dimensional filter masks $h_1 = [1, 1, 1]$, $h_2 = [1, 0, -1]$, $h_3 = [1, -2, 1]$ are used for the implementation. This yields nine independent $3 \times 3$ DCT masks which generates a 9-dimensional feature vector. The DCT feature space should be quantised to greyscale values $(0 - 255)$. Choosing an appropriate quantisation level is a vital task as lower quantisation level may result in the loss of textural information. The DCT is orthogonal and separable and is widely used in image coding applications.

*c) Segmentation Method*

Colour features such as mean, standard deviation, energy, entropy are computed from the chrominance planes. The distribution of DCT and the colour features are used for colour texture description. Here the nine DCT features are combined with two colour features and the distribution was computed. Similarly for a comparative study the DCT features are drawn from both the luminance and the chrominance planes constituting a total of twenty seven features. The discrimination between the distributions was performed using G-Statistic. The value of G-Statistic indicates the probability that whether the two sample distributions come from the same population, higher value of G-Statistic illustrates the probability that the two samples are from same population is low. This procedure is followed by an unsupervised texture segmentation as developed by Ojala *et al.* [4] which performs hierarchical splitting and agglomerative merging. Hierarchical splitting divides the image into blocks of roughly uniform texture and agglomerative merging procedure merges similar adjacent regions until a stopping rule is satisfied. This results in segmentation of different homogeneous texture regions in the image. This technique is followed by a pixelwise classification to improve the localisation of the boundaries and to obtain an enhanced segmented image. A detailed description about G-Statistic and unsupervised segmentation method was found in Ojala *et al.* [4].

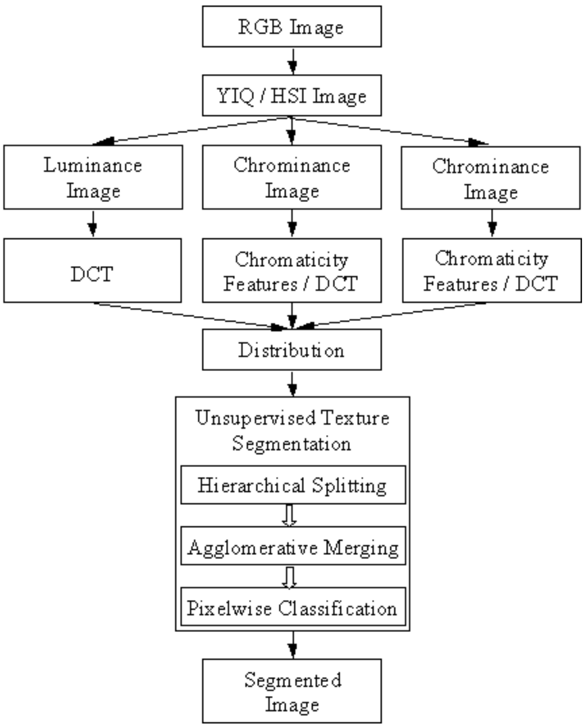


Fig. 1: An overview of the colour texture segmentation system

## IV Experimental Evaluation

The proposed method was evaluated on a set of 10 texture mosaic images obtained from the MIT Media Lab VisTex [9] texture image database. The size of each image is $256 \times 256$, constructed using random selection of four images of size $128 \times 128$. Various experiments are conducted to demonstrate the effectiveness of the proposed method. These images are processed using the proposed segmentation algorithm with various parameter values. The parameter values are image dependent and are set in order to achieve minimum segmentation error. Figure 2 shows the mosaic images used for the colour texture analysis.

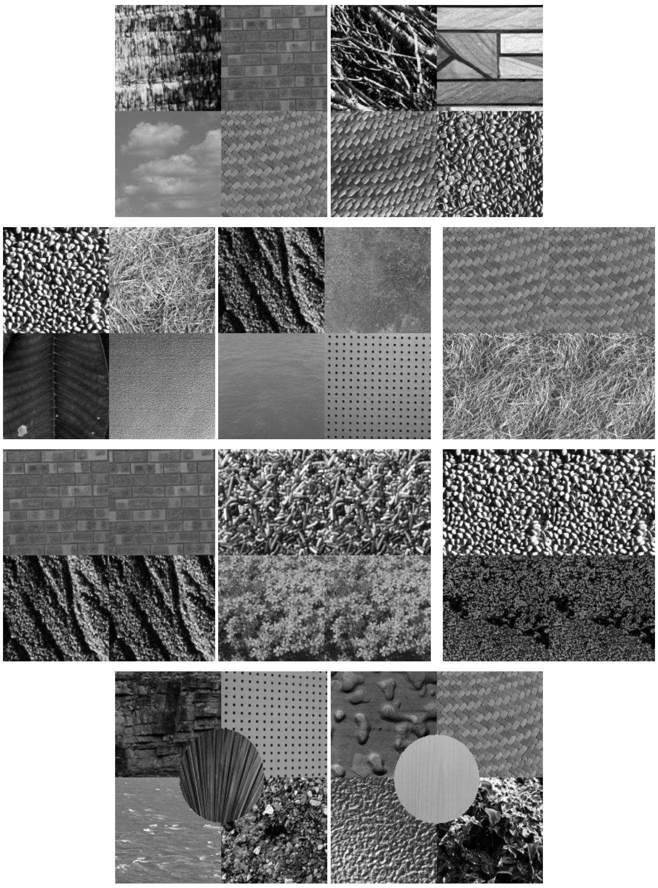

Fig. 2: Mosaics of colour texture images

The first stage of the experiments exhibit the significance of the colour information. This experimentation compares the percentage of results obtained from greyscale and colour images. Table 1 illustrates the average percentage of the segmentation results in greyscale, RGB, YIQ and HSI space. Results obtained show that the addition of colour improves the segmentation.

| Technique | Greyscale | RGB | YIQ | HSI |
|---|---|---|---|---|
| DCT | 81.8% | 87.2% | 98% | 92.1% |

Table 1: Percentage of segmented results for the first experiment

As a quantitative analysis, a receiver operating characteristic curve is drawn to determine the efficiency of the method. The segmented errors are used to evaluate the segmentation results. The number of pixels correctly classified and the number of pixels misclassified in the segmented image were the discriminative features for drawing the ROC curves. The ground truth of the image was obtained for boundaries between different textured regions when the images were constructed using the VisTex textures. The ROC curve explains the tradeoff between sensitivity and specificity. The curves in Figure 3 shows that the segmentation performance increases due to incorporation of the colour information. The curves are closer to the left hand border and to the top border of the ROC space. The results are more accurate and is 100% for some images with square regions, as shown in Figure 4. The execution time for the proposed method was 1.28 seconds on a standard PC ( Pentium 3 processor, 1.6GHz/ 256MB RAM ).

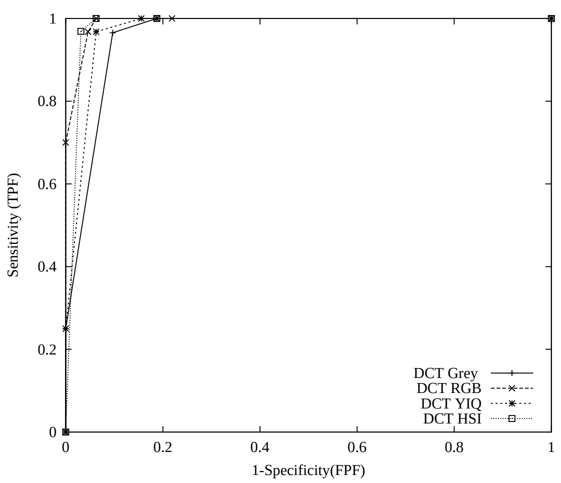


Fig. 3: ROC curves for Greyscale, RGB, YIQ and HSI spaces respectively

Some of the sample segmentation results are shown in Figure 4. The image in Figure 4(c) consists of bark, brick, cloud and fabric. Here the bark texture is divided into two different regions. It is evident from the segmented image that the texture exhibits a significant colour difference. The application of the segmentation algorithm correctly identifies these regions which is in agreement with the human visual system. This shows that colour plays a vital role in the experiments. The result in Figure 4(b) shows small unmerged blocks of segments of texture. This occurs due to the difference in the colour component within a texture region. For clarity purposes the results shown here are obtained after agglomerative merging stage.

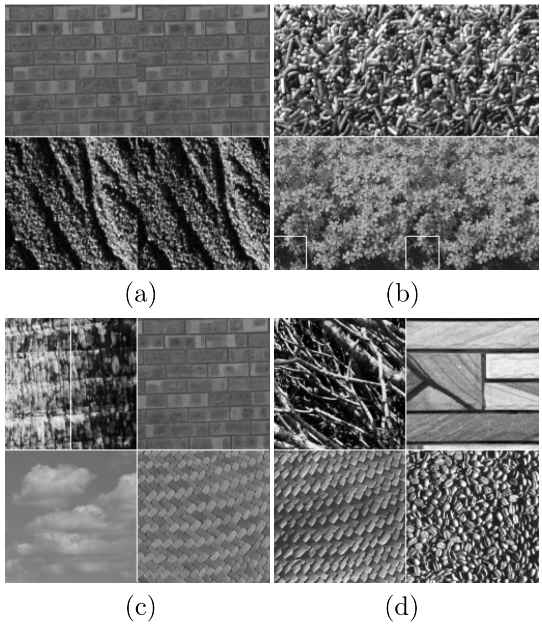


Fig. 4: (a)-(d) Sample segmented images after agglomerative merging

The next stage of the experiment shows the significance of colour features in colour texture analysis. A comparison of chromaticity features was performed. Colour features such as mean, standard deviation, energy, entropy and DCT are extracted from the colour planes together with the DCT features from the intensity plane. These are some of the standard features used in colour texture analysis. Table 2 lists the average percentage of segmentation results using different chromaticity features. Results imply that the segmentation performance was consistent for colour feature entropy. Comparatively, nine DCT features together with two colour features outperforms the twenty seven DCT features.

| CS | Chromaticity Features | | | | |
|---|---|---|---|---|---|
| | Mean | Stddev | Energy | Entropy | DCT |
| RGB | 76.4% | 90.7% | 82.6% | 87.2% | 59.2% |
| YIQ | 91.3% | 75.5% | 81.1% | 98% | 75.1% |
| HSI | 80.6% | 85.6% | 80.1% | 92.1% | 60.5% |

Table 2: CS-Colour Space. Percentage of segmented results for the second experiment using DCT features

This method uses a small bank of filters and results in a low feature dimensionality. This method does not require any prior knowledge about the number and types of textures or the number of regions in the image.

## V Conclusion

This paper proposes a method for colour texture segmentation using the distributions of DCT and chromaticity features. The method examines the contribution of colour in the analysis of textures. From the segmented results, the role of colour was observed. The inclusion of colour improves the performance of segmented result.

## References


[1] A.Drimbarean and P.F.Whelan. "Experiments in colour texture analysis". *Pattern Recognition Letters*, 22:1161-1167, 2001.

[2] T.Caelli and D.Reye. "On the classification of image regions by colour, texture and shape". *Pattern Recognition*, 26(4):461-470, 1993.

[3] I.Ng, T.Tan and J.Kittler. "On local linear transform and gabor filter representation of texture". *Proc.Int.Conf.Pattern Recognition*, 627-631, 1992.

[4] T. Ojala and M. Pietikainen. "Unsupervised texture segmentation using feature distributions". *Pattern Recognition*, 32:477-486, 1999.

[5] N.Padmapriya, P.P.Pradeep and P.F.Whelan. "A new data structure for the implementation of unsupervised texture segmentation". *Proc.of The Irish Signals and Systems Conference*, 109-113, 2002.

[6] D.K.Panjwani and G.Healey. "Markov Random Field models for unsupervised segmentation of textured colour images". *IEEE Transactions on Pattern analysis and Machine Intelligence*, 17(10):939-954, 1995.

[7] A.K.Jain and G.Healey. "A multiscale representation including opponent colour features for texture recognition". *IEEE Trans on Image Processing*, 7(1):124-128, 1998.

[8] G.Paschos and K.P.Valavanis. "A color texture based visual monitoring system for automated surveillance". *IEEE Trans of Systems, Man, and Cybernetics-Part C:Applications and Reviews*, 29(1):298–307, 1999.

[9] VisTex. Colour Image Database. *http: //www-white.media.mit.edu/vismod/imagery/VisionTexture/vistex.html.*,2000.

[10] M.Pietikäinen, T.Mäenpää and J.Viertola. "Color texture classification with color histograms and local binary pattern". *Proc.Texture2002. 2nd International Workshop on Texture Analysis and Synthesis. In Conjunction with ECCV2002*, 2002.

[11] Outex. Image Database. *http: //www.outex.oulu.fi/outex.php*

[12] M. Jolly and A. Gupta. "Color and texture fusion: application to aerial image segmentation and GIS updating". *IEEE Workshop on Applications of ComputerVision* 2-7, 1996.

[13] Kan-Min Chen and Shu-Yuan Chen. "Colour texture segmentation using feature distributions". *Pattern Recognition Letters*, 23:755-771, 2002.

[14] W.Skarbek and A.Koschan. "Color Image Segmentation: A survey". *Technical Report*, 1994.

[15] P.F.Whelan and D.Molloy. "Machine Vision Algorithms in Java:Techniques and Implementation". *Springer (London)*, 2000.

[16] T.Randen and J.H.Husoy. "Filtering for Texture Classification: A Comparative Study". *IEEE Trans on Pattern Analysis and Machine Intelligence*, 291-310, 1999.