Combining GLCM features and Markov Random Field Model for Colour Textured Image Segmentation

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***Abstract*- In this paper, we propose a new approach for color textured image segmentation. It is a two stage technique, where in the first stage, textural features using gray level co-occurrence matrix (GLCM) are computed for regions of interest (ROI) considered for each class. ROI act as ground truths for the classes. Ohta model (I1, I2, I3) is the colour model used for segmentation. Mean at inter pixel distance (IPD) 1 of I2 component was found to be the optimized textural feature for further segmentation. In the second stage, the feature matrix obtained is assumed to be the degraded version of the image labels and Markov random field model is employed to model the unknown image labels. The labels are estimated through maximum *a posteriori* estimation criterion using iterated conditional modes algorithm. The performance of the proposed approach is compared with that of using GLCM and Maximum Likelihood classifier and with the one which uses GLCM and MRF in RGB colour space. The proposed method is found to be better in terms of accuracy than the other two methods.**

Keywords-Gray level co-occurrence matrix, Markov random field model, texture, segmentation, Ohta colour space

I. INTRODUCTION

Image segmentation, one of the important modules of early vision problem can be defined as the process of partitioning an image into some discrete regions, each region being homogenous as regards the three fundamental pattern elements to wit spectral, textural and contextual features. Although versatile methods of monochrome image segmentation techniques are accounted in the literature, colour image segmentation has appealed the researchers for rendering more information and solving much high level vision problems including image analysis, object identification, shape analysis etc. But taking into consideration mere color information may cause problems when identical reflectance values correspond to very different objects. Hence, texture which is one of the most potent additional characteristics of an image is utilized in image analysis on account of its extensive pertinence in various fields. Texture can be defined as the variability in the tone with in a neighbourhood, or the spatial relationships among the gray levels of neighbouring pixels. Whether the data is a remote sensing image or a medical image, texture takes on a very significant role in the analysis of data. The final objective of data analysis in the field of remote sensing range from simple land cover classification to specific applications like recognition of agricultural fields, buildings, roads, estimation of vegetation, diseased trees, flood mapping and so forth. In medical images it helps in the automated diagnosis of diseases [1, 2].

For visual interpretation texture is a definitive feature. Consequently the texture descriptors are anticipated to increase the performance of digital classification schemes. Among the approaches that have been followed to assess texture are the structural approach and statistical approach [3, 4, and 5]. In the structural approach, a texture is considered as a structure composed of a large number of more or less ordered, similar elements or patterns with a certain rule of placement. The complex problem associated with this approach is the extraction of such primitives. In statistical approach the stochastic properties of the spatial distribution of the gray levels in the image are characterized. Among the early statistical approaches mention may be made on the use of gray level co-occurrence matrices (GLCM) [3, 6] to extract the textural features. Recently, textural analysis by GLCM approach has also been successfully used to classify panchromatic satellite data [7] as well as lower resolution multispectral satellite data [8]. Stochastic model especially Markov random field (MRF) model has also been used to a great extent for handling the problem of colored and textured image segmentation [9, 10]. As the model utilizes both spectral and spatial information to model the local structure of an image, it is undoubtedly, a potent mathematical tool for contextual modeling of spatial data [11, 12]. Hidden Markov random field model has been implemented by Destrempes et al. [13] in unsupervised frame work for colour image segmentation. To model natural scenes and color textures Constrained Markov random field (CMRF) model was proposed for pixel labelling problem [14]. Besides image model, color model too takes on a significant role in image segmentation. Since the similarity in colour is better interpreted in transformed spaces like HSV, YIQ, Ohta (I1, I2, I3), CIE (XYZ, Luv, Lab), these have been utilized in image segmentation.

In this work, we propose a new approach, which adopts the features of both gray level co-occurrence matrix and Markov Random field model using Ohta color space to segment color textured image. GLCM represents the distance and angular spatial relationships over an image sub-region of specified size

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from which several textural measures may be computed. These measures are considered in classifying the textured image. In MRF based segmentation, the most popular criterion for optimality has been the maximizing a posteriori probability (MAP) distribution criterion. Simulated annealing (SA) and iterated conditional modes (ICM) algorithm are two unremarkably used methods for pixel labeling, among the existing MAP criterion algorithms. ICM has the ability of faster convergence but depends heavily on the initial state. In our proposed work GLCM feature matrix obtained in Ohta colour space provides a very good initialization for ICM algorithm. Section II reports Grey Level Co-occurrence matrix and texture measures. MRF model based segmentation is explained in section III. Section IV describes the proposed segmentation approach based on GLCM and MRF. Results are presented in section V and section VI makes conclusion.

II. Grey Level Co-occurrence Matrix And Textural Measures

Texture features based on GLCM are an efficient means to study the texture of an image. Given the image composed of pixels each with an intensity, the GLCM is an illustration of how frequently different combinations of grey levels concur in an image. A GLCM denote the second order conditional joint probability densities of each of the pixels, which is the probability of occurrence of grey level i and grey level j within a given distance ‘d’ and along the direction ‘θ’. These second order statistics are calculated for all pair wise combinations of grey levels.. Generated the GLCM, 14 types of texture features have been defined by Haralick et. al. [3]. The depiction of the texture information is then extracted by these series of texture statistics computed from GLCM. In our study we have looked at eight conventional measures. These are described below,

A. Contrast (CON):

Contrast is defined as the difference between the highest and the smallest values of the adjacent set of pixels considered. The GLCM cumulous around the principal diagonal interprets a low contrast image and high contrast values mean a coarse texture.

$$CON = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-j)^2\, p(i,j) \tag{1}$$

B. Dissimilarity (DSM):

The heterogeneity of the grey levels is shown by dissimilarity. Over again the coarser textures are portrayed by higher values of dissimilarity.

$$DSM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} Abs(i-j)\, p(i,j) \tag{2}$$

C. Homogeneity (HOM):

Homogeneity assesses image homogeneousness and for smaller difference between grey values it takes on larger values

$$HOM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{p(i,j)}{\left[1+(i-j)^2\right]} \tag{3}$$

D. Mean (MEAN):

The average grey level with respect to the central position is given by mean.

$$MEAN = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} i\, p(i,j) \tag{4}$$

E. Standard Deviation (SD):

Standard deviation reflects the degree of distribution of the grey level values and the copiousness of the data in the image.

$$SD = \sqrt{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left(i * MEAN - p(i,j)\right)^2} \tag{5}$$

F. Angular Second Moment (ASM):

Angular second moment evaluates the consistency of textural information

$$ASM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)^2 \tag{6}$$

G. Correlation (COR):

Correlation is a measure of grey tone linear dependencies in the image and hence the linear relationship between the grey levels of pixel pairs is speculated in this.

$$COR = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{\left[(i-\mu)(j-\mu)\, p(i,j)\right]}{\sigma_i \sigma_j} \tag{7}$$

H. Entropy (ENT):

The disorderliness of an image is given by entropy. Texturally inconsistent image having very low values for many GLCM elements entails that the entropy is very large.

$$ENT = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)\log\left(p(i,j)\right) \tag{8}$$

III. Segmentation Using Markov Random Field Model

In image analysis process MRF models represent a potent tool due to their ability to incorporate contextual information associated with the image data [12]. The MRF approach shows the global model of the contextual information by using only local relations among neighbouring pixels.

Let the images are assumed to be defined on discrete rectangular lattice S = (M × N). Let W denotes the random field associated with the label process related to segmented image with respect to neighbourhood system η and w is the segmented image to be obtained. We have one more random field that is the observed image Y which is assumed to be Gaussian and degraded version of the label process.

$$P\left(W_{ij}=w_{ij} \mid W_{kl}, kl \in S, (k,l) \neq (i,j)\right) = P\left(W_{ij} = w_{ij} \mid W_{kl} = w_{kl}, k,l \in \eta\right) \quad (9)$$

Through MRF–Gibb's equivalence the joint probability distribution can be expressed as,

$$P(W=w|\phi) = \frac{1}{Z'} e^{-U(w,\phi)} \quad (10)$$

where $Z = \sum_{w} e^{-U(w,\phi)}$ is the partition function

ϕ denotes the clique parameter vector

$U(w,\phi)$ is the energy function and is of form

$U(w,\phi) = \sum_{c(i,j)\in c} V_c(w,\phi)$

$V_c(w,\phi)$ is the clique potential

Y is the observed image random field.

The random variables Y_i are conditionally independent for any realization of w. The problem is devised as pixel labelling problem and the $\hat{w}$ is found by maximum *a posteriori* probability condition,

$$(\hat{w}) = \underset{(w)}{\arg\max}\, P\left(W=w \mid Y=y, \hat{\phi}\right) \quad (11)$$

w is unknown and hence can only be computed using Bayes' theorem as follows,

$$P\left(W=w \mid Y=y, \hat{\phi}\right) = \frac{\underset{(w)}{\arg\max}\, P(Y=y \mid W=w,\phi) P(W=w)}{P(Y=y|\phi)} \quad (12)$$

$P(Y=y|\phi)$ is a constant quantity as the Y corresponds to the given image and $P(W=w)$ is the *a priori* probability of the labels. Therefore $P(Y=y|W=w,\phi)$ can be written as $P(Y=y|W=w,\phi) = P(Y=w+t|W,\phi) = P(T=y-w|W,\phi)$. T is the Gaussian process and as we have considered only single component for segmentation we obtain,

$$P(T = y - w|W,\phi) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{1}{2\sigma^2}(y-w)^2} \quad (13)$$

From (12) and (13) the problem reduces to,

$$\hat{w} = \underset{(w)}{\arg\min}\left[\frac{1}{2\sigma^2}(y-w)^2 + \sum_{c\in C} V_c(w)\right] \quad (14)$$

V_c is clique potential function and C is set of all cliques.
The energy function considered is given by,

$$U(w,h,v) = \sum_{i,j} \alpha\left[\left|w_{i,j} - w_{i,j-1}\right|^2 \left(1-v_{i,j}\right) + \left|w_{i,j} - w_{i-1,j}\right|^2 \left(1-h_{i,j}\right)\right] + \beta\left[v_{i,j} + h_{i,j}\right] \quad (15)$$

The vertical line field $v_{i,j} = 1$ if, $f_v\left(w_{i,j}, w_{i-1,j}\right) \succ threshold$

The horizontal line field $h_{i,j} = 1$ if $f_h\left(w_{i,j}, w_{i,j-1}\right) \succ threshold$

Finally the posteriori energy is given by,

$$U_p(w,h,v) = \frac{(y-w)^2}{2\sigma^2} + U(w,h,v) \quad (16)$$

α *and* β are selected on ad hoc basis.

IV. Approach

In this work, the gray level co-occurrence matrix used to compute the textural statistics is calculated taking into account three factors, namely, (i) the number of grey levels (ii) inter pixel distance (IPD) and (iii) direction. The inter pixel distance of 1, 45^{o} direction and number of grey levels equal to 256 has been considered for computation of GLCM. The success of segmentation procedure relies greatly on the selected window size. Thus initially GLCM values are calculated for six window sizes (3×3, 5×5, 7×7, 9×9, 11×11, 13×13). And it is observed that the window size of 3×3 yields best results for the color textured images containing two classes comprising of both coarse and fine texture which are considered in our work. In addition to this, the main issue of concern is the identification of appropriate textural features out of numerous combinations, which would improve the segmentation accuracies. In this study, by normalizing the textural features, the optimal textural feature was identified in a semi-quantitative manner. The following procedure was followed,

a) The colour space used is the Ohta colour space, the colour coordinates being,
   $I_1 = (R+G+B)/3;\ I_2 = (R-B)/2;\ I_3 = (2G-R-B)/4$
b) A number of regions of interest (ROI) in each class is taken as ground truth for computing eight textural features as described in section 2. The one which evidently distinguishes the classes is considered for

segmentation. Fig. 1 shows few of them. From the figure it can be seen that the most appropriate is the one which does not involve the overlapping of the classes. It is found that the Mean texture matrix is the most appropriate one and is used for segmentation using MRF model described in section 3.

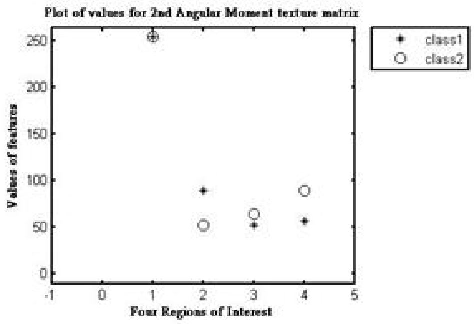

Fig. 1 (a)

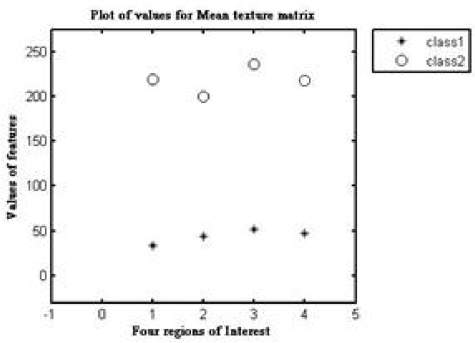

Fig. 1 (b)

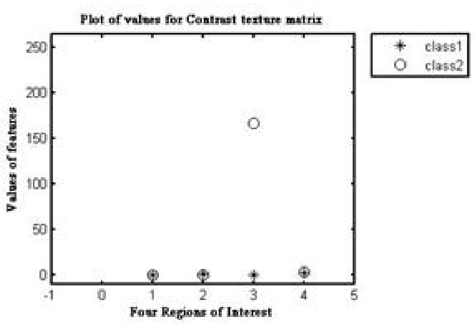

Fig. 1 (c)

Fig.1. Plots showing the values of features for four ground truth images (a) For second angular moment (b) Mean (c) Contrast and (d) Entropy

V. SIMULATION RESULTS

Noisy image corrupted with Gaussian noise and color textured image have been considered in simulation as shown by Figure 2 and Figure 3. The posteriori energy given in (16) is taken for the energy minimization problem. The mean feature matrix of I2 component obtained in 45^{o} direction is selected for segmenting the image. ICM algorithm is used and the mean feature matrix acts as an initial state for ICM algorithm. The *a priori* image model parameters are chosen on trial and error basis. The values are given in Table 1. For colour textured image the results of the proposed method is compared with the method as proposed in [10] and with the one which uses GLCM and MRF in RGB colour space. The error rate of all the three methods is given in Table 2 and can be seen that the proposed method yields better results.

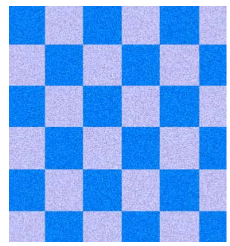

Figure 2(a)

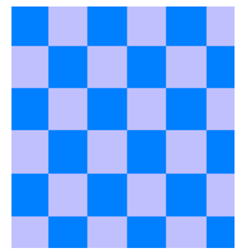

Figure 2(b)

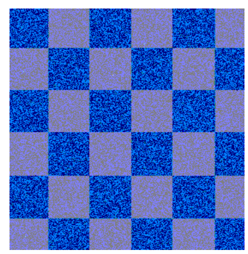

Fig. 2(c)

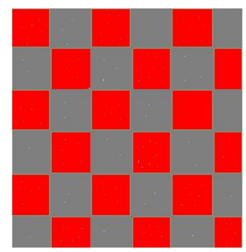

Fig. 2(d)

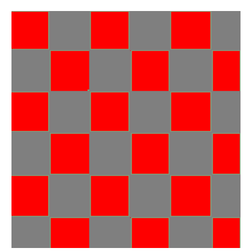

Fig. 2(e)

Fig.2. Segmentation results of checker board image (a) Noisy checker board image (b) ground truth (c) segmentation in RGB color space using GLCM and MRF (d) segmentation using GLCM and Maximum Likelihood classifier (e) segmentation in Ohta color space using GLCM and MRF

TABLE II. TABLE SHOWING THE MODEL PARAMETERS FOR MRF BASED SEGMENTATION

Images	Model	α	β	σ
Figure 2	Ohta	0.0352	4.03	5.33
	RGB	0.0352	4.03	5.33
Figure 3	Ohta	0.0025	3.0	5.0
	RGB	0.00001	3.0	5.0

The error rate can be calculated by the following equation,

$$\frac{Number\ of\ misclassified\ pixels}{Total\ number\ of\ pixels\ in\ the\ image}\ x\ 100$$

Fig. 3(a)

Fig. 3(b)

Fig. 3(c)

Fig. 3(d)

Fig. 3(e)

Fig. 3. Segmentation results of 2 class color textured image (a) Original image (b) ground truth (c) segmentation in RGB color space using GLCM and MRF (d) segmentation using GLCM and Maximum Likelihood classifier (e) segmentation in Ohta colour space using GLCM and MRF

TABLE II. ERROR RATE OF SEGMENTATION RESULTS

	GLCM and MRF based segmentation using RGB colour space	**GLCM and Maximum Likelihood classifier**	**GLCM and MRF based segmentation using Ohta colour space**
Error Rate (%)	40%	3.32%	1.6301%

VI. CONCLUSION

This study confirms the utility of Ohta colour space, GLCM and MRF model to enhance the accuracy of segmentation of colour textured images. The statistical properties of colour textured images in Ohta colour space are explored by means of GLCM and the segmentation is done by contextual modeling of the data through MRF modeling. The Haralick feature Mean at IPD 1, as optimized with this approach, appears to be the best textural feature to improve interclass discrimination. The results obtained in this study are compared with that of MRF modeling in RGB colour space and our method found to be the better choice.

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