International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:5, No:5, 2011

Featured based Segmentation of Color Textured Images using GLCM and Markov Random Field Model

Dipti Patra, Mridula J

Abstract**—** In this paper, we propose a new image segmentation approach for colour textured images. The proposed method for image segmentation consists of two stages. 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 acts as ground truth for the classes. Ohta model (I_1, I_2, I_3) is the colour model used for segmentation. Statistical mean feature at certain inter pixel distance (IPD) of I_2 component was considered 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 modeled as Markov Random Field (MRF) model to model the unknown image labels. The labels are estimated through *maximum a posteriori* (MAP) estimation criterion using ICM algorithm. The performance of the proposed approach is compared with that of the existing schemes, JSEG and another scheme which uses GLCM and MRF in RGB colour space. The proposed method is found to be outperforming the existing ones in terms of segmentation accuracy with acceptable rate of convergence. The results are validated with synthetic and real textured images.

Keywords**—**Texture Image Segmentation, Gray Level Co-occurrence Matrix, Markov Random Field Model, Ohta colour space, ICM algorithm.

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 color models are used to represent different colours and the similarity in colour is better

Dr. Dipti Patra is with the National Institute of Technology, Electrical Engineering Department, Rourkela, India-769008; e-mail: dpatra@nitrkl.ac.in).
Mridula J is with the National Institute of Technology, IPCV Lab, Electrical Engineering Department, Rourkela, India-769008 (e-mail: mridulamahesh3@gmail.com).

interpreted in transformed spaces like HSV, YIQ, Ohta (I_1, I_2, I_3), CIE (XYZ, La*b*), 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 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. SA can converge to global optimum, but suffers from intensive computation. On the other hand, ICM has the ability of faster convergence but the results obtained heavily depend on initial state. Hence in our proposed work GLCM feature matrix obtained in Ohta colour space provides a very good initialization for ICM algorithm. Section II reports GLCM 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 conclusion is presented in section VI.

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 as follows.

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

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

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.

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

C. Homogeneity (HOM):

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

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

D. Mean (MEAN):

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

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

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.

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

F. Angular Second Moment (ASM):

Angular second moment evaluates the consistency of textural information.

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

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.

$$COR = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(i-\mu)(j-\mu)p(i,j)}{\sigma_i \sigma_j} \qquad (7)$$

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.

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

III. Image 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–Gibbs equivalence the joint probability distribution can be expressed as,

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

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 the form

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

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

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,

$$\hat{w} = \arg\max_{w} P(W=w \mid Y=y, \hat{\phi}) \quad (11)$$

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

$$P(W=w \mid Y=y, \hat{\phi}) = \frac{\arg\max_{w} P(Y=y \mid W=w, \phi)\, P(W=w)}{P(Y=y \mid \phi)} \quad (12)$$

$P(Y=y \mid \phi)$ 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 $P(Y=y \mid W=w, \phi)$ can be written as $P(Y=y \mid W=w,\phi) = P(Y=w+t \mid W, \phi) = P(T=y-w \mid W, \phi)$. T is the Gaussian process and as we have considered only single component for segmentation we obtain,

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

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

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

The energy function considered is given by,

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

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

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

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, viz, (i) the number of grey levels (ii) inter pixel distance (IPD) and (iii) direction. The inter pixel distance of 1, directions namely 0^o, 45^o, 90^o and 135^o and number of grey levels equal to 256 has been considered for computation of GLCM. The success of segmentation procedure using textural features 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 found 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 have been considered in our work. In addition to this the main issue of concern is the identification of appropriate textural features, out of numerous combinations, that 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 (I1, I2, I3) 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. All the eight textural features are computed for the ROI. The one which evidently distinguishes the classes is considered for segmentation. This is shown in fig. 1. The values of only four features are shown in the figure and in simulations it is calculated for all features. From the figure it can be concluded that the most appropriate is the one which does not involve the overlapping of the classes. The Mean texture matrix is the most appropriate one and is used for segmentation using MRF model described in section 3. We can see that the features angular moment, contrast and correlation does not give a clear differentiation of the classes. Besides mean feature, all others show overlapping of values for classes for different ground truth data.

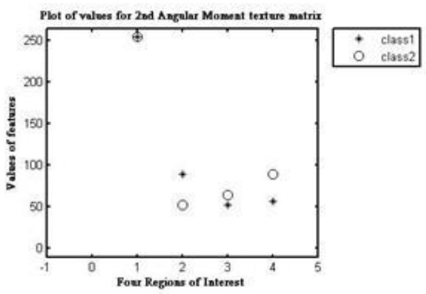

Fig. 1 (a)

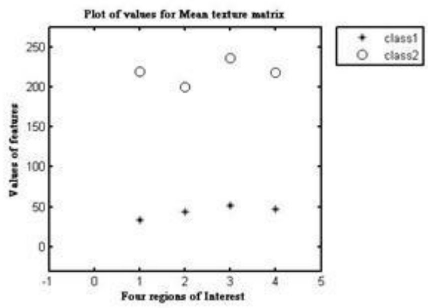

Fig. 1 (b)

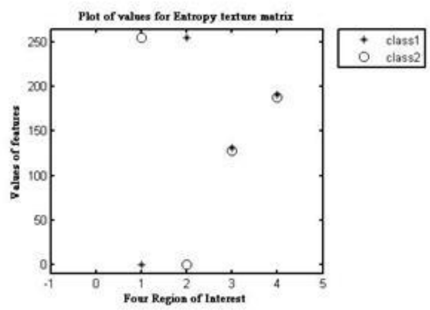

Fig. 1 (c)

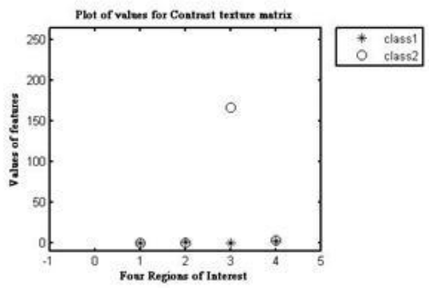

Fig. 1 (d)

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

Color textured images; both synthetic and real are 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 I_2 component obtained in 45^o direction 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 trial and error basis. The values are given in Table 1. For two class synthetic colour textured image the result of the proposed method is compared with the popular method JSEG and that with which uses GLCM and MRF in RGB colour space. After knowing the misclassification error of more than 40% in RGB colour space, for two class real image as shown in figure 3, it is compared with only JSEG method. Although JSEG method is able to give almost satisfactory results for synthetic image, it is found that, it fails to give accurate results for real images. Hence the proposed method yields better results.

TABLE I
THE MODEL PARAMETERS FOR MRF BASED SEGMENTATION

Image	Model	α	β	σ
Figure 2	Ohta	0.0352	4.03	5.33
Figure 3	Ohta	0.0352	4.03	5.33

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. 2(a)

Fig. 2(b)

Fig. 2(c)

Fig. 2(d)

Fig. 2(e)

Fig. 2. Segmentation results of 2 class color textured synthetic image (a) Original image (b) ground truth (c) segmentation in RGB color space using GLCM and MRF (d) segmentation using JSEG method (e) segmentation in Ohta colour space using GLCM and MRF model.

Fig. 3(a)

Fig. 3(b)

Fig. 3(c)

Fig. 3(d)

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

TABLE II
MISCLASSIFICATION ERROR OF SEGMENTATION RESULTS

	GLCM and MRF based segmentation using RGB colour space	JESG method of segmentation	GLCM and MRF based segmentation using Ohta colour space
Figure 2	40%	3.56%	1.36%
Figure 3	40%	6.74%	2.52

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 is found as optimal one with this approach as it appears to be the best textural feature to improve interclass discrimination. The segmentation results obtained in the proposed approach are compared with that of existing methods and our method is found to be the better choice for colour textured image segmentation.

REFERENCES

[1] John C. Russ, "The image processing Handbook," 5th edition, CRC Press, Boca Raton, FloridA

[2] B. Kartikeyan, A. Sarkar, and K. Majumdar, "A segmentation approach to classification of remote sensing imagery," *International Journal of Remote Sensing,* Vol. 19, No.9, pp. 1695-1709, 1998.

[3] R. M. Haralick, K. Shanmugam and T. Dinstein, T, " Textural features for image classification," *IEEE Trans. Syst., Man, Cybern*., SMC-3, pp. 610-621, 1973.

[4] R. M. Haralick, "Statistical and structural approaches to texture," *Proceedings of IEEE,* Vol. 67, No. 5, 1979.

[5] L. Wang and D. C. He, "A new statistical approach for textural analysis," *Photogrammetric Engineering and Remote Sensing, Vol.* 56, pp. 61-66, 1990.

[6] R.W.Connors, M.H.Trivedi, and C. A. Harlow, "Segmentation of a high resolution urban scene using texture operators," *Comput. Graphics Image Processing*, vol. 25, pp. 273-310, 1984.

[7] P.V. Narasimha Rao, M. V. R. Sesha Sai, K. Sreenivas, M. V. Krishna Rao, B. R. M. Rao, R. S. Dwivedi and L. Venkataratnam, "Textural analyses of IRS-1D panchromatic data for land cover classification," *International Journal of Remote Sensing,* Vol. 23, No. 17, pp. 3327-3345, 2002.

[8] Anne Puissant, Jacky Hirsch and Christiane Weber, "The utility of textural analysis to improve per-pixel classification for high to very high spatial resolution imagery," *International Journal of remote Sensing,* Vol. 26, No. 4, pp. 733-745, 2005.

[9] Z. Kato, T. C. Pong, "A Markov random field image segmentation model for colored textured images," *Image. Vision. Comp.* Vol. 24, pp. 1103-1114, 2006.

[10] Z. Kato, T. C. Pong and S. G. Qiang, "Multicue MRF image segmentation: combining texture and color features,". *IEEE Comp. society. ICPR*, 2002.

[11] J. Besag: "On the statistical analysis of dirty pictures," *J.Roy. Statist.Soc.B.* Vol. 62, pp.259-302, 1986.

[12] Brandt C. K. Tso and Paul M. Mather , "Classification methods for remotely sensed data," 2nd Edition, CRC press, 2009.

[13] F. Destrempes, M. Mignotte and J. F. Angers, "A stochastic method for Bayesian estimation of hidden Markov random field models with

application to a color model," *IEEE. Trans. Image. Processing,* Vol. 14, pp. 1096-1108, 2005.

[14] Rahul Dey, P. K. Nanda and Sucheta Panda, "Constrained Markov Random Field Model for Color and Texture Image Segmentation,". In *Proceedings of the IEEE International Conference on Signal processing, Communications and Networking (Chennai, India, Jan 04 – 06, 2008.*

Dr. Dipti Patra: was born in 1968. She received B.Sc engineering in electrical engineering, M.E degree in electronic systems and communication and PhD in image processing from National Institute of Technology, Rourkela, India in 1989, 1993 and 2006 respectively.
She is currently an associate professor in the department of electrical engineering, National Institute of Technology, Rourkela, India. Her research interests include signal and image processing, computer vision and pattern recognitionwithin the biography is: title of book (city, state: publisher name, year) similar to a reference. Current and previous research interests ends the paragraph.

Mridula J: was born in 1980. She received B.E degree in computer science engineering from Visveswaraiah Technological University in the year 2002. She is presently perusing M.Tech degree in electrical engineering department under specialization electronics system and communication at National Institute of Technology, Rourkela, India. Her research interests include image processing, computer vision and pattern recognition.