Texture Based Image Clustering Using COM and Spatial Information

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Abstract:
Clustering is traditionally viewed as an unsupervised method for data analysis. The primary objective of cluster analysis is to partition a given data set into homogeneous clusters. In this paper, we present a novel algorithm for performing texture based clustering using com matrix and spatial information's of pixels. In this work the co-occurrence features energy and entropy which can easily differentiate non homogeneous region from homogeneous region are considered. Run length features are based on computation of continuous probability of the length and gray level of the primitive in the texture. The final parameters are obtained by using the Expectation and Maximization algorithm. The segmentation is determined by Maximum Likelihood function. It is observed that the proposed method is computationally efficient allowing the segmentation of large images and performs much superior to the earlier image segmentation methods.

Introduction:

A central problem, called *segmentation*, is to distinguish objects from background. An image consists of a number of natural objects defined by distinct regions. The image background in itself is a distinct region. These regions are defined by their boundaries that separate them from other regions. Image segmentation aims at identifying these boundaries and as to which pixel comes from which region. The segmentation problem can be informally described as the task of partitioning an image into homogeneous regions. For textured images one of the main conceptual difficulties is the definition of a homogeneity measure in mathematical terms.

A texture method is a process that can be applied to a pixel of a given image in order to generate a measure (*feature*) related to the texture pattern to which that pixel and its neighbors belong. The performance of the different families of texture
methods basically depends on the type of processing they apply, the neighborhood of pixels over which they are evaluated (*evaluation window*) and the texture content.
Texture methods used to categorized as: statistical, geometrical, structural, model-based and signal processing features [1]. Van Gool et al. [2] and Reed and Buf [3] present a detailed survey of the various texture methods used in image analysis studies. Randen and Husoy [4] conclude that most studies deal with statistical, model-based and signal processing techniques. Weszka et al. [5] compared the Fourier spectrum; second order gray level statistics, co-occurrence statistics and gray level run length statistics and found the co-occurrence were the best. Similarly, Ohanian and Dubes [6] compare Markov Random Field parameters, multi-channel filtering features, fractal based features and co-occurrence matrices features, and the co-occurrence method performed the best. The same conclusion was also drawn by Conners and Harlow [7] when comparing run-length difference, gray level difference density and power spectrum. Buf et al. [8] however report that several texture features have roughly the same performance when evaluating co-occurrence features, fractal dimension, transform and filter bank features, number of gray level extrema per unit area and curvilinear integration features. Compared to filtering features [9], co occurrence based features were found better as reported by Strand and Taxt [10], however, some other studies have supported exactly the reverse.

II. Proposed Method

We proposed texture based clustering using Co occurrence matrix probability feature and run length method. The spatial information of pixels used for segmentation of these images performed by using EM algorithm.

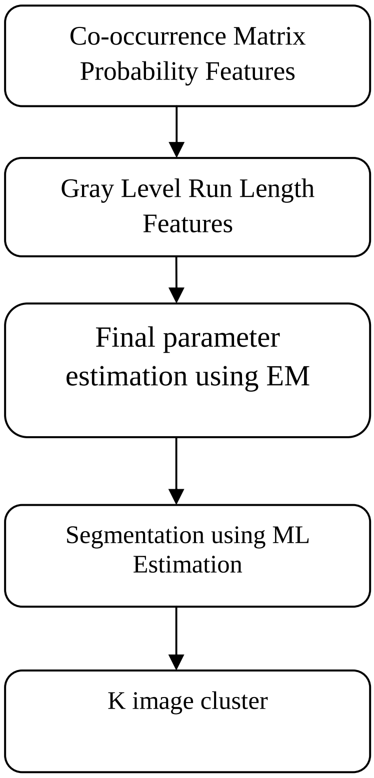

Fig: 1: Algorithm Flow

Co-occurrence Matrix Probability Features:

A Co-Occurrence Matrix (COM) is square matrices of relative frequencies P (i, j, d, θ) with which two neighboring pixels separated by distance d at orientation ɵ occur in the image, one with gray level i and the other with gray level j "Fig. 1". A COM is therefore a square matrix that has the size of the largest pixel value in the image and presents the relative frequency distributions of gray levels and describe how often one gray level will appear in a specified spatial relationship to another gray level within each image region. There are 14 features that may be extracted from COM matrix, but usually 4 or 5 features are more interested ones. In this paper 2 textural features were calculated from the COM for direction h values of 0° and a distance d of 1.[18] The matrix was normalized by the following function:

$$\boldsymbol{P(i,j,d,\theta) = P\frac{(i,j,d,\theta)}{R}} \qquad \text{---- } \textbf{\textit{(2)}}$$

R is the normalized function, which is usually set as the sum of the matrix.

In this work the co-occurrence features energy and entropy which can easily differentiate non homogeneous region from homogeneous region are considered. Energy is called Angular Second Moment. It is a measure the homogeneousness of the image and can be calculated from the normalized COM. Higher values for this feature mean that fewer changes in the image amplitude or intensity result in a much sparser COM.

$$J = \sum_{i=1} \sum_{j=1} (\boldsymbol{P(i,j)})^{\boldsymbol{2}} \qquad \text{------ (3)}$$

Entropy gives a measure of complexity of the image. Complex textures tend to have higher entropy. Entropy is represented by the following equation

$$\boldsymbol{S = -\sum_{i=1}\sum_{j=1} P(i,j)\log\big(P(i,j)\big)} \text{ ------ } \mathbf{(4)}$$

The value of energy and entropy are high for homogeneous regions and low for non homogeneous regions so these parameters can identify homogeneous regions. Some cases the Feature is selected non homogeneous. This draw back can be avoided by the calculating run length features that will describe in next section.

Gray Level Run Length Features:

Run length features are based on computation of continuous probability of the length and gray level of the primitive in the texture. After the selection of seed pixel from co-occurrence features, we can check whether the selected seed pixel belongs to abnormal region or not. This can be checked by calculating the Run length features. These features are calculated from the Run length matrix *P*(i, j) which describes the number of times that the image contains a run of length j in a given direction consisting of points having gray level i[6].
The following two features that give the good difference between homogeneous and non homogeneous regions are considered.

Long run emphasis

$$\boldsymbol{\sum_{i=1}^{G}\sum_{j=1}^{R} j^2 P(i,j) / \sum_{i=1}^{G}\sum_{j=1}^{R} P(i,j)} \text{ ----- } \mathbf{(5)}$$

Run length Non Uniformity

$$\boldsymbol{\sum_{i=1}^{G}\sum_{j=1}^{R} jP(i,j)^2 / \sum_{i=1}^{G}\sum_{j=1}^{R} P(i,j)} \text{ ---- } \mathbf{(6)}$$

That P(i,j) is run length matrix, G denotes number of gray levels and R is longest run. The long run length emphasis is high for homogeneous region and low for non homogeneous region and the run length non uniformity is low for homogeneous and high for non homogeneous. The run length features have been calculated around the points selected by co occurrence features. If all the run length features of selected point and its neighborhood points are equal then the point is considered as a seed point. The seed point value has been assigned as a centroide value and perform the k cluster segments. Here we consider K=2 to segment into foreground and background .Before apply the EM algorithm obtained mean, variance and mixing parameter for the *k* regions are considered as the initial parameters. **[6][7][8]**

***Mean*:** The average intensity of a region is defined as the *mean* of the pixel intensities within that region.
The mean μ of the intensities over *M* pixels within a region *K* is given by Equation (7)

$$\boldsymbol{\mu = \frac{1}{M}\sum_{i=1}^{M} x_i} \text{ ----- } \mathbf{(7)}$$

***Variance*:** The *variance* of the intensities (σ) within a region *K* with *M* pixels is given by Equation (8)

$$\sigma_z^2 = \frac{1}{M}\sum_{i=0}^{M}\left(x_i - \mu_z\right)^2 \text{ ------ } \mathbf{(8)}$$

Expectation and Maximization:

The EM algorithm is an efficient iterative procedure to compute the ML estimate in the presence of missing or hidden data. There are two main applications of the EM algorithm. The first occurs when the data indeed has missing values, due to problems with or limitations of the observation process. The second occurs when optimizing the likelihood function is analytically intractable but when the likelihood function can be simplified by assuming the existence of and values for additional but *missing* (or *hidden*) parameters. The latter application is more common in the computational pattern recognition community.[][]

For obtaining the EM algorithm a sample of the coefficients *z1*, *z*,..., *zn*, are drawn with PDF $f(z,\theta)$ given in Equation (15) where θ is set of initial parameters

$$\boldsymbol{\theta = (J, S, P)} \text{ ----- } \mathbf{(9)}$$

Each iteration of the EM algorithm consists of two steps as shown in Figure2
(i)E-step: It computes the expected complete data Log-Likelihood function $Q(\theta,\theta(i))$given by Equation

$$Q\left(\theta,\theta^{(i)}\right)=\sum_{s=1}^{N}\sum_{t=1}^{K}\left[\log\left(\alpha_t f\left(z_s,\theta_t^{(i)}\right)\right)\right]t_t\left(z_s,\theta^{(i)}\right)$$

----- (10)

Where $t_i(Z_s,\theta^t)$is a Posterior Probability and is given by Equation (10)

$$t_t\left(z_s,\theta^{(i)}\right)=\frac{\alpha_t^{(i)} f\left(z_s,\theta_t^{(i)}\right)}{h\left(z_s,\theta^{(i)}\right)}$$

------- (11)

$$h(z_s,\theta^{(i)})=\sum_{t=1}^{K}\alpha_t f\ (z_s,\theta_t^{(i)})$$

-------- (12)

(ii)M-step: It finds the $(i+1)th$ estimation $\theta^{(i+1)}$ by updating seed using Equations (12), (13) and (14) respectively to maximize Log- Likelihood function $Q(\theta,\theta^{(i)})$

$$\alpha_t^{(i+1)}=\frac{1}{N}\sum_{s=1}^{N}t_t\left(z_s,\theta^{(i)}\right)$$

------ (13)

$$\mu_t^{(i+1)}=\frac{\sum_{s=1}^{N}t_t\left(z_s,\theta^{(i)}\right)\ z_s}{\sum_{s=1}^{N}t_t\left(z_s,\theta^{(i)}\right)}$$

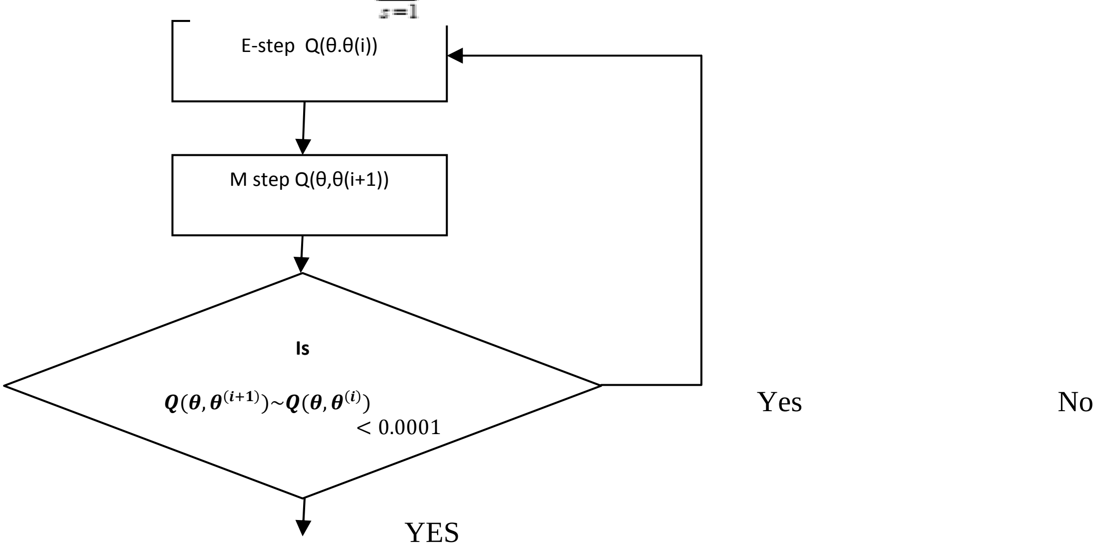

Fig 2: Flow chart of EM

$$\sigma_t^{(i+1)} = \left[\frac{\sum_{s=1}^{N} t_t\left(z_s, \theta^{(i)}\right) \left(\frac{\Gamma(3/P)}{P\Gamma(1/P)} \right) \left| z_s - \mu_t^{(i)} \right|^{\frac{1}{P}}}{\sum_{s=1}^{N} t_t\left(z_s, \theta^{(i)}\right)} \right]^{\frac{1}{P}} \quad \text{------ (15)}$$

The EM algorithm will converge when the difference of the old estimates and the new estimates is less than the threshold value 0.001. The EM algorithm used for estimating the final parameters is heavily dependent on number of segments and the initial parameters of the model.

Generalized Gaussian distribution model:

The GGD model is obtained using the final parameters. The approximation band coefficients of each image region follow a particular distribution such as Gaussian, Laplacian, Uniform etc., and characterize the GGD Model with shaping parameter *P*. The PDF is given by Equation

$$f(z,\theta) = \frac{1}{2\Gamma\left(1+\frac{1}{P}\right) A(P,\sigma)} e^{-\left|\frac{(z_s-\mu_i)}{A(P,\sigma)}\right|^P} \quad \text{----- (16)}$$

Where,
s=1 to N and i=1 to K

$$\text{for } \sigma > 0, \quad A(P,\sigma) = \left[\frac{\sigma^2 \Gamma\left(\frac{1}{P}\right)}{\Gamma\left(\frac{3}{P}\right)} \right]^{\frac{1}{2}} \quad \text{----- (17)}$$

The function $A(P,\sigma)$is a scaling factor and *P* is the shape parameter. The GGD becomes Laplacian Distribution if $P = 1$, Gaussian distribution if $P = 2$ and Uniform Distribution if $P \to +\infty$.

Segmentation using Maximum Likelihood Estimation:

The segmentation is carried out by assigning each coefficient into proper cluster according to the ML estimation given by Equation (16)

$$\boldsymbol{L = max_t\{f(Z_s, \theta_t)\}} \quad \textbf{----- (18)}$$

K image segments: The *K* segmented regions are obtained and for K=2, the image is segmented into foreground and background.

Performance Analysis:

Images Flower, football, lifting body of sizes 128*128, 256*256 and 512*512 respectively are considered for performance analysis. If the number of segments are selected as two i.e., K=2 foreground and background can be differentiated in an image.

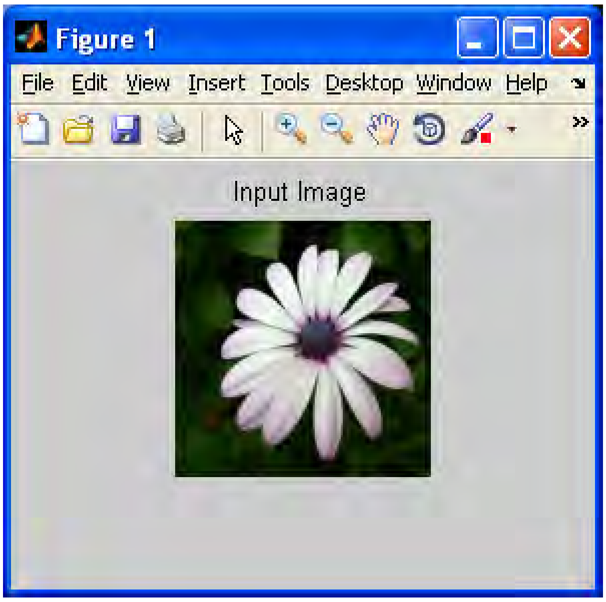

Fig 3: Input Image

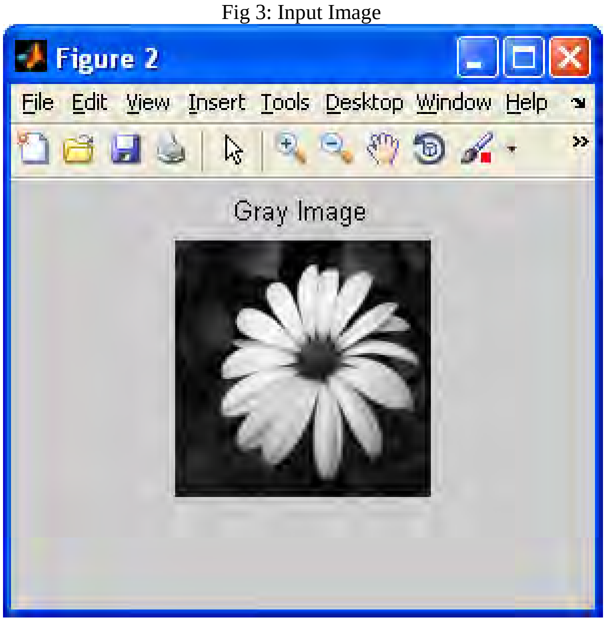

Fig 4: Gray Image

Fig 5: COM and RL based segmentation

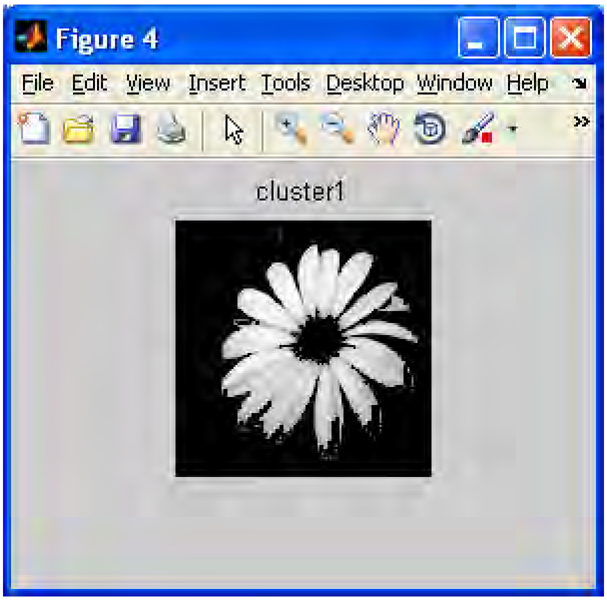

Fig 6: EM based cluster1

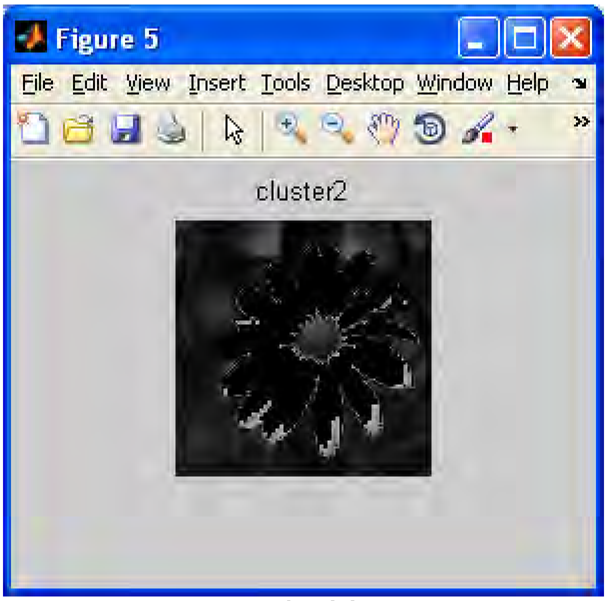

Fig 7: EM based cluster2

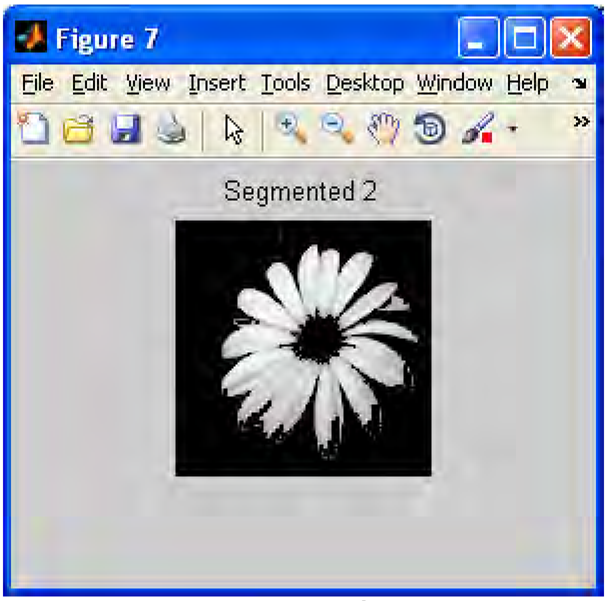

Fig 8: segmented 1

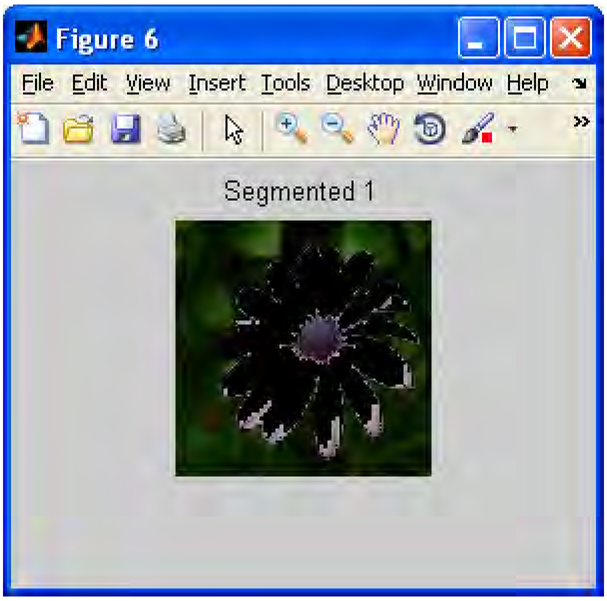

Fig 9: segmented 2

(1)Similarity index:

$$S_i = \frac{2N_{T_p}}{N_M + N_A} * 100\%$$

Where *NTp* the number of true positive values and *NM* is the cardinality of M and *NA* is the cardinality of A

(2) Jaccard index

$$J_i = \frac{N_{T_p}}{N_M + N_A + N_{T_p}} * 100\%$$

(3)Ratio of correct detection (Sensitivity):

$$T_p = \frac{N_{T_p}}{N_M} * 100\%$$

(4) Specifity:

$$S_E = 100 - F_p$$

$$F_p = \frac{N_{F_p}}{N_A} * 100\%$$

Where *NFp* is the number of false positive.

Images	SI	JI	Sensitivity	Specifity
Flower	67.71	62.43	74.24	83.45
Football	62.43	60.78	78.56	88.29
lifting body	54.32	68.48	72.56	80.43

CONCLUSION:

This paper proposed texture based clustering approach for homogeneous images. First the threshold point automatically found using textural features (calculated from COM matrix) and Runlength features. At the next step a clustering algorithm applied based on spatial information of pixels using k segment the region. The initial parameters are estimated using Histogram based method. Through EM algorithm, the final parameters are obtained. The segmentation is done by ML estimation. Results show that this method can segment homogeneous regions boundary accurately.

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