SEGMENTATION USING 'NEW' TEXTURE FEATURE

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ABSTRACT

Color, texture, shape and luminance are the prominent features for image segmentation. Texture is an organized group of spatial repetitive arrangements in an image and it is a vital attribute in many image processing and computer vision applications. The objective of this work is to segment the texture sub images from the given arbitrary image. The main contribution of this work is to introduce "NEW" texture feature descriptor to the image segmentation field. The NEW texture descriptor labels the neighborhood pixels of a pixel in an image as N,W,NW,NE,WW,NN and NNE(N-North, W-West).To find the prediction value, the gradient of the intensity functions are calculated. Eight component binary vectors are formed and compared to prediction value. Finally end up with 256 possible vectors. Fuzzy c-means clustering is used to segment the similar regions in textural image Extensive experimentation shows that the proposed methodology works better for segmenting the texture images, and also segmentation performance are evaluated.

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KEYWORDS

NEW' texture feature; Fuzzy c-means clustering; brodatz dataset

1. INTRODUCTION

With advances in digital imaging, digital photography collection there is an explosive growth of image databases. Searching of an image in such large collections take enormous amount of time. Typically, the simplest way to manage the large image collections is conventional database-management systems like relational databases or object-oriented databases. In this type of systems, images are annotated with keywords. But these kinds of system have failed when the collection of images growing larger. To overcome this problem, Content Based Image Retrieval (CBIR) has been emerged. In CBIR, images are indexed by their own visual contents.

Image classification is necessary for CBIR to classify the visual contents of images. Feature extraction is one the techniques used to classify the images. Features such as texture, color and shape are commonly used in state of art methods. In the literature, most of the attention has been focused on the texture features.

Texture is a key characteristic of an image helps to identify objects or regions of interest in the image. Texture gives information about the spatial arrangement of intensities in an image (Jain 1998). Haralick et al (1973) mentioned that textures can be fine, coarse, smooth, rippled, irregular, lineated etc. An example of textures is shown Figure 1.

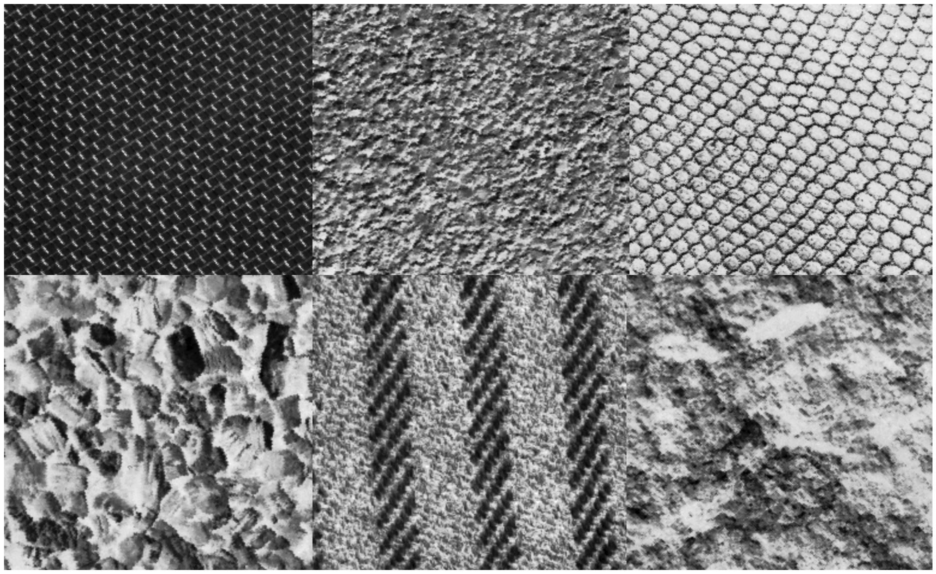


Figure 1 Sample texture images Source: Brodatz texture dataset

For texture feature extraction various methods like model based, statistical and single processing methods are used (Zhang et al 2006). Model based methods describe the texture images based on the probability distribution. In model based technique, number of random field models such as fractals, autoregressive models, fractional differencing models, and Markov random fields (MRF) have been used for modeling and synthesis of texture. MRFs are widely used because it yields a local and economical texture description. Zi (1995) defines a MRF on a discrete lattice with respect to a neighbourhood system by local conditional probabilities. Efficient parameter estimation scheme is must for a model based approach to be successful.

In statistical methods, textures are characterized using statistical measures, such as co- occurrence or spatial autocorrelation of the gray levels. Haralick et al (1973) proposed a Grey Level Co occurrence Matrices (GLCM) to extract geometrical features like energy, entropy, correlation, etc. By estimating pair wise statistics of pixel intensity, GLCM is built from the image. The problem is co occurrence matrix is calculated based on the displacement vector. In statistical method, when the order of statistics (k) is large (k >2) it is hard to handle because enormous amount of data are involved.

Most recently the signal processing methods using multi resolution and multi channel are introduced for texture analysis and classification. In this method, by using bank of filters such as Gabor (Jain et al 1997), neural network (Karu et al 1996), wavelet based filters (chen et al 1997), a textural image is decomposed into feature images. Smith et al (2005) proposed a method to extract the texture feature from the mean and variance of wavelet sub bands. Later, to perform texture analysis wavelet Transform together with KL expansion and kohenon maps was developed by Cross et al (2007), Bourchani et al (2005) combine the wavelet transform with co occurrence matrix to get the advantages of statistics based and transform based texture analysis. Tree structured wavelet transform and Gabor wavelet transform is introduced by W.Y Ma et al (2008) to perform texture image annotation. As a result, with help of set of well selected filters a high dimensional textural pattern can be extracted. Therefore, the major issue of this method is the selection of good set of filters.

In this paper we concerned with the task of proposing a method to compute NEW texture descriptor. Context Adaptive Lossless Image Compression (CALIC) scheme is used for image compression. This scheme calculates a prediction value of a current pixel based on the neighbourhood pixels which forms eight component binary vector after that a context is constructed for compressing the given image. The author mentions that the eight component binary vector is a texture descriptor [ ]. We have used this texture descriptor for image segmentation with the help of Fuzzy C-Means algorithm. The texture is determined by labeling the neighbourhood pixels as North, East and West. So, we named the texture feature as NEW texture descriptor.

The main contributions of this paper include:

A novel 'NEW' texture feature is introduced to extract the texture information from the texture image A methodology to segment and classify the texture image into four regions Fuzzy C-Means algorithm is used to segment the texture image based on 'NEW' texture feature Extensive experiments are carried out to prove the efficiency of the proposed methodology The rest of this paper is organized as follows: Section II explains about the proposed methodology. The experiment results are reported in Section III, and Finally, section IV presents conclusion.

2. Proposed Methodology

2.1. Feature extraction using 'NEW' texture descriptor

This section discusses about a novel framework to extract the NEW texture descriptor for classification of images. Figure 3 shows the overview of the proposed NEW feature extraction.

Consider a pixel marked as X in an image label, the top pixel of X is denoted as N, left pixel as W , likewise all the neighborhood pixels of X are labeled as shown in Figure 3
Figure 2 Labeling the neighbors of pixel X

		NN	NNE
	NW	N	NE
WW	W	X	

Fig.2 labeling the neighbors of pixel

The information about the neighborhood pixels are quantified by forming the eight component vector as N, W, NW, NE, NN, WW, 2N-NN and 2W-WW. Depending on the vertical and horizontal edges of the neighborhood of the pixel X may give the best prediction value denoted as $\hat{X}$. How close the prediction value is purely depends on the surrounding texture. The information about the kind of boundary can be calculated from the gradients of the intensity as shown in equation 1 and equation 2.

$$dh=|W-WW|+|N-NW|+|NE-N| \quad (1)$$
$$dv=|W-NW|+|N-NN|+|NE-NNE| \quad (2)$$

The prediction value is computed from the intensity gradients dh and dv. If the value of dh is much higher than the value of dv (dh >>dv), there will be a horizontal variation. So N is selected as the prediction value. Vertical variation will be found, if the value of the dh is much smaller than the value of dv (dh <<dv), and the prediction value is assumed to be W. If the difference of dh and dv is moderate then the weighted average of neighboring pixels is assigned to prediction value.

Pseudo code for finding prediction value is given below:

if dh-dv > 80
    $\hat{X}$ =N
else if dv-dh >80
$\hat{X}$ =W
else
{
    $\hat{X}$ = (N+W)/2+(NE-NW)/4
        if dh-dv >32
            $\hat{X}$ =($\hat{X}$ +N)/2
        else if dv –dh>32
            $\hat{X}$ =($\hat{X}$ +W)/2
        else if dh –dv>8
            $\hat{X}$ =(3 $\hat{X}$ +N)/4
        else if dv –dh>32
            $\hat{X}$ =(3 $\hat{X}$ +W)/4
}

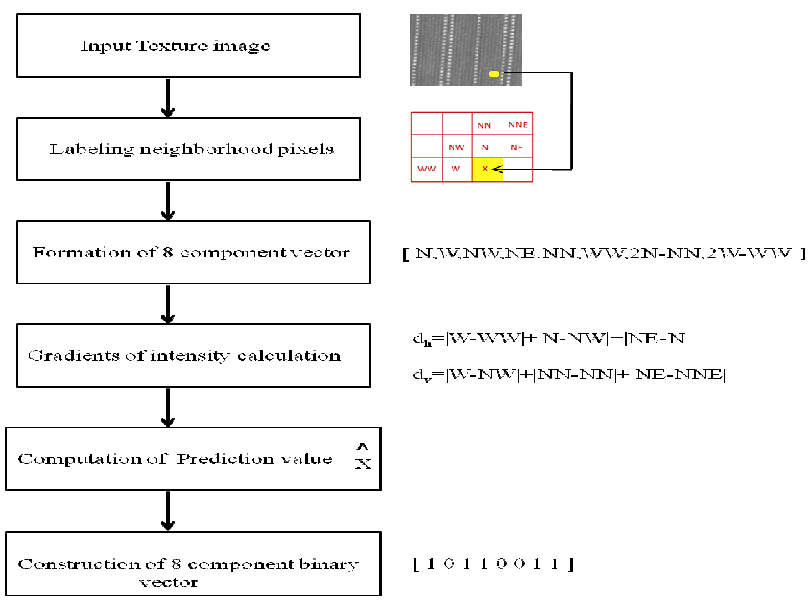


Fig.3 Overview of NEW texture descriptor extraction

After finding the prediction value, eight component binary vectors is constructed. To do so, each component of eight component vector formed by neighbors of x is compared with the prediction value $\hat{x}$. If the value of component is less than the $\hat{x}$ then replace the value with 1 else 0. Thus, eight component binary vectors created is called NEW texture descriptor.

2.2. Texture image segmentation

In this paper, Fuzzy C-Means algorithm [18] is used to cluster the image into multiple segments using 'NEW' texture feature. Fuzzy C-Means clustering algorithm segments the image based on the distance between cluster center and other feature domain.This features are clustered by minimizing the objective function (3)

$$J_{FCM} = \sum_{i=1}^{r}\sum_{p=1}^{n} u_{ip}^{q} d_{ip}^{2} \tag{3}$$

Where 'r' represents number of clusters , i=1, 2,…,r and p is the number of pixels p=1,2….n, d_{ip} is the distance and u_{ip} is the updation of cluster centers .

Fig. 4. Shows the proposed approach to segment the image into multiple regions. Initially, the input image is divided into 32x32 overlapping blocks. 'NEW' texture feature is extracted from each block to segment the region. This segmentation algorithm requires user interaction to assign number of clusters (K) for segmenting the image. To circumvent this problem, this paper uses an automatic assigning of number of labels for segmentation algorithm using the number of peaks estimated from the histogram of the input texture image after smoothing the histogram using Gaussian filter[17].

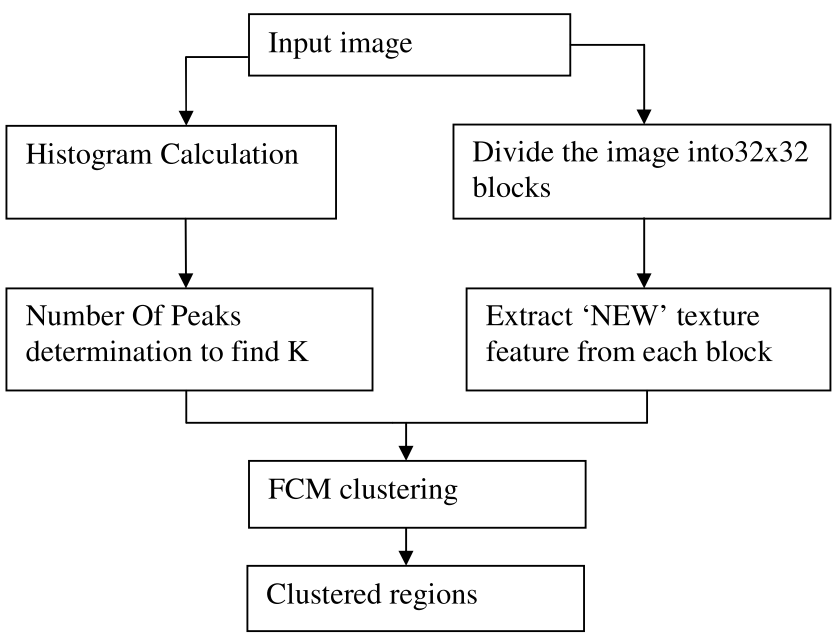


Fig.4 Flow diagram for image segmentation

Histogram of the grayscale image is calculated as

$$H(x) = \sum_{i=1}^{MXN} \delta(x, x_i) \quad \text{and} \quad x \in [x_0, x_{L-1}] \tag{4}$$

Where $\delta(x, y) = \begin{cases} 1 \\ 0 \end{cases}$ (5)

$$H_s(p) = K(p) * H(p) \tag{6}$$

Where ‘K’ is Gaussian smoothing kernel [19] and ‘H’ is the histogram of the image and p=0, 1, 2,…… 255.

2.3. Experimental results and discussion

In this section, the efficiency of the proposed methodology is analyzed and results are shown.

2.4. Data description

In this area 12 different texture images are taken by brodatz dataset. The images are available in online. Fig.5 shows the combination of 4 different texture images.

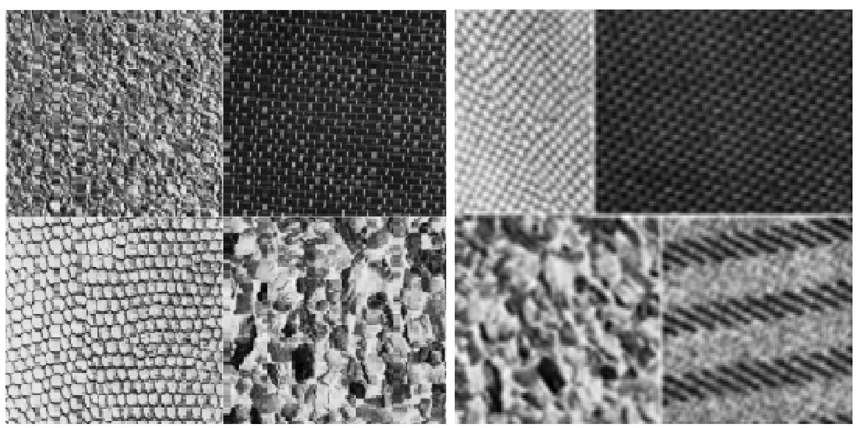


Fig. 5. Texture image from brodatz dataset

2.5. Results on Texture image Segmentation

In this paper fuzzy c means clustering used to segmenting the texture image. The image is divided into 32x32 overlapping blocks to segment the image as pixel wise segmentation. From each blocks ‘NEW’ texture descriptor is extracted to cluster the image using Fuzzy C-means clustering algorithm. To choose the K value automatically, first input image converted into gray scale and the histogram is calculated. This histogram contains more number of unwanted peaks because of the some percentage of noise and a considerable level of uncertainty. Hence, histogram is smoothened using Gaussian filter and the number of peaks detected. Fuzzy C-Means clustering algorithm clusters the texture image. Fig.5 (a) the original texture image; fig.5 (b) histogram of the original image; fig.5 (c) the number of peaks detected is four (K=4). So the segmented regions are four; segmented image is shown in fig.5 (d). Four different texture images segmented with four different colors. Blue color shows the texture 1 and red color shows the texture 2 and pink, green shows the texture 3 and texture 4. (e) Input four texture image with different size (f) clustered region using Fuzzy C-Means algorithm. Same method applied into K means clustering algorithm. K means clustering clusters the texture image.Fig.6 (a) the original texture image; fig.6 (b) histogram of the original image; fig.6 (c) the number of peaks detected is four (K=4). So the segmented regions are four; segmented image is shown in fig.6(d). Four different texture images segmented with four different colors. Blue color shows the texture 1 and green color shows the texture 2 and pink, red shows the texture 3 and texture 4. (e) Input four texture image with different size (f) clustered region using K-Means algorithm

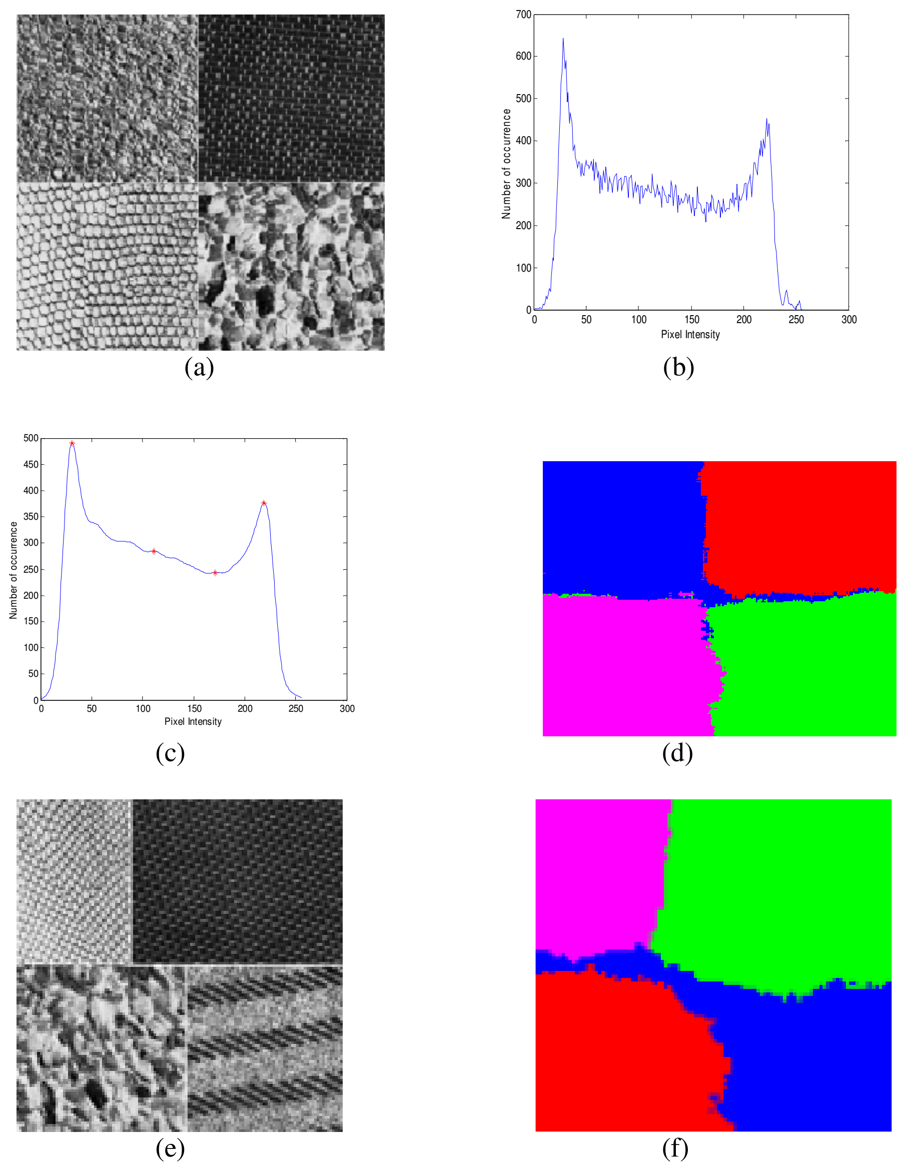


Fig. 5. (a) Input four texture image with same size (b) histogram of the image (c) Peaks detection after smoothing the histogram (d) clustered regions using Fuzzy C-Means algorithm (e) Input four texture image with different size (f) clustered region using Fuzzy C-Means algorithm

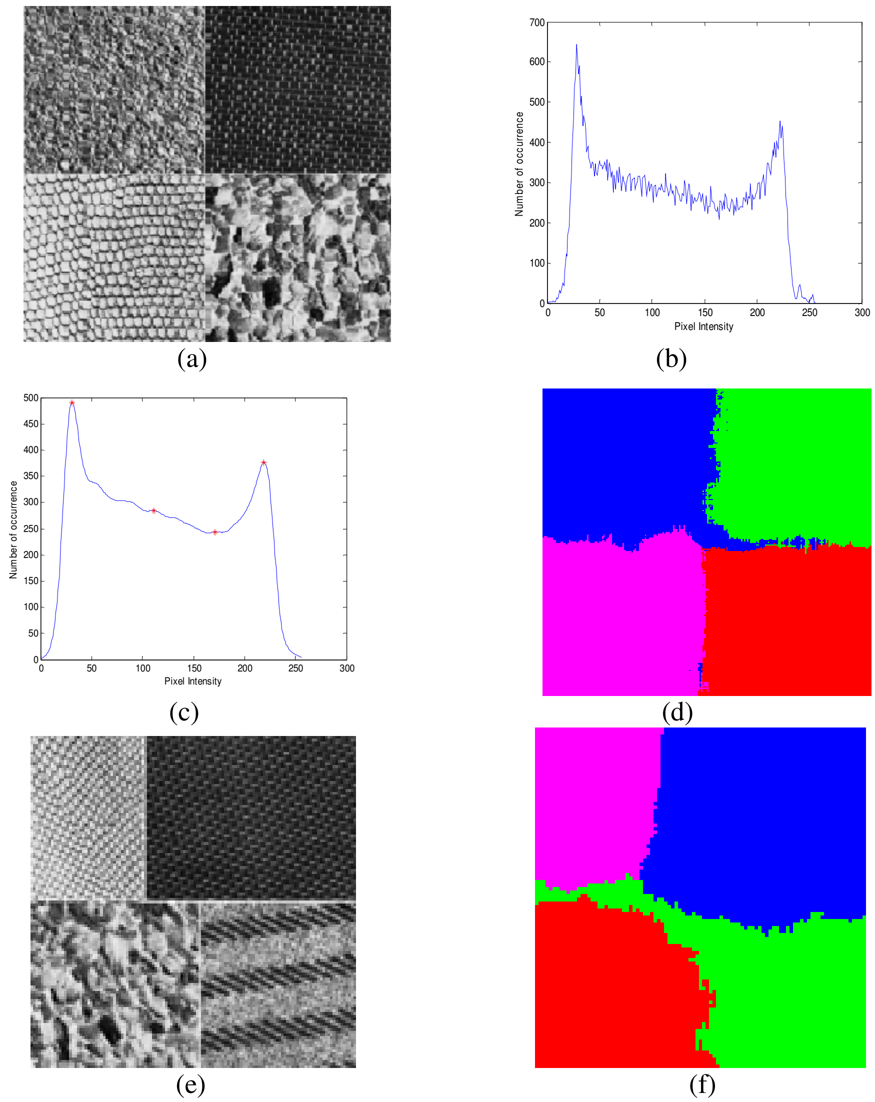
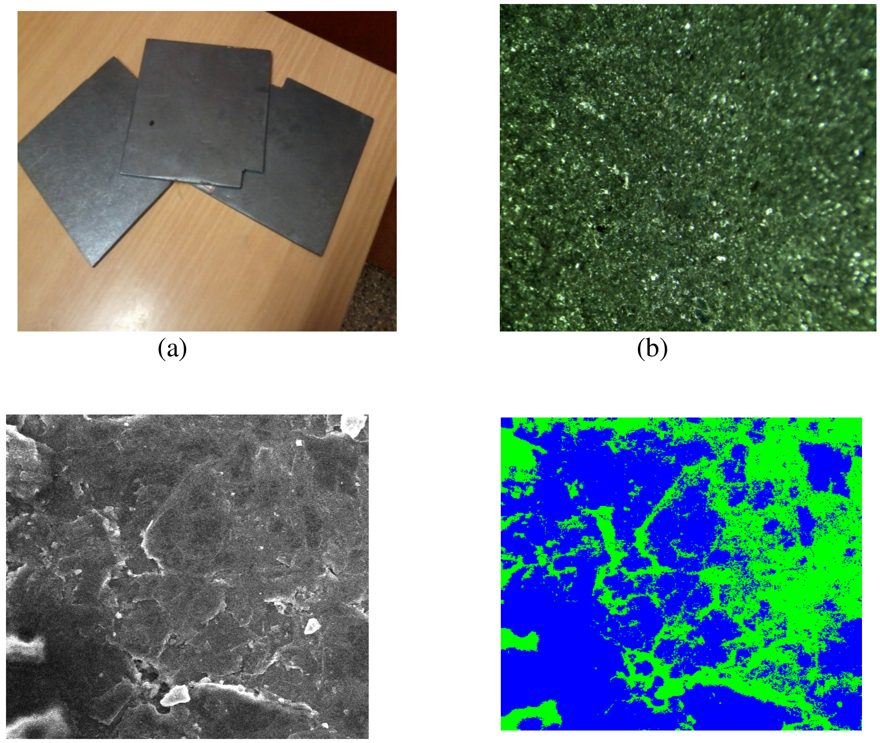


Fig. 6. (a) Input four texture image with same size (b) histogram of the image (c) Peaks detection after smoothing the histogram (d) clustered regions using K-Means algorithm (e) Input four texture image with different size (f) clustered region using K-Means algorithm

Fig.7 (a) shows the bipolar plate samples, and same methodology applied for this image. Green color shows the presence of carbont in the image, blue color shows the presence of epoxy in the image.



(a) (b) (c) (d)

Fig. 7. (a) Bipolar plate samples (b) Microscopic image (c) SEM image (d) clustered image using Fuzzy C-Means algorithm based on 'NEW' texture descriptor

2.6. Performance Analysis

To test the performance of the algorithm we have used three measurement parameters viz: Accuracy, Precision and Recall. These are calculated from confusion matrix.

2.6.1 Precision

Precision is defined the ratio of the number of relevant records retrieved to the total number of irrelevant and relevant records retrieved. It is usually expressed as a percentage.

$$Precision = \frac{t_p}{t_p + f_p} \tag{7}$$

Where tp - true positive, tn is true negative, fp is false positive and fn is false negative

2.6.2 Recall

Recall is defined as the ratio of the number of relevant records retrieved to the total number of relevant records in the database. It is also expressed interms of percentage.

$$Recall = \frac{t_p}{t_p + f_n} \tag{8}$$

2.6.3 Accuracy

Accuracy gives the measure of overall correctness of the proposed work, and is calculated as the sum of correct clusters divided by the total number of clusters.

$$Accuracy = \frac{t_p + t_n}{t_p + t_n + f_p + f_n} \tag{9}$$

Table 1 feature relevance

Features	Classifier	Accuracy (%)
NEWfeature	K-means	46%
	FCM	**60.12%**

3. CONCLUSION

In this paper an effective method to segment the texture image based on texture feature. In the proposed method, 'NEW' texture feature descriptor is used to extract the texture feature. It allows the system to segment the texture image using Fuzzy C-Means algorithm. For noiseless images, Fuzzy C-Means algorithm produced the best results compared to K-Means algorithm. Selection of K value by automatic system. Finally, experimental results are reported and investigate the effectiveness of the proposed methodology.

REFERENCES

[1] A.K. Jain and F. Farrokhnia (1991) 'UnsupervisedTexture Segmentation Using Gabor Filters' Pattern Recognition, vol.24, no. 12, pp. 1167-1186.

[2] A.K.Jain and K. Karu(1996) 'Learning Texture Discrimination Masks," IEEE Trans. Pattern Analysis Machine Intelligence, vol. 18, no. 2, pp. 195-205.

[3] Anil K. Jain (1998) 'Texture Analysis' The Handbook of Pattern Recognition and Computer Vision (2nd Edition), pp. 207-248.

[4] B. S. Manjunath, W. Y. Ma (2008) 'Texture Features for Browsing and Retrieval of Image Data' IEEE Transactions on Pattern Analysis and Machine, Volume 18, Issue 8, Pages: 837 –842.

[5] Cross,G.R., Jain, A.K (2007) 'Markov random field texture models' IEEE Trans. Pattern Anal. Machine Intell, PAMI-5(1), 25-39.

[6] C.S. Lu, P.C. Chung, and C.F. Chen(1997) 'Unsupervised Texture Segmentation via Wavelet Transform' Pattern Recognition, vol. 30, no. 5, pp. 729-742.

[7] Fernando Rodriguez, Guillermo Sapiro (2008) ' Sparse Representations for image classification: Learning discriminative and reconstructive non-parametric dictionaries' IMA Preprint Series # 2213.

[8] John Wright,y. yang(2009) 'Robust Face Recognition via Sparse Representation' IEEE trans. On Pattern Analysis and Machine Intelligence vol.31.

[9] J. R. Smith and S.-F. Chang (2005) 'Visually searching the web for content' IEEE Multimedia Magazine 4(3), pp. 12–20.

[10] J. Yang, J.Wang, and T. S. Huang (2011) 'Learning the sparse representation for classification' In Proc. ICME, pages 1–6.

[11] J. Yang, Z. Wang, Z. Lin, X. Shu, and T. Huang (2012) 'Bilevel sparse coding for coupled feature space'. In Proc. CVPR.

[12] J. Zhang and M. Marszalek (2006) 'Local Features and Kernels for Classification of Texture and Object Categories: A Comprehensive Study' International Journal of Computer Vision DOI: 10.1007/s11263-006-9794-4.

[13] M.Haralick, K. Shanmugam (1973) 'Textural features for Image Classificaion' IEEE tansactions on system, man and cybernatics vol SMC-9, pp-610- 621.

[14] Mohamed Borchani, Georges Stamon (2005) 'Texture features for Image Classification and Retrieval' SPIE, Vol.3229, 401.
[15] S.Z. Li (1995) 'Markov Random Field Modeling in Computer Vision' New York Springer-Verlag.
[16] Zhaowen Wang, Jianchao Yang(2013) 'A Max-Margin Perspective on Sparse Representation-based Classification' ICCV 2013.
[17] S.M.M.Roomi, R.Raja, D.Dharmalakshmi, "Classification and retrieval of natural scenes", Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT), DOI:10.1109/ICCCNT.2013.6726534, pp.1- 8,2013.
[18] Deepali Aneja and Tarun Kumar Rawat Fuzzy Clustering Algorithms for Effective Medical Image Segmentation, Intelligent Systems and Applications, DOI:10.5815/ijisa.2013.11.06,pp-55-61, 2013.
[19] R. Gonzalez and R. Woods Digital Image Processing, Addison-Wesley Publishing Company, pg 191, 1992.

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