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Texture Segmentation Approach Based on Entropy Based Local Binary Pattern Operator

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ABSTRACT

In this paper an efficient approach for unsupervised Texture Segmentation is proposed, based on features extracted from Entropy Based Local Binary Pattern Operator using Fuzzy-c-Means and K-Means clustering with spatial information. In this approach, the texture mosaic image is reconstructed using LBP. After the reconstruction, the entropy values are extracted from the LBP image. Finally, FCM and K-Means are used to cluster the entropy values. The proposed method is tested with different texture databases .The results are compared with the existing approach and it shows that the efficiency of the proposed outperforms well. This makes the algorithm ideally suited for texture image segmentation and extracts the textural information of an image with a more complete respect of texture characteristics.

Keywords: Texture, Texture Segmentation, Texture Classification, Entropy, Local Binary Pattern, Entropy based LBP, FCM, K means Clustering.

1. INTRODUCTION

Textures have attracted attention both from the computer vision community and the computer graphics community. Indeed to understand the processed behind the human perception of an image as a pattern or texture involves deep questions about human brain organizations that are relevant for those that key to stimulate the human vision mechanism. Only rarely have real world objects surfaces of uniform intensity most of the time they are textured. The word texture is used to refer to a number of commonly encountered visual patterns in natural scenes such as forlage, grass, pebbles, clouds etc., while there is no proper definition of texture, it is widely accepted that the term generally refers to a reputation of certain basic elements sometimes called texels. Texture is an important spatial feature, useful for identifying objects or regions of interest in an image. The gray-level co-occurrence matrix approach is one of the most popular statistical methods used in practice to measure the textural information of images.. Texture analysis may require the solution of two different problems i.e., Segmentation of a given image according to the different texture and Classification of a given texture with respect to a set of known textures.

Texture Segmentation is the fundamental process which partitions a data space into meaningful salient regions. Image segmentation essentially affects the overall performance of any automated image analysis system thus its quality is of the utmost importance. Image regions, homogeneous with respect to some usually textural or color measure, which result from a segmentation algorithm are analyzed in subsequent interpretation steps. Texture based image segmentation is an area of intense research activity in the past thirty years and many algorithms were published in consequence of all this effort, starting from simple threshold methods up to the most sophisticated random field type methods. Unsupervised methods which do not assume any prior scene knowledge which can be learned to help segmentation process are obviously more challenging than the supervised ones.

Texture classification is a key field in many computer vision applications ranging from quality control to remote sensing. The problem of feature selection is defined as follows given a set of candidate features; select a subset that performs the best under classification system. The procedure can reduce the cost of recognition and provide better classification accuracy. Image classification systems have received a recent boost from methods using local features generated over interest points, delivering higher robustness against partial occlusion and cluttered backgrounds

There are two widely used approaches to describe the texture of a region, these are statistical and structural. The statistical approach consolers that the intensities are generated by a two dimensional random field and examples of statistical approaches of texture analysis are auto correlation function, gray level co-occurrence methods, Fourier texture analysis, edge frequency and law's texture energy measures. The co-occurrence matrix is found a fairly good texture analysis method. The structural techniques deal with the arrangement of image primitives such as the description of texture based on regularly spaced parallel lines. Statistical methods analyze the spatial distribution of gray values by computing local features at each point in the image and deriving a set of statistics from the distributions of the local features (Ojala and Pietikyinen, 2004). The use of statistical features is one of the early methods proposed in the research literature (Tuceryan and Jain, 1998). The reason behind is the fact that the spatial distribution of gray values is one of the defining qualities of texture. Statistical methods can be classified into first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics based on the number of pixels defining the local feature (Ojala and Pietikyinen, 2004).

The first-order statistics estimate properties like the average and variance of individual pixel values, ignoring the spatial interaction between image pixels, second- and higher-order statistics on the other hand estimate properties of two or more pixel values occurring at specific locations relative to each other. Co-occurrence features and gray level differences (Weszka et al., 1976) are the most widely used statistical methods, which inspired a variety of modifications later on (Ojala and Pietikyinen, 2004) including signed differences (Ojala et al., 2001) and the Local Binary Pattern (LBP) operator (Ojala et al., 1996). LBP operator combines statistical and structural approaches to texture analysis by incorporating occurrence statistics of simple local microstructures. Autocorrelation function, which has been used for analyzing the regularity and coarseness of texture (Kaizer, 1955; Emerson et al., 1999; Lam et al., 2002; Al-Hamdan, 2004), and gray level run lengths (Galloway, 1975) are examples of other statistical approaches (Ojala and Pietikyinen, 2004). . The method involves weighting each pixel by the surrounding entropy such that each element in the final image is in high relief but lacks abrupt contrast changes due to the different light sources that might introduce spurious lines and other artifacts. The method also allows for fast addition and removal of images from the collective images (A. German, M. R. Jenkin, and Y. Lesp´erance, 2005).

In this paper Entropy based LBP operator method is used to extract the features from the images to perform Unsupervised Segmentation. This paper is organized as follows. In section 2, the Entropy operator is discussed. The LBP operator is explained in section 3. In section 4, Unsupervised Entropy based LBP operator segmentation algorithm is reviewed. Experiments results are shown in section 5 and finally conclusion is on section 6.

2. ENTROPY OPERATOR

Entropy, as defined by Clausius, is the true cornerstone of equilibrium thermodynamics. Entropy was chosen as a measure of the detail provided by each picture. The word "entropy" was created by Rudolf Clausius and it appeared in his work "Abhandlungen uber die mechanische Warmetheorie" published in 1864. The word has a Greek origin, its first part reminds us of "energy" and the second part is from "tropos" which means turning point. Clausius' work is the foundation stone of classical thermodynamics. According to Clausius, the change of entropy of a system is obtained by adding the small portions of heat quantity received by the system divided by the absolute temperature during the heat absorption. This definition is satisfactory from a mathematical point of view and gives nothing other than an integral in precise mathematical terms. Clausius postulated that the entropy of a closed system cannot decrease, which is generally referred to as the second law of thermodynamics.

The entropy is defined as the average number of binary symbols necessary to code a given input given the probability of that input appearing on a stream. High entropy is associated with a high variance in the pixel values, while low entropy indicates that the pixel values are fairly uniform, and hence little detail can be derived from them. Therefore, when applied to groups of pixels within the source images, entropy provides a way to compare regions from the different source images and decide which provides the most detail. The method developed for this task, though simple, is both flexible and powerful. Every pixel in the final image is computed as the weighted average of the corresponding pixels in the source images where each value is weighted by the entropy of the surrounding region. For each pixel p = (u, v) in the final image there are corresponding pixels p1, p2. . . p_N, one for each source image. For each pixel pi in each image, the local entropy (measured within a fixed window) vi is computed, and the weighted average p is computed .The entropy for the pixel window is computed as,

$$Entropy = \sum_{i=1}^{8} P_i \log P_i \qquad (1)$$

Where P_i – Probability value if the i^{th} pixel in the window. The block diagram of texture segmentation is shown in Fig. 1

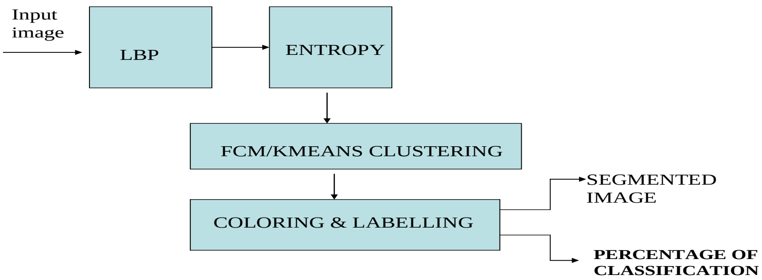


Fig. 1 Block Diagram of Texture Segmentation

2.1 Algorithm for Entropy with FCM/K-Means Clustering

1. Input the texture mosaic image with size m x n.
2. Take a window of size 30 x 30 in the image and find the value of Entropy using the equation,
   Entropy= - $\sum$ pi log (pi)
   Pi – Probability value if the ith pixel in the window
3. Move the window towards the whole image by using overlapping method and find the Entropy for all the windows.
4. Cluster the all Entropy values using FCM clustering.
5. Label the different clusters and Colour the different labels.
6. Output the segmented image.

3. LOCAL BINARY PATTERN OPERATOR

The original LBP method was first introduced as a complementary measure for local image contrast. It operated with eight neighboring pixels using the center as a threshold. The final LBP code was then produced by multiplying the threshold values by weights given by powers of two. By definition LBP is invariant to any monotonic transformation of the gray scale and its quick to compute with larger neighborhoods, the number of possible LBP codes increased exponentially. This can be avoided to some extent by considering only a subset of that codes one approach is to use so called uniform patterns representing the statistically most LBP code. With them the size of the feature histogram generated by an LBP operator can be reduced without significant loss in its discrimination.

LBP is described with 2^8 possible texture units. The texture unit is obtained by applying the threshold operation using the following rule

$$E_i = \{0, V_i < V_0, 1, V_i \geq V_0 \qquad (2)$$

Where V_0 is the center pixel. The LBP is determined as

$$LBP = \sum_{i=1}^{8} E_i 2^{i-1} \qquad (3)$$

LBP does not take into account the contrast of texture which is the measure of local variations present in an image and is important in the description of some textures. Texture spectrum operator is similar to LBP but it uses three levels ie two thresholds instead of two levels used in LBP. This leads to a more efficient representation and implementation than with LBP and according to our tests the three level operator does not perform any better that LBP. The LBP histogram computed over a region used for texture description. LBP provides as with knowledge about the spatial features.

4. ENTROPY BASED LBP OPERATOR

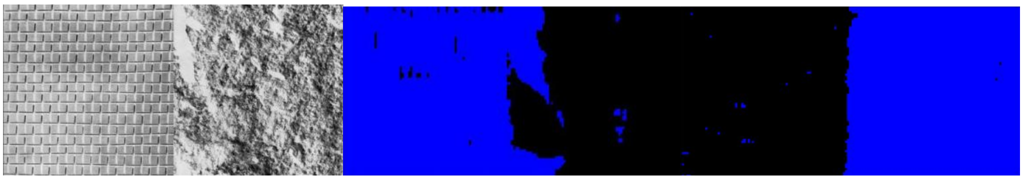
The input image is reconstructed using LBP. After reconstruction, Entropy values of reconstructed image are taken as the texture features. The algorithm for Entropy based Local Binary Operator with FCM/K Means Clustering methods are explained in the following steps as

1. Input the texture mosaic image with size m x n.
2. Take a window of size 30 x 30 in the image and reconstruct the window by LBP using the following steps.
   i. Take a sub-window of size 3 x 3 in the window image.
   ii. Compare the all pixel values of the window with the center pixel.
   iii. Note the difference: If pixel value less than center pixel value, note the difference is 0. If pixel value greater than or equal to center pixel value, note the difference is 1.
   iv. Form a eight digit binary value from the noted difference values (totally 8 pixels except center pixel).
   v. Find the gray value of the eight digit binary value.
   vi. Replace the pixel of the window image using the gray value.
   vii. Move the sub-window towards the whole window image using overlapping method and find the gray value of the all sub-windows using above mentioned LBP method and replace the all pixels of the window image using these gray values.
   viii. Return the Reconstructed LBP window image.
3. Find the value of Entropy for reconstructed LBP window using the below equation, Entropy= - ∑ pi log (pi), where Pi – Probability value if the ith pixel in the window.
4. Move the window towards the whole image by using overlapping method and find the LBP-Entropy value for all the windows.
5. Cluster the all LBP-Entropy values using FCM clustering.
6. Label the different clusters and Colour the different labels.

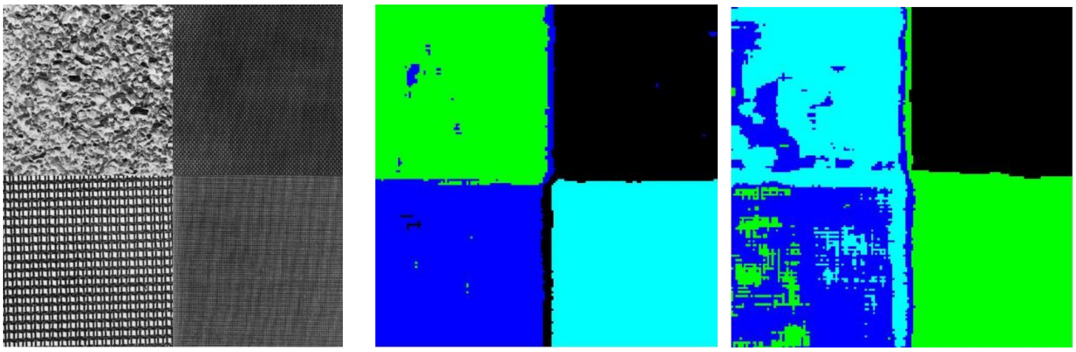
7. Output the segmented image.

5. EXPERIMENTAL RESULTS

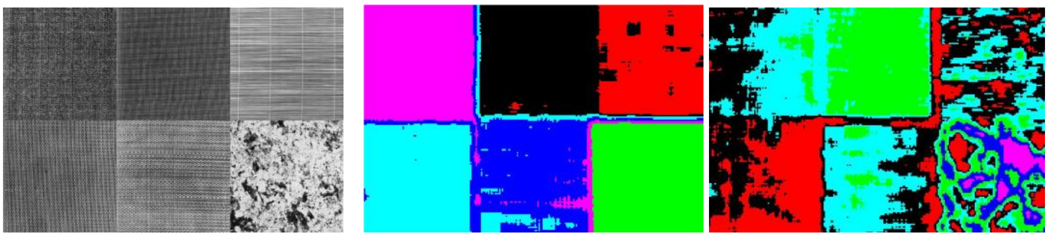
The experimental results for 2 images, 4 images and 6 images for Entropy Based Local Operator for FCM and K means clustering output is shown in Figure 2 and 3.In Figure 2, (a) is the combination of D1 and D2 images, (b) is the combination of D5, D6, D20 and D21 and (c) is the combination of D17, D21, D49, D53, D55 and D60.



(a)



(b)

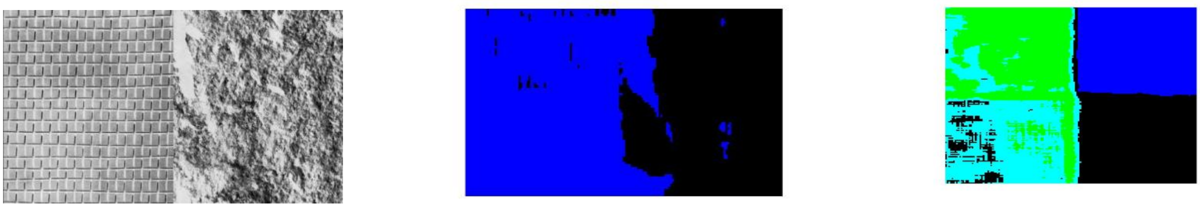


(C)

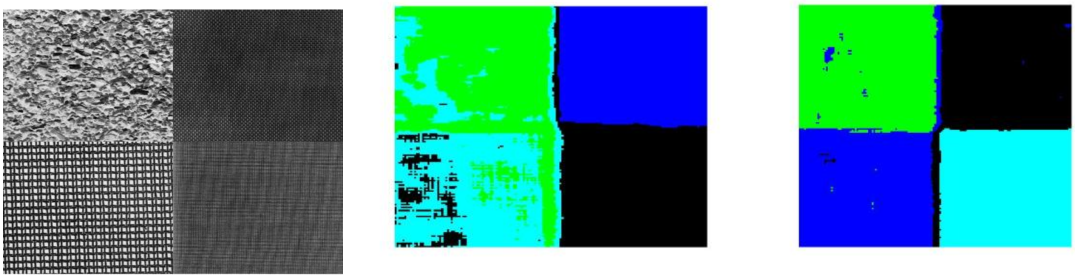
Input Image **Entropy Operator** **Entropy Based LBP Operator**

Figure 2 Unsupervised Texture Segmentation of Brodatz Images using Entropy based LBP method with FCM Clustering

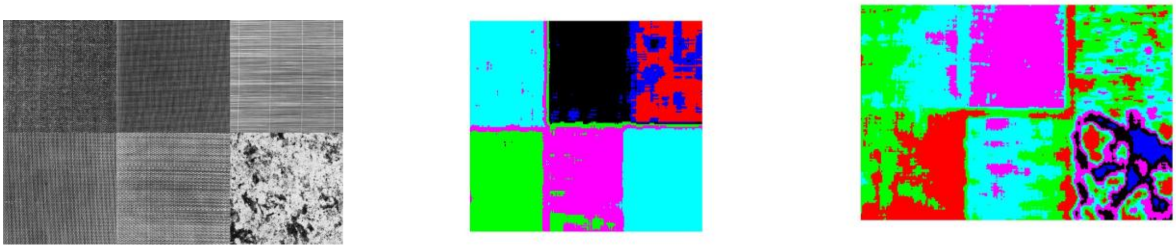
In Figure 3 (a) is the combination of D1 and D2 images, (b) is the combination of D5, D6, D20 and D21 and (c) is the combination of D17, D21, D49, D53, D55 and D60.



(a)



(b)



Input Image **Entropy Operator** **Entropy Based LBP Operator**

(c)

Figure 3 Unsupervised Texture Segmentation of Brodatz Images using Entropy based LBP method with K-Means Clustering

6. CONCLUSION

In this paper, Entropy based LBP features are extracted and successfully implemented for unsupervised segmentation. This method is tested with publicly available Brodatz images. The results of the proposed method are compared with the existing method. The Entropy based LBP method gives the better efficient results for segmentation. The experiments show that the proposed method can achieve better results than existing unsupervised texture segmentation approaches. The effect of changing textures on the texture classification system performance is under current investigation and the research work is under progress.

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