Unsupervised Hybrid Classification for Texture Analysis Using Fixed and Optimal Window Size

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***Abstract*-For achieving better classification results in texture analysis, it is to combine different classification methods. Though there are existing methods which have been using fixed window size that resulted lack of classification accuracy and in order to improve the classification accuracy, the window size must be increased. Moreover the optimal window size is to be selected is also an important thing in the improvement of better classification output. In addition, since some classification techniques are used for micro textured structures and some are for large scale textured images, it is better to integrate different classification methods to achieve higher classification rate. This paper presents a new classification technique named unsupervised hybrid classification for texture analysis (UHCTA) that extracts the properties of different methods for achieving higher classification rate. Also comparison with the existing methods conform the merits of the proposed unsupervised hybrid classification for texture analysis method in terms of accuracy in various image conditions**.

Keywords-Texture spectrum operator, K-means clustering, local binary pattern operator, hybrid classification.

1. INTRODUCTION

An essential problem in computer vision is texture analysis and they are characterized into two types namely structural and statistics [1]. Many texture classification methods already have been implemented and each one has its own advantages and disadvantages. Firstly, the 'texture spectrum operator' method has the advantage that the texture aspects of an image are characterized by the corresponding texture spectrum instead of a set of texture measures and the texture spectrum can be directly used for image classification . On the other hand 'local binary pattern operator' method is attractive to some extent but with the implementation difficulty in the form of delta values definition form a user to set the threshold values which makes it dependent on the gray scale values [3]. The 'Gray Level Co- occurrence Matrix' method is even though suitable for unsupervised texture classification analysis but with the limitation in classifying the large primitives [4]. The 'Entropy based local descriptor' method has the disadvantage of considering the data in terms of probability resulting uncertainty and instability of data [8] [9] [10]. But in general any image which is to be classified should undergo two basic processes namely feature extraction and determination of the optimal window size. The previous methods which have been used well for single image window size(fixed) that resulted some degree of compromise in achieving the classification accuracy and for better results in accuracy, the advantages of existing different features could be taken and simultaneously to improve the classification accuracy. The objective of this paper is to propose an unsupervised hybrid classification for texture analysis (UHCTA) algorithm by varying the window size for different images. This paper is organized by four sections to apply the optimal window size namely Texture Spectrum Operator, Entropy Based Local Descriptor, Local Binary Pattern Operator and Gray Level Co occurrence Matrix for Broadtz database.

11. EXISTING TEXTURE ANALYSIS METHODS

A) *Texture Spectrum Operator*

The local texture for a given pixel and its neighborhood is characterized by the corresponding texture unit and an image can be characterized by its texture spectrum in statistical approach for texture analysis which is the occurrence frequency function of all texture units within the image [2]. In a square raster digital image each pixel is surrounded by eight neighborhood pixels. The local texture information for a pixel can be extracted from a neighborhood of 3×3 pixels which is denoted by a set containing nine elements V= $\{v_0, v_1 \ldots\ldots v_8\}$, Where v_0 represents the intensity value of the central pixel and vi{i=1,2,….8} is the intensity value of the neighboring pixel i) to define the corresponding texture unit by a set containing eight elements. Texture Unit (TU) = {E1, E2, …..,E8}where E_I\{i=1,2,…8\} is determined by the formula in equation 1.

$$Ei = \begin{cases} 0 \text{ if } Vi < Vo \\ 1 \text{ if } Vi = Vo \\ 2 \text{ if } Vi > Vo \end{cases} \qquad (1)$$

For i =1,2,…8 and the element Ei occupies the same position as the pixel i. As each element of texture unit (TU) has one of three possible values with the combination of all eight elements results in 3^8=6561 possible texture units in total. Since there are three comparison levels (<, =,>) and have called this method as Texture Spectrum Operator. For N= 3, the combinations of all the elements results in 3^8=6561 possible texture units. There is no unique way to label and order the 6561 texture units that are labeled by using the formula in equation.2.

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

Where N_{TU} represents the texture unit number and Ei represents the element of the texture unit set TU= {E1, E2,…E8}. For example, if eight elements are ordered clockwise as shown in Figure 1 and the first element may take eight possible positions from the top left to the middle left and then the 6561 texture units can be labeled by the above formula under eight different ordering ways from a to h.

A	B	C
H		D
G	F	E

Figure 1: Eight Clock wise, successive ordering ways of eight element of the texture unit

Neighborhood

63	28	15
88	40	35
67	40	21

$\longrightarrow$

Texture unit

2	0	2
2		0
2	1	0

V=(40,63,28,15,35,21,40,67,88), TU=(2,0,2,0,0,1,2,2)

Texture Unit Number (NTU) = 6096

Figure 2: Example of transforming a neighborhood to a texture unit with the texture unit number.

In Figure 2, where the defined set of 6561 texture units describes the local texture aspect of a given pixel and its neighbors. Thus the statistics of the frequency of occurrence of an image should reveal texture information and texture spectrum is sensitive to the directional aspect of texture. The undesirable influence of the regional intensity background is eliminated from the texture spectrum. Here sample images from Broadtz data base have been taken and the optimal window size is selected for the further

B) Entropy Based Local Descriptor

Entropy based local descriptor is a measure of information content which measures the randomness of intensity distribution. The entropy based local descriptor finds the average number of binary symbols needed to code a given input in terms of probability of that input appearing an a stream.

$$EBLD = \sum_{I=1}^{8} P(i) \log p(i) \qquad (3)$$

Such a matrix corresponds to an image in which there are no preferred gray level pairs for the distance vector d. Entropy based local descriptor is highest when all entries in P[i,j] are of similar magnitude, and small when the entries in P[i,j] are unequal. Entropy based local descriptor operator described with 2^8 possible textures and calculates the entropy of brightness in a local region of the picture. The entropy value is higher when the brightness in a local region of the picture is low and vice versa resulting the region seems to be small depending on the entropy value[7][11]. The main objective of Entropy based method is for the texture measure widely used to quantify the smoothness of image texture since Entropy does not depend on actual values in texture. High entropy based local descriptor is associated with a high variance in the pixel values, while low entropy based local descriptor indicates that the pixel values are fairly uniform. Here sample images from Broadtz data-base have been taken before fixing the optimal window size for the further classification is done.

C) *Local Binary Pattern Operator*

In Local Binary Pattern Operator method uses the operators with eight neighboring pixels using the center as a threshold by multiplying the threshold values by weights given by powers of two[5][6]. By definition Local Binary Pattern Operator shown in Figure 3 is invariant to any monotonic transformation of the gray scale and its quick to compute with larger neighborhoods, the number of possible Local Binary Pattern Operator codes increased exponentially. This can be avoided to some extent by considering only a subset of that codes and one approach is to use so called uniform patterns representing the statistically most Local Binary Pattern Operator.

7	1	12	1	0	4	1	0	1
2	5	5	0		16	0		1
5	3	0	32	0	0	1	0	0

Pixels (example) Threshold weights

Figure 3: Computation of Local binary patterns

The Local Binary Pattern operator shown in Figure 3 is determined by the formula is given in equation 4.

$$\text{LBP} = \sum_{I=1}^{8} E_i \times 2^{i-1} \qquad (4)$$

Local Binary Pattern Operator 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 Operator but it uses three levels that is, two thresholds instead of two levels used in Local Binary Pattern Operator. This leads to a more efficient representation and implementation than with Local Binary Pattern Operator and according to experimental tests with the help of varying the widow size for different images, three level operators does not perform any better that Local Binary Pattern Operator.

D) Gray Level Co-Occurrence Matrix

Grey-level co-occurrence matrix (GLCM) is one of the most widely used statistical texture measures [12]. The idea of the method is to consider the relative frequencies for which two neighboring pixels are separated by a distance on the image. Since the GLCM collects information about pixel pairs instead of single pixels, it is called a second-order statistic. Texture measures, such as homogeneity, contrast, and entropy are derived from the co-occurrence matrix. The different sets of images of Broadtz have been tested for the classifications.

111. PROPOSED HYBRID UNSUPERVISED CLASSIFICATION METHOD

In the proposed method, histogram techniques and K-means classifier have been used for the unsupervised classification. The histogram technique is used for compressing the textured images and K-Means classifier is used for the purpose of avoiding the use of prior information. The histogram technique is not only for the compression but also reducing the computational cost. Once the images are selected from the Broadtz texture database in our proposed method, the local window is spilt to sub window of M×N if window size is X. A sample of 20 images has been chosen for classification with the size of 512×512 for all the different unsupervised classification methods by varying different window sizes. The proposed hybrid unsupervised texture classification algorithm is as follows.

Step 1

Initialize the process.

Step 2

Sample of different sets of images are taken.

Step 3

Compress the image dimension.

Step 4

Fix the optimal window size as 32 that is calculated by means of finding minimum classification accuracy attained already.

Step 5

Window is split to 4 sub windows of 8×8, if window size is 32 which is set to be optimal.

OR

Else no optimal value and take the other window size after histogram.

Step 6

Finding classification accuracy for varying window size of different levels at 8*8, 16*16 and 32*32 pixels and for fixed level as 8*8.

Step 7

Finishing procedure.

A) *Experimental Results and Analysis*

Here Texture Spectrum Operator, Entropy Based Local Descriptor, Local Binary Pattern Operator Gray Level Co occurrence Matrix and proposed unsupervised hybrid classification for texture analysis (UHCTA) method have been evaluated by choosing different window sizes respectively. The results of classification accuracy have been computed and compared with the different texture images shown in Table1. The classification accuracy for Texture Spectrum operator and Entropy Based Local Descriptor operator achieve less accuracy as compared with Local Binary Pattern operator and Gray Level Co occurrence Matrix. But our proposed unsupervised hybrid classification for texture analysis (UHCTA) outperforms in terms of classification accuracy among all previous methods and it is because of the utilization of hybrid features. The proposed algorithm and flowchart are shown in Figure 4.

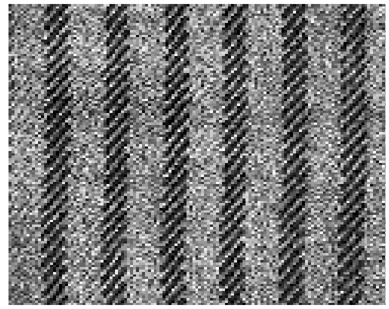

Figure 5: D11 Broadtz image

Table1. Average Classification Accuracy

Different classification methods	Different window size			Percentage of Classification %
TSO	72	76	79	77
EBLD	78	80	81	79.6
LBP	79	83	90	84
GLCM	80	85	92	85.6
UHCTA (proposed)	89	90	93	90.6

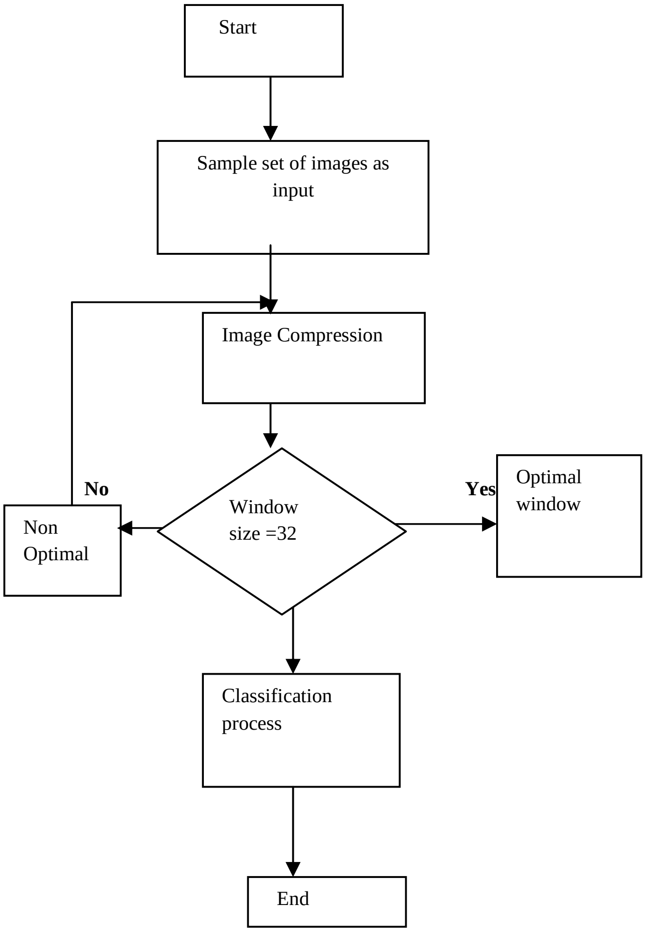

Figure 4: UHCTA algorithm flowchart

The D11 image as shown in Figure 5 has been taken for the comparative analysis for both the cases of fixed window size and for different window sizes. At first the proposed UHCTA algorithm is compared with TSO and it is found that the proposed method is so attractive in classification accuracy than the TSO while using fixed window size. The average window size for UHTCTA is 90.6% which is higher than the 77% of TSO.

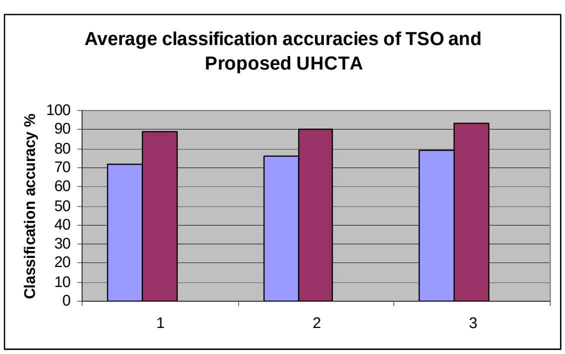

Figure 6: Classification accuracy of TSO and proposed UHCTA.

At first the proposed UHCTA algorithm is compared with TSO and from the Figure 6, it is found that the proposed method is so attractive in classification accuracy than the TSO while using fixed window size. The average window size for UHTCTA is 90.6% which is higher than the 77% of TSO.

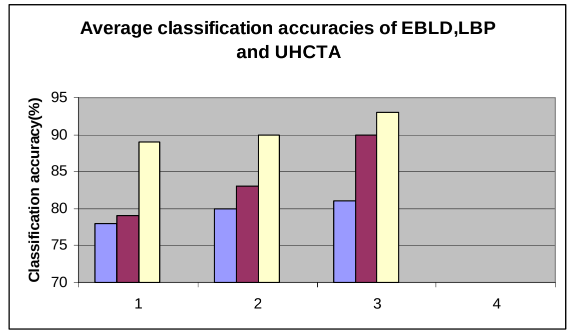

Figure 7: Classification accuracy of EBLD LBP and proposed UHCTA.

Secondly the proposed UHCTA algorithm is compared with EBLD, LBP and UHCTA in Figure 7.It is found that the proposed method has more classification accuracy than the other methods while using fixed window size. The average window size for UHTCTA is 90.6% which is higher than the 79.6% and 84% of EBLD, and LBP respectively.

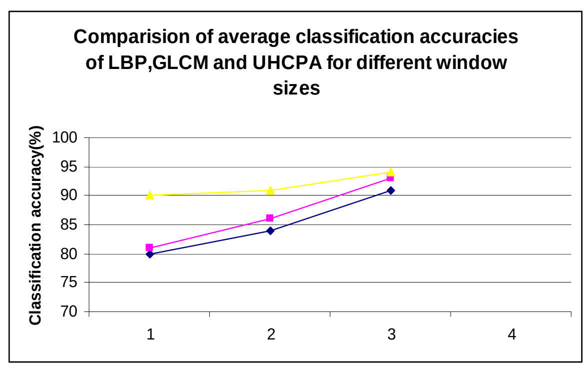

Figure 8: Classification accuracy COMPARISION of LBP, GLCM and UHCPA proposed UHCTA.

Finally the proposed UHCTA algorithm is compared with LBP, GLCM and UHCTA in Figure 8.It is found that the proposed method has more classification accuracy than the other methods while using different window sizes. The average window size for UHTCTA is 91.6% which is higher than the 85% and 86.6% of LBP, and GLCM respectively.

IV. CONCLUSION

An unsupervised hybrid classification for texture analysis has been implemented that comprises the features of various classification methods to improve the classification accuracy. In the proposed technique contains three issue that are selection of window size, fixing the optimal size of the window and compressing the texture image by means of splitting into subsets. After applying hybrid features, different sets of images have been tested. From the experimental results, it is concluded that our proposed method imparts higher classification rate than the existing method with the average classification accuracy of 92%.In the feature work the proposed algorithm can be applied in the supervised image classification of texture analysis.

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