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TEXTURE CLASSIFICATION METHODS: A REVIEW

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Abstract:- Texture classification is an important area of re-search in pattern recognition and image processing. It is widely used in real world applications like object detection, face recognition, medical image processing, agriculture etc. Texture has no deterministic shape or specific structure like other natural images. Texture is treated as indication for getting significant knowledge about the texture class. Since last one decade texture classification methods mainly uses patch based local features and feature encoding techniques. So in this paper some representative methods for each of the context are analysed.

Keywords :- Patch based local features, Feature encoding, Texture Classification

I INTRODUCTION

Texture is present in almost all images and represents important visual indication for number of image analysis applications such as image retrieval, image segmentation and shape from texture. Unlike natural images which have certain structure and objects, texture has no particular shape. Texture images neither follow any global structure nor they show any specific geometry. But for analysis of the visual content from images, texture plays significant role. It is found in the structural patterns of surfaces of objects such as wood, grain, sand, grass, cloth, etc. Figure 1 shows some samples of texture images. It identifies smoothness, regularity or coarseness of the surface. So it can be treated as indication for getting significant knowledge about the texture class.

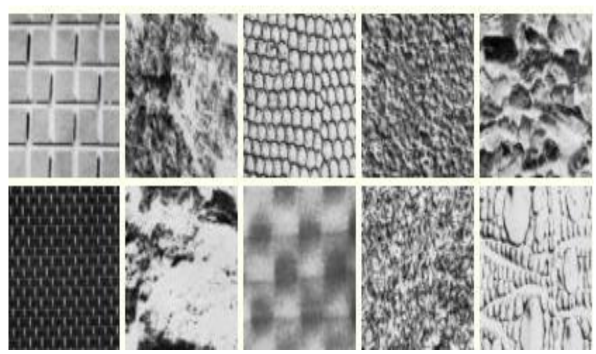

Fig. 1. Samples of images from Brodatz dataset

In image processing there are three principal approaches to describe the texture of a region are: statistical, structural and spectral.

1. Statistical approach: It uses statistical measures computed from grayscale intensities (or colours) alone, and characterises the texture as smooth, coarse, grainy etc. Tamura features and co-occurrence matrices are examples of statistical representations of texture.

2. Structural approach: This technique deals with arrangement of image primitives, for example the description of texture based on regularly spaced parallel lines. Also in mathematical morphology powerful tool for structural analysis is provided.

3. Spectral approach: This technique is established on the properties of Fourier spectrum and used mainly to detect global periodicity in an image by identifying narrow peaks, high-energy in the spectrum. For example Gabor filter, wavelet transform.

Classification refers to as assigning any object or entity into one of a set of predefined categories. In texture classification the objective is to assign an unknown sample image to one of a set of correct known texture classes. Texture classification is divided into two types supervised classification and unsupervised classification. In supervised classification, with the features of known classes classifier is trained. While in unsupervised classification classifier is not trained, it identifies distinct classes based on input feature similarity.

Texture classification is an important area of research in pattern recognition and image processing. It is widely used in real world applications like object detection, face recognition, medical image processing, agriculture etc. Because of its importance, texture classification has been progressive research topic from several decades. In spite of these research and development, building accurate and robust texture classification system is still challenging. Its challenge consists of wide variety of diverse natural texture types and conditions in which images are captured such as contrast, scale, brightness etc.

Most of the feature extraction techniques tend to use either local image features or global image features. Global features describe an image as whole and have the ability to represent an entire object with a single vector. On the other hand, a local feature represents image patches and is calculated at multiple points in the image which results in many feature vectors per image. But global features are susceptible to occlusion and clutter, while local features are robust to occlusion and clutter. Texture images form a special category of images that are repetitive in nature. They have no definite shape, structure or objects like other images. So patches extracted from texture images are similar in appearance and from these patches it is possible to predict class of the texture. So most of the earlier methods are also based on patch based local features like SIFT, SRP, LHS etc.

From last one decade texture classification methods are mainly based on local features approach and Bag-of-Words (BoW) approach. Both approaches have its own advantages and disadvantages. So there is need for a hybrid method based on these approaches, which will take advantages of both approaches and reduce the loss caused by them.

Decision about which category the texture belongs to is taken in texture classification phase. This is done based on classification algorithms like support vector machine (SVM), nearest neighbour etc.

Section II focuses on brief literature of local features and encoding techniques. Performance measures are described in section III and section IV concludes the paper.

II TEXTURE CLASSIFICATION METHODS

The aim of this section is to provide a review of different texture classification techniques. In last one decade efficient texture classification approaches are based on two categories: Local features and Bag-of-Words (BoW) model. Various methods based on these approaches are explained here.

A. Local Features:

Many local features based on patch rely on the concept that the local region of the image presents a certain characteristic structure. Therefore several methods have been implemented to capture that structure.

- Local Binary Patterns :

Timo Ojala et al. presented Local Binary Patterns [1] technique for texture classification. It is simple, but effective multi-resolution method to rotation invariant and gray-scale texture classification based on local binary patterns and non parametric discrimination of sample and prototype distributions.

The approach is based on identifying specific local binary patterns, called "uniform", are basic properties of local image texture and their occurrence histogram has proven to be a very effective texture feature. In this method a generalized rotation invariant and gray-scale operator presentation is derived that permits, detecting the "uniform" patterns for any quantization of the angular space and for any spatial resolution and presents a method for concatenating multiple operators for multi-resolution analysis.

LBP works in a local circular region by taking the difference of the central pixel with respect to its neighboring pixels. By taking the sign of the difference of image pixel values from the image patch in a circular geometry these features capture the local structure. Mathematically formula of this is given as:

$$LBPp,r(Nc) = \sum_{p=0}^{p-1}(Np - Nc)2^{p} \qquad (1)$$

where, neighborhood pixels N_p in each block is thresholded by its center pixel value N_c and 'p' is sampling point (e.g., p = 0, 1, …, 7 for a 3x3 cell, where P = 8) and r is radius (for 3x3 cell, it is 1). Binary threshold function g(x) is,

$$g(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \qquad (2)$$

But, the information provided by the magnitude of the difference is not considered, which causes loss of the discriminative power of these features. To overcome this drawback, X. Tan and B. Triggs [2] compared the magnitude with a predefined threshold parameter, while Guo et al. [3] incorporated the magnitude by comparing it with a mean value of the image. The outcomes from these approaches indicate that in the patch based features magnitude can be used, as it provides discriminative information.

- Sorted Random Projections :

Liu, L. et al. presented Sorted Random Projections [4] technique for texture classification. In this technique compressibility of the pixel intensity difference taken from a circular geometry in the patch is used. The contribution of this work is a sorting strategy is applied to a universal but information-preserving random projection (RP) technique, and two different texture image representations (signatures and histograms) are compared with various kernels in the SVMs.

- Local higher-order statistics :

G. Sharma et al. proposed Local higher-order statistics (LHS) [5] for texture categorization. In LHS based descriptor, from a patch the high order statistics of the pixel difference is incorporated. Both of these methods SRP and LHS are based on pixel difference in the patch and considers the circular geometry of the sampling points. Circular geometry can only take the radial variation in the image patch as the difference is taken between central pixel and its neighboring pixels, thus remaining directions are not considered.

- Scale Invariant Feature Transform

In image analysis Scale Invariant Feature Transform (SIFT) [6] is one of the most extensively used local features. It was primitively designed to recognize the same object under different conditions like translation, scale and rotation trans-formations. Using a quantized image gradient SIFT captures the local structure.

Tuan Do proposed framework for texture classification and retrieval using SIFT [7]. Here for generating local features SIFT algorithm is used. A texture dictionary is built for each texture class depending on the local features. For constructing texton dictionary, with all local features, an adaptive mean shift clustering algorithm is run for creating fundamental features defined as texton. And for matching local features from the texton dictionaries with sextons a framework is presented for classifying images into specific category. But the disadvantage of this method is high dimensionality.

B. Encoding :

In the texture classification task Bag-of-Words (BoW) [8]-[11] model is used widely. Three important steps in this process are: 1) Extraction of features from image 2) Obtain a descriptor by encoding these features 3) Classification of the image descriptor. General pipeline of encoding is shown in figure 2.

In BoW model image is represented as histograms on the basis of vocabulary of local features. For local features gradient based features [12] and filter bank response [13] are used. But a gradient based feature consists of quantization that leads to loss of information and the filter response causes computation complexity and high dimensionality.

Jorge Sanchez used Fisher kernel [14] for Image classification. This method is improvement of BoW model as it encodes both statistics of the distribution of the local features i.e., zero order statistics and higher order statistics. As Fisher Vector is dense and very high-dimensional it is not practical to use for large-scale applications because of limited storage.

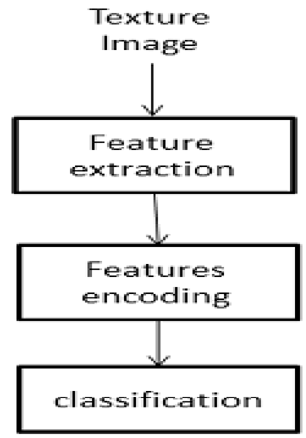

Fig. 2 General pipeline of Encoding technique

But this problem is also considered by the author by implementing product quantization, which balances memory usage, CPU cost and accuracy.

- Dense Micro-block Difference

R. Mehta and K. Egiazarian proposed method for texture classification based on local features and encoding. In this method block based local features called as dense micro-block difference (DMD) are used for feature extraction and fisher vector is used for encoding for texture classification [15]. In these features small blocks from an image are used instead of the pixels, for capturing local structure. [16] is advancement of DMD features in which DMD blocks of different sizes are combined instead of single size micro-block. Because of this intensity difference between blocks is densely captured at multiple resolutions, orientations and scales. Let patch of size L x L and two set of sampling points

$X = \{x_1, x_2, .., x_N\}$ and $Y = \{y_1, y_2, \dots, y_N\}$ is given. Then DMD for micro-block of size 's' is given as :

$$V_s(p) = \{ M_s(x_1) – Ms(y_1),\dots, M_s(x_N)- M_s(y_N) \} \qquad (3)$$

The average intensity of the pixel in micro-block at position $x = (a,b)^T$ is given as :

$$Ms(a,b) = \sum_{i=0}^{s-1} \sum_{j=0}^{s-1} p(a+i,b+j)/s^2 \qquad (4)$$

Here p(a,b) is pixel intensity of the patch ‘p’ at location {a,b}. The DMD features are described using four parameters: X, Y, L and s i.e., sampling points, size of the patch and size of micro-block. Sampling points X and Y are selected randomly by using Gaussian distribution. DMD features are better than SIFT in terms of dimensionality and computational speed

III PERFORMANCE MEASURES

For comparison of texture image classification system recognition rate of the image and computation time are important parameters. Recognition rate is how accurately class of the texture is predicted from the input image. And time refers to computational speed of the system. Ideal texture classification system should have high recognition rate and low computation time.

IV SUMMARY AND CONCLUSION

In this work existing methods related to texture classification are explained. Texture classification methods from last ten years are mainly based on two categories local features and encoding. So methods related these categories are discussed here. Each method have it’s own advantage and disadvantage. So there is a need for a method who is best combination of both categories and reduces losses caused by them need. The performace of the texture classification system is measured in terms of recognition rete and time.

REFERENCES

[1] T. Ojala, M. Pietikainen, and T. Maenpa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 971-987, Jul. 2002.

[2] X. Tan and B. Triggs, “Enhanced local texture feature sets for face recognition under difficult lighting conditions,” IEEE Trans. Image Process., vol. 19, no. 6, pp. 1635-1650, Jun. 2010.

[3] Z. Guo and D. Zhang, “A completed modeling of local binary pattern operator for texture classification,” IEEE Trans. Image Process., vol. 19, no. 6, pp. 1657-1663, Jan. 2010.

[4] L. Liu, P. Fieguth, G. Kuang, and H. Zha, “Sorted random projections for robust texture classification,” in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), Nov. 2011, pp. 391-398.

[5] G. Sharma, S. ul Hussain, and F. Jurie, “Local higher-order statistics (LHS) for texture categorization and facial analysis,” in Computer Vision. Berlin, Germany: Springer, 2012, pp. 1-12.

[6] D. G. Lowe, “Distinctive image features from scale-invariant keypoints,” International journal of computer vision, vol. 60, no. 2, pp. 91–110, 2004.

[7] Tuan Do, Aikala, A., and Saarela, O., "Framework for texture classification and retrieval using scale invariant feature transform," in Computer Science and Software Engineering (JCSSE), 2012 International Joint Conference on , vol., no., pp.289-293, May 30 2012-June 1 2012.

[8] S. Lazebnik, C. Schmid, and J. Ponce, “A sparse texture representation using local affine regions,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 8, pp. 1265-1278, Aug. 2005.

[9] J. Zhang, M. Marszałek, S. Lazebnik, and C. Schmid, “Local features and kernels for classification of texture and object categories: A comprehensive study,” Int. J. Comput. Vis., vol. 73, no. 2, pp. 213-238, Jun. 2007.

[10] M. Varma and A. Zisserman, "A statistical approach to texture classification from single images," Int. J. Comput. Vis., vol. 62, nos. 1-2, pp. 61-81, 2005.

[11] M. Crosier and L. D. Griffin, "Using basic image features for texture classification," Int. J. Comput. Vis., vol. 88, no. 3, pp. 447-460, 2010.

[12] S. Lazebnik, C. Schmid, and J. Ponce, "A sparse texture representation using local affine regions," IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 8, pp. 1265-1278, Aug. 2005.

[13] M. Varma and A. Zisserman, "A statistical approach to texture classification from single images," Int. J. Comput. Vis., vol. 62, nos. 1-2, pp. 61-81, 2005.

[14] F. Perronnin, J. Sánchez, and T. Mensink, "Improving the Fisher kernel for large-scale image classification," in Computer Vision. Berlin, Germany: Springer, 2010, pp. 143-156.

[15] R. Mehta and K. Egiazarian, "Texture classification using dense microblock difference (DMD)," in Proc. Asian Conf. Comput. Vis., 2015, pp. 643-658.

[16] R. Mehta and K. Egiazarian, "Texture Classification Using Dense Micro-Block Difference" in IEEE Transactions on Image Processing, vol. 25, no. 4, april 2016