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Survey on Texture Classification Methods

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ABSTRACT
The paper contains survey on texture classification techniques. Texture classification categories the unknown texture sample image to one of known texture categories based on distinguishing feature. Texture classification methods are classified into three categories: pixel based, local feature based and region based methods. These methodologies vary in their principles of describing and analyzing textures. The basic objective of this paper is to understand the research work carried out in the field of texture classification.
Keywords:- Feature extraction, local feature based methods, pixel based methods, region based methods, Texture Classification

I. INTRODUCTION

Texture is characterized by a non-uniform spatial distribution of image intensities. Texture based classification techniques are being used in variety of the real world applications like content-based image retrieval [1], face recognition [2] ,rock classification, wood species recognition , fabric classification, geographical landscape segmentation .

In texture classification the objective is to classify a sample image to one of a set of known texture classes. There are two types of texture classification, supervised and unsupervised classification. In supervised classification method, classifier trained with the features of known classes. In unsupervised classification method, classifier recognizes different classes based on input feature similarity, no prior classifier training happens. Texture classification methods can be classified into three categories: Pixel based, Local Feature based and Region Based [3]. This paper covers various approaches in each of the texture classification technique. A successful classification requires an efficient description of image texture.

Section 2 gives overview of texture classification workflow. Section 3 includes literature survey of texture classification methods used in the recent years. Section 4 concludes the paper.

II. TEXTURE CLASSIFICATION WORKFLOW

The texture classification system can be summarized as shown in Figure 1.It consist of three phases, texture image acquisition, feature extraction and classification.

In the first phase of texture classification, texture image is acquired and pre-processed. Various pre-processing techniques are applied, like image enhancement, noise removal, color space transformation. Distinctive features are extracted in next phase. Feature extraction methods fall into the categories of either spatial or spectral domain. 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 built on extracted features. If the classes have not been defined a priori, the classification is referred to as unsupervised texture classification. On the other hand, if the classes have already been defined through the use of training textures, then the process is referred to as supervised texture classification.

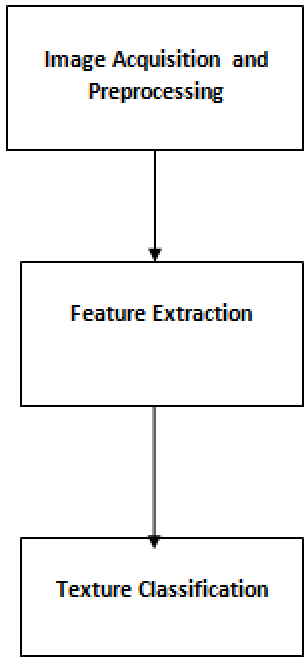

Figure 1: Texture classification system

III. LITERATURE SURVEY

A. Pixel based methods

In pixel based methods, statistical properties obtained from intensities or gray levels of pixels of image, are used to describe the texture.

1) ***Gray level co-occurrence matrix (GLCM):*** Gray level co-occurrence matrix (GLCM) was introduced by Haralick et al for image classification [4]. Using intensity histograms in calculation will result in measures of texture that carry only information about distribution of intensities, but not about the relative position of pixels with respect to each other in that texture. Using a statistical approach such as co-occurrence matrix will help to provide valuable information about the relative position of the neighbouring pixels in an image.

Given an image I, of size N×N, the co-occurrence, matrix P can be defined as

$$P(i,j)=\sum_{x=0}^{N}\sum_{y=0}^{N}\begin{cases}1 & \text{if } I(x,y)=i \text{ and } I(x+\Delta x, y+\Delta y)=j\\ 0 & \text{else}\end{cases} \quad (1)$$

Where, the offset (Δx, Δy), is specifying the distance between the pixel-of-interest and its neighbour.

Davis et al [5] proposed the extraction of features like contrast, uniformity and Detecting Clusters from gray level concurrence matrix for feature classification.

2) ***Local Binary Pattern (LBP):*** Ojala et al proposed used of Local Binary Pattern for rotation invariant texture classification [6].

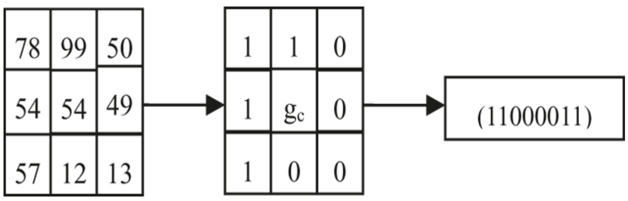

Figure 2: The basic LBP feature vector

LBP feature vector is calculated as how in Figure 2.Each pixel is compared with its 8 neighbors. If the center pixel's value is greater than the neighbor's value, bit is set to 1 in LBP feature vector.

$$LBP = \sum_{p=0}^{p-1} s\,(g_p - g_c) \quad (2)$$

$$\text{Where, } s(x)\begin{cases}1, & \text{if } x > 0\\ 0 & \text{else}\end{cases} \quad (3)$$

g_c denote the gray level of an arbitrary pixel P and g_p denote the gray value of a sampling point in an evenly spaced circular neighborhood of *P* sampling points.

B. Local feature based methods

Local image features such as edges, blobs are used to describe the texture in local feature based models. When texture elements are relatively large consisting of several pixels, texture classification is achieved with local feature based model.

1) ***Edge based:*** Marr proposed extracting first-order statistical features from the edge map [7], while Zucker et al. [8] suggest that histograms of simple, local image features (e.g., of edge magnitude, or orientation) 'can be used to discriminate between different textures.

Khouzani. Et al used radon transform to detect the principal orientation of image.

The projection function g(Θ,s) can be rewritten as

$$g(\Theta,S)=\iint f(x,y)\,\delta(x\sin\Theta - y\cos\Theta - s)\,dx\,dy \quad (4)$$

g(Θ,s) is the line integral of the image intensity, f(x,y), along a line l that is distance s from the origin and at angle Θ off the x-axis. The collection of these g(Θ,s) at all phi is called the Radon Transform of image f(x, y). Texture principal direction can be roughly defined as the direction along which there are more straight lines. The Radon transform along this direction usually has larger variations. Therefore, the variance of the projection at this direction is locally maximum. Then, the texture is rotated to place its principal direction at 0 degrees. A wavelet transform is applied to the rotated image to extract texture features. This helped to achieve rotation invariance in texture detection.

2) ***Scale Invariant Feature Transform (SIFT):*** The algorithm was proposed by David Lowe in 1999 [10] .SIFT descriptors are invariant to scale, translation and rotation transformations. Feature points are maxima and minima of the result of difference of Gaussians function applied in scale space to a series of smoothed and resample images. The gradient magnitude and orientation at each point in the region used as descriptor in SIFT.

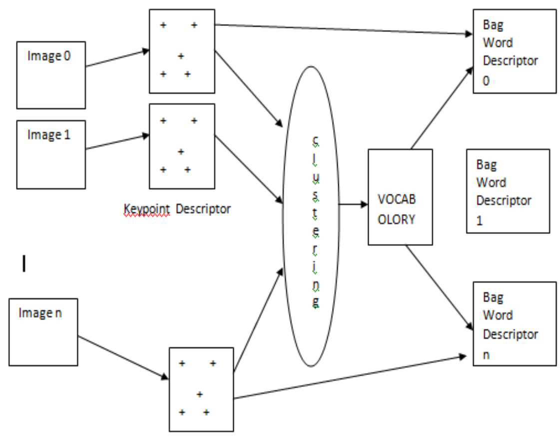

Figure 3: Bag of Word Model [12]

Tuan et al [11] proposed the use of the SIFT for texture feature classification. The local features are selected as inputs for texture classification framework. For each texture category, a texton dictionary is built based on the local features as shown in Figure 3. Adaptive mean shift clustering is used rather than K-mean to generate the texton dictionary from key features.

3) ***Speedup Robust Features (SURF)*:** Speedup Robust Features is an algorithm in computer vision to detect and describe local features in images. The algorithm was published by H. Bay [13], in 2006. Key locations are defined as maxima and minima of the result of difference of Hessian-based function applied in scale space to a series of smoothed and resample images. Feature vector is of 64 dimensional. The Hessian matrix, H, is the matrix of partial derivates of the function f.

$$H(f(x,y)) = \begin{bmatrix} \frac{\partial 2 f}{\partial 2 x} & \frac{\partial 2 f}{\partial x \partial y} \\ \frac{\partial 2 f}{\partial x \partial y} & \frac{\partial 2 f}{\partial 2 y} \end{bmatrix} \quad (5)$$

Huage et al [14] proposed wood image retrieval scheme based on Speeded Up Robust Features (SURF) feature points and performed matching based on the texture information around the feature points using SURF method.

C. Region-based methods

Region-based approaches try to find partitions of the image pixels into sets corresponding to coherent image properties such as brightness, color and texture. Spatial variability within in the image can provide useful information for region based texture classification.

*1) **Block Counting Method***: Alrawi et al [15] proposed block based method for texture analysis. The algorithm based on blocking procedure where each image divide into block (16×16 pixels) and extract vector feature for each block to classification these block based on these feature.

*2) **An Active Patch Model**:* Mao, et al [16] used bag of-words model where the features are based on a dictionary of active patches. Active patches are raw intensity patches which can undergo spatial transformations (e.g., rotation and scaling) and adjust themselves to best match the image regions. The dictionary of active patches is required to be compact and representative, in the sense that it can be used to approximately reconstruct the images that needs to be classified. Images are classified based on the occurrence frequency of the active patches.

IV. CONCLUSIONS

Various texture classification techniques have been discussed in the paper. Texture classification methods are categorized into three classes, i.e. local feature based, pixel based or region based methods. Now days, for better accuracy various methods are combined. A major problem is the textures in the real world are often not uniform, due to changes in orientation, scale or other visual appearance. With improving the recognition accuracy, the problems like scaling, rotation, and affine transformation are being addressed in recent research on texture classification. Improving speed along with the accuracy will be prospective of further research in texture classification field.

REFERENCES

[1] B. S. Manjunathi and W. Y. Ma, “Texture features for browsing and retrieval of image data,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 18, no. 8, pp. 837–842, Aug. 1996

[2] Chengjun Liu, Wechsler, H., "A shape- and texture-based enhanced Fisher classifier for face recognition," in Image Processing, IEEE Transactions on , vol.10, no.4, pp.598-608, Apr 2001

[3] Davis Larry S. “Image Texture Analysis Techniques - A Survey,” Springer conference on Digital Image Processing,1981

[4]] R.M. Haralick, K. Shanmugam, and L. Dinstein, “Textural Features for Image Classification,” IEEE TSMC, vol. 3, pp. 610-621, 1973.

[5] L. Davis, S. Johns, and J. Aggarwal, “Texture analysis using generalized co-occurrence matrices,” IEEE Transactions Pattern Analysis and Machine Intelligence, vol. PAMI-1, no. 3, pp. 251–259, Jul. 1979.

[6] T. Ojala, M. Pietikainen, and T. T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with Local Binary Pattern,” IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971-987, 2002.

[7] D. Marr, "Early processing of visual information," Phil. Trans. Roy. Soc. B, to be published.

[8] S. Zucker, A. Rosenfeld, and L. Davis, "Picture segmentation by texture discrimination," IEEE Trans. Comput., vol. C-24, pp. 1228-1 233, 1975.

[9] K. Khouzani and H. Zaden, “Radon transform orientation estimation for rotation invariant texture analysis,” IEEE Transactions Pattern Analysis and Machine Intelligence, vol. 27, no. 6, pp. 1004–1008, Jun. 2005.

[10] D. Lowe, “Distinctive image features from scale-invariant keypoints,” IJCV, vol. 60, no. 2, pp. 91–110, 2004.

[11] 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.

[12] G. Csurka, C. Dance, L. Fan, J. Willamowski, and C. Bray, “Visual categorization with bags of keypoints,” in ECCV Workshop on statistical learning in computer vision, 2004.

[13] Herbert Bay, Tinne Tuytelaars, and Luc Van Gool. “Surf: Speeded up robust features,” in Springer conference on Computer Vision, pp 404–417 , 2006.

[14] ShaoLi Huang, Cheng Cai, FengFu Zhao, Dongjian He, and Yang Zhang, "An efficient wood image retrieval using SURF descriptor," in Test and Measurement, 2009. ICTM '09. International Conference on , vol.2, no., pp.55-58, 5-6 Dec. 2009.

[15] Azmi Tawfik Alrawi, Ali makki Sagheer and Dheyaa Ahmed Ibrahim, "Texture Segmentation Based on Multifractal Dimension", International Journal on Soft Computing (IJSC) Vol.3, No.1, February 2012.

[16] Junhua Mao, Jun Zhu, and Alan L. Yuille ,"An Active Patch Model for Real World Texture and Appearance Classification" Springer conference on Computer Vision, pp. 140-155, 2014.

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