A Survey on Feature Descriptors for Texture Image Classification

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Abstract – *Texture is a fundamental feature which describes the appearance of the surface of some entity. Nowadays texture based image classification methods have an important role in various computer vision problems. Many descriptors can be used to perform texture classification. The descriptors will identify and describe the textural features of an image. Texture classification system encounters the problems such as the scale variations, illumination changes, and rotation. This paper attempts in exploring the survey of various image classification techniques using different textural feature descriptors. All these approaches have used an appropriate classifier to classify the textural features. The effective combination of descriptive image features and the selection of a suitable classification method are very much significant for improving classification accuracy.*

Key Words: Texture image, local binary pattern, classification accuracy, local features, feature extraction.

1. INTRODUCTION

Nowadays due to the rapid development in technology and high availability of computing facilities, tremendous amount of data is generated. As a result, there has been a huge increase in the amount of image data on the Web. The accumulation of large collections of these digital images has created the need for intelligent and efficient schemes for image classification. The image classification techniques must maximize its performance for intelligent decision making. In order to classify images, initially we want to find out the basic type of features which describe the visual properties of that image such as its color, texture, shape, gradient, etc. Texture is an important feature of objects in an image.

Texture is actually a visual characteristic which describing the appearance of the surface of some object. Most objects have their own distinct texture, such as the surface of earth, tree trunk, sky, and bunch of flowers etc. Texture classification is an active research area in number of computer vision problems such as object detection, material classification, fabric inspection, face recognition, content-based image retrieval, medical image analysis, facial expression recognition, image segmentation, biometrics and remote sensing. Therefore, the fundamental problems associated with texture classification are highly relevant.

Texture classification consists of mainly two steps: feature extraction and classifier designation. A successful classification requires an efficient description of image texture. A variety of new feature descriptors for texture classification have been proposed in last few decades. An effective descriptor has to solve the problems such as rotation, illumination change, scale, blur, noise and occlusion. In order to achieve classification accuracy, the quality of the descriptor and its computational complexity must be balanced. Much work has been done on creating advanced feature descriptors to improve the texture classification accuracy. This paper attempts to study various feature descriptor generation methods for effectively classifying the images based on their texture.

2. LITERATURE SURVEY

In [1] Timo Ojala et al. proposed a simple and efficient descriptor called local binary patterns for gray-scale and rotation invariant texture classification. This descriptor derives an operator which is invariant against any monotonic transformation of the gray scale. This paper describes that, the fundamental properties of local image texture are certain local binary texture patterns termed as "uniform". In order to detecting these "uniform" patterns, a generalized rotation invariant and gray-scale operator has been developed. The term "uniform" indicates that the uniform appearance of the local binary. The name of the descriptor reflects the functionality of the operator, i.e., the local neighborhood values are threshold at the gray value of the center pixel into a binary code pattern. The spatial configuration of local image texture is characterized by these operators. The performance can be improved by combining them with rotation invariant variance measures that characterize the contrast of local image texture.

In [2] Liao et al. proposed a new feature extraction method that is robust to histogram equalization and rotation. In order to effectively capture the dominating patterns in texture images, this method extended the conventional LBP approach into the dominant local binary pattern (DLBP). Unlike the conventional LBP approach which exploits only the uniform LBP, DLBP approach computes the occurrence frequencies of all rotation invariant patterns. These patterns are then sorted in descending order. The first several most frequently occurring patterns should contain dominating patterns in the image and therefore which are the dominant patterns. In order to retrieve the DLBP feature vectors from an input image, initially the pattern histogram of the input image is constructed, and then the histogram bins are sorted in non-increasing order. Based on the previously computed number of patterns, the occurrence frequencies corresponding to the most frequently occurred patterns in the input image is computed and these are served as the feature vectors. The DLBP feature vectors do not bear information regarding the dominant pattern types, but they only contain the information about the pattern occurrence frequencies.

In [3] Zhenhua Guo, Lei Zhang, and David Zhang proposed a new local feature descriptor to generalize and complete LBP, called completed LBP (CLBP). CLBP represented, a local region is by its center pixel and a local difference sign-magnitude transforms (LDSMT). This method generating a binary map called CLBP-Center (CLBP-C) by coding the center pixel into a binary code after global thresholding. The LDSMT decomposes the image local structure into two complementary components: the difference signs and the difference magnitudes. Then two operators called, CLBP-Sign (CLBP-S) and CLBP-Magnitude (CLBP-M), are introduced to code them. All the maps generated are in binary format so that they can be readily combined to form the final CLBP histogram. Some classifier, such as the nearest neighborhood classifier, can be used for texture classification. The CLBP could achieve much better rotation invariant texture classification results when compared with conventional LBP-based schemes. The texture classification using the sign features achieves much higher accuracy than using the magnitude features. By coding both the sign features and magnitude features into rotation invariant binary codes, much better texture classification results can be obtained than using only one of them.

In [4] Jie Chen et al. proposed a robust local descriptor called the Weber Local Descriptor (WLD), inspired by Weber's Law. This descriptor has two components: differential excitation and orientation. The differential excitation component finds the ratio between two terms: The relative intensity differences of a current pixel against its neighbors and the current pixel intensity. The orientation component is the current pixel gradient orientation. For a given image, the combination of the two components can be used to construct a concatenated WLD histogram.

In [5] Yang Zhao et al. proposed a new local operator that discards the structural information from LBP operator, called Local Binary Count (LBC). This method illustrated that the micro structures information is not the most discriminative information of local texture for rotation invariant texture classification, but the local binary grayscale difference information. Unlike LBP, this method only counting the number of value 1's in the binary neighbor sets instead of encoding them. Motivated by the CLBP, this method also introduced a completed LBC (CLBC). Compared with the existed CLBP, the introduced CLBC can achieve comparable accurate classification rates. In addition, the introduced CLBC allows slight computational savings in the process of training and classification.

In [6] Zhen Lei et al. proposed a novel discriminant face descriptor (DFD) which introduced the discriminant learning into feature extraction process. In DFD, the discriminant image filters learning and the optimal soft neighborhood sampling are introduced to enhance the essential face patterns and suppress the external variations. In the learning phase, the discriminant learning is adopted to learn the discriminant image filters. In order to form the discriminant pattern vector, the PDM is then projected and regrouped. Finally, the dominant patterns can be obtained by using any unsupervised clustering method. In the face labelling phase, for each pixel in face image, initially the PDM is extracted. The discriminant pattern vector is obtained by mapping the PDM using the learned discriminant image filters and the neighborhood sampling strategy. The pixel is finally labeled to the dominant pattern ID, which is the one most similar to the discriminant pattern vector. In order to achieve high face recognition accuracy, this work has incorporated the discriminant learning into an LBP-like feature extraction process.

In [7] Zhibin Pan, Hongcheng Fan, and Li Zhang proposed a new local descriptor named local vector quantization pattern (LVQP). It was introduced to overcome the disadvantages of LBP like methods, such as noise sensitivity, coarse conversion into binary format etc. In LVQP, both the sign and the magnitude information of the difference vector has preserved simultaneously during vector quantization. A local pattern codebook can be defined by means of training difference vectors from different kinds of texture images. In this work, each difference vector finds its best match codeword in the codebook, where codeword index is defined as the LVQP code of the central pixel in a local region. After the LVQP code of each pixel of the image is generated, the algorithm proceeds by generating a histogram of the LVQP code as the classification feature to represent the whole texture image. Finally the images are classified using the nearest neighborhood classifier.

In [8] Rakesh Mehta and Karen Egiazarian introduced a set of novel features called dense micro-block difference (DMD). The features in this work are based on idea that small patches in a texture image exhibit a characteristic structure and, if it captured efficiently, more discriminative information can be obtained. Unlike the earlier works, this method randomly selecting the pixel coordinates and considering the pixel difference from a circular geometry. Individual pixels are more affected by noise, therefore small blocks in image patch is used instead of raw pixel values. To encode the local structure of the patch, the pair wise intensity differences of smaller blocks in the image patch is taken. The smaller square blocks in an image patch can be address as "micro-blocks" and their average intensity is considered to capture variations. Then, the DMD vector is mapped using a random matrix to obtain the compressed feature vector. The projection is obtained by multiplying the DMD vector by a random matrix. The local features from an image have to be encoded by using Fisher vector to obtain a descriptor.

3. CONCLUSIONS

This paper has surveyed the different feature descriptors for texture based image classification systems. Various feature extraction methods provide different visual feature descriptors of images and which were discussed. The paper also discussed how various methods solved the problems such as rotation, illumination change, scale, blur, and noise and how it achieved classification accuracy. Improving speed along with better classification accuracy still need further attention in the field of texture classification.

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