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RELATED LBP OPERATORS FOR TEXTURE ANALYSIS

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ABSTRACT

Texture plays an important role in numerous computer vision applications. Many methods for describing and analyzing textured surfaces have been proposed. The LBP operator is a theoretically simple yet very powerful method of analyzing textures. With its recent extension to different variants, it has become a really powerful measure of image texture, showing excellent results in terms of accuracy and computational complexity in many empirical studies. The LBP operator can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. In addition, real-world applications like face recognition and medical imaging tend to produce a great deal of complex texture data to be processed that should be handled effectively in order to be exploited. In the proposed work, the basic LBP is extended to facilitate the analysis of textures by combining two available operators namely MILBP & CSLBP to inherit the feature of these operators thus reducing the limitations we have while using a single operator out of these at a time.

I. LITERATURE SURVEY

Ojala T, Pietikäinen M & Harwood [6] in his paper on "Calculating the Original LBP Code & a Contrast Measure" have first introduced local binary pattern as a complementary measure for local image contrast. The first incarnation of the operator worked with the eight-neighbors of a pixel, using the value of the center pixel as a threshold.An LBP code for a neighborhood was produced by multiplying the threshold values with Since the LBP was, by definition, invariant to monotonic changes in gray scale, it was supplemented by an orthogonal measure of local contrast weights given to the corresponding pixels, and summing up the result, and shows how the contrast measure was derived. He has showed that LBP is invariant to any monotonic gray level change and computationally it is very simple.Timo Ojala, Matti Pietikainen [7] in his paper on "Unsupervised texture segmentation using feature distributions" have presented an unsupervised texture segmentation method, which uses distributions of local binary patterns and pattern contrasts for measuring the similarity of adjacent image regions during the segmentation process. Nonparametric log-likelihood test, the *G* statistic, is engaged as a pseudo-metric for comparing feature distributions. A region-based algorithm is developed for coarse image segmentation and a pixel wise classification scheme for improving localization of region boundaries.In the presented method texture is described by joint occurrences of LBP and C. Obvious generalizations are to use other texture features or feature domains (e.g. color) and scale.

Although LBP/C is a very powerful texture transform, he expects to achieve better results by combining a larger number of features in the analysis. Other powerful texture measures, like distributions based on gray-level deference histograms or co-occurrence matrices, can be easily incorporated into our algorithm. Texture information is measured with a method based on local binary patterns and contrast (LBP/C) that he has recently developed. A region-based algorithm is developed for coarse image segmentation and a pixel wise classification scheme for improving the localization of region boundaries.The method performed very well in experiments. It is not sensitive to the selection of parameter values, does not require any prior knowledge about the number of textures or regions in the image, and seems to provide significantly better results than existing unsupervised texture segmentation approaches. The method can be easily generalized, e.g. to utilize other texture features, multi-scale information, color features, and combinations of multiple features. Timo Ojala, et al.[8] in his their paper on "Multi resolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns" have presented a theoretically very simple, yet efficient, multi resolution approach to gray-scale and rotation invariant texture classification based on local binary patters and nonparametric discrimination of sample and prototype distributions. The method is based on recognizing that certain local binary patterns, termed "uniform." are fundamental properties of local image texture and their occurrence histogram is proven to be a very powerful texture feature. He has derived a generalized gray-scale and rotation invariant operator presentation that allows for detecting the "uniform" patterns for any quantization of the angular space and for any spatial resolution and presents a method for combining multiple operators for multi resolution analysis. The proposed approach is very robust in terms of gray-scale variations since the operator is by definition, invariant against any monotonic transformation of the gray scale. Another advantage is computational simplicity as the operator can be realized with a few operations in a small neighborhood and a lookup table. Excellent experimental result obtained in true problems of rotation invariance, where the classifier is trained at one particular rotation angle and tested with samples from other rotation angles demonstrate that good discrimination can be achieved with the occurrence statistics of simple rotation invariant local binary patterns. These operators characterize the spatial configuration of local image texture and the performance can be further improved by combining them with rotation invariant variance measures that characterize the contrast of local image texture. The joint distributions of these orthogonal measures are shown to be very powerful tools for rotation invariant texture analysis.Topi Maenpaa and Matti Pietikainen [9] in their: - paper on "Multi-Scale Binary Patterns for Texture Analysis" presents two novel ways of extending the local binary pattern (LBP) texture analysis operator to multiple scales. First, large-scale texture patterns are detected by combining exponentially growing circular neighborhood with Gaussian low-pass filtering. Second, cellular automata are proposed as a way of compactly encoding arbitrarily large circular neighborhoods. The performance of the extensions is evaluated in classifying natural textures from the Outex database.Topi Maenpaa and Matti Pietikainen and Jaakko Viertola [10] in their paper on "Separating Color and Pattern Information for Color Texture Discrimination" have analyzed the colors surface textures. It is a challenging research problem in computer vision. Current approaches to this task can be roughly divided into two categories: methods that process color and texture information separately and those that utilize multi spectral texture descriptions. Motivated by recent psychophysical findings, we find the former approach quite auspicious. This paper propose the use of complementary color and texture measures that are combined on a higher level, And empirically demonstrate the validity of our proposing using a large set of natural color textures.Markus Turtinen, Mutti Pietikainen and Olli Silven {11} have studied in their paper on "Visual Characterization of Paper Using Isomap and Local Binary Patterns" in their paper, they have studied multidimensional Local Binary Pattern (LBP) texture feature data can be visually explored and analyzed. The goal is to determine how true paper properties can be characterized with local texture features from visible light images. They have utilized isometric feature mapping (Isomap) for the LBP texture feature data and perform non-linear dimensionality reduction for the data. These 2-D projections are then visualized with original images to study data properties. Visualization is utilized in the manner of selecting texture models for unlabeled data and analyzing feature performance when building training set for a classifier. The approach is experimented with simulated image data illustrating different paper properties and on –line transilluminated paper images taken from running paper web in the paper mill. The simulated image set is used to get quantitative figures of the performance while the analysis of real-world data is an example of semi supervised learning.Shu Liao and Albert C.S. Chung [12] in their paper on "Texture Classification by Using Advanced Local Binary Patterns and Spatial Distribution of Dominate Patterns" have proposed a new feature extrication method, which is robust against rotation and histogram equalization for texture classification to this end, we introduce the concept of Advanced Local Binary Patterns (ALBP), which reflects the local dominant structural characteristics of different kinds of textures. In addition, to extract the global spatial distribution feature of the ALBP patterns, they in cooperate ALBP with the Aura Matrix measure as the second layer to analyze texture images. The proposed method has three novel contributions. (a) the proposed ALBP approach captures the most essential local structure characteristics of texture images (i.e. edges, corners); and (b) the proposed method extract global information by using Aura Matrix measure based on the spatial distribution information of the dominant patterns produced by ALBP: and (c) the proposed method is robust to rotation and histogram equalization. The proposed approach has been compared with other widely used texture classification tests to randomly rotated and histogram equalized images in two different texture databases: Brodatz and CUReT. The experimental results show that the classification accuracy of the proposed method exceeds the ones obtained by other image features.Zhenhua Guo, Lei Zhang [13] in their paper on "A Completed Modeling of Local Binary Pattern Operator for Texture Classification" have given a completed modeling of the LBP operator is proposed and an associated completed LBP (CLBP) scheme is developed for texture classification. A local region is represented by its center pixel and a local difference sing-magnitude transform (LDSMT). The center pixels represent the image gray level and they are converted into a binary code, namely CLBP-Center (CLBP_C) by global thresholding. LDSMT decomposes the image local differences into two complementary components: the signs and magnitudes, and two operators, namely CLBP-Sign (CLBP_S) and CLBP-Magnitude (CLBP_M) are proposed to code them. The traditional LBP is equivalent to the CLBP-S part of CLBP, and we show the CLBP_S preserves more information of the structure than CLBP_M, which explains why the simple LBP combining CLBP_S, CLBP_M and CLBP_C features into joint or hybrid distributions, significant improvement can be made for rotation invariant texture classification.Rafi Md. Etal [14] in their paper on "Texture Classification Using Multimodal Invariant Local Binary Pattern" have given texture information among pixels can be effectively represented using Local binary patterns (LBPs), image descriptors built using LBPs or its variants have been frequently used for various image analysis applications, e.g. medical image and texture image classification and retrieval. However, neither LBP nor any of its existing variants can be used to build descriptors for classifying multimodal images effectively. This is because the same object when captured in different modalities may result in opposite pixel intensity in some corresponding parts of the images, which in turn will cause their descriptors to be very different. To solve this problem, we propose a novel modality invariant texture descriptor which is built by modifying the standard procedure for building LBP. In this paper, we explain how proposed descriptor can be built efficiently. We also demonstrate empirically that compared to all the state of the art LBP-based descriptors, the proposed descriptor achieves better accuracy for classifying multimodal images. Mohamed Eisa [15] in their paper on "Local Binary Patterns as Texture Descriptors for User Attitude recognition" have described that texture plays an important role in numerous computer vision application. Many method for describing and analyzing of textured surfaces have been proposed. Variations in the appearance of texture caused by changing illumination and imaging conditions for example, set high requirement on different analysis methods. In addition, real-world applications tend to produce a great deal of complex texture data to be processed that should be handled effectively in order to be exploited.A local binary pattern (LBP) operator offers an efficient way of analyzing textures. It has a simple theory and combines properties of structural and statistical texture analysis methods. LBP is invariant against monotonic gray-scale variations and has also extensions to rotation invariant texture analysis. Analysis of real-world texture data is typically very laborious and time consuming. Often there is no ground truth or other prior knowledge of the data available, and important properties of the textures must be learned from the images. This is a very challenging task in texture analysis.Janne Heikkil¨a and Ville Ojansive [16] in their paper on **"**Methods for local phase quantization in blur-insensitive image analysis" have proposed that Image quality is often degraded by blur caused by, for example mis-focused optics or camera motion. Blurring may also deteriorate the performance of computer vision algorithms if the image features computed are sensitive to these degradations. In this paper, he presents an image descriptor based on local phase quantization that is robust to centrally symmetric blur. The descriptor referred to as local phase quantization (LPQ) can be used to characterize the image texture. He has also presented a de-correlation scheme and propose three approaches for extracting the local phase information. He has showed experimentally that these operators have slightly varying performance under different blurring conditions. In all test cases, including also sharp images, the new descriptors can outperform two state-of-the-art methods, namely, local binary pattern (LBP) and a method based on Gabor filter banks.K. Meena, Dr. A. Suruliandi [17] in their paper on "Local Binary Patterns and Its Variants for Face Recognition" observed that face recognition is one of the most important tasks in computer vision and Biometrics. Texture is an important spatial feature useful for identifying objects or regions of interest in an image. Texture based face recognition is widely used in many applications. LBP method is most successful for face recognition. It is based on characterizing the local image texture by local Binary Pattern (LBP) and its modified models Multivariate Local Binary Pattern (MLBP), Center Symmetric Local Binary Pattern (CS-LBP) and Local Binary Pattern Variance (LBPV) re investigated. Facial features are extracted and compared using K nearest neighbor classification. Experiments were conducted on JAFFE female, CMU-PIE and FRGC version2 databases. The results shows that CS-LBP consistently performs much better than the remaining other models. B.Sujatha, Dr. V.Vijaya Kumar, Dr. P.Harini [18] in their paper on "A New Logical Compact LBP Co-Occurrence Matrix for Texture Analysis" have observed that texture is an important spatial feature, useful for identifying objects or regions of interest in an image. Statistical and structural approaches have extensively studied in the texture analysis and classification where as little work has reported to integrate them. One of the most popular statistical methods used to measure the textural information of images is the grey-level co-occurrence matrix (GLCM). The present paper combines the Logical Compact LBP with OR operator (LCLBP-OR), which is derived on textons, with GLCM approach and LCLBPCM using three stages. The LCLBP-OR reduces the texture unit size from 0 to 255 to 0 to 15 and achieves much better rotation invariant classification than conventional LBP. The LCLBP-OR values are obtained by applying the logical OR operator in between relative positions of LBP window. To evaluate micro texture features in stage one textons are evaluated. To make texture features relatively invariant with respect to changes in illumination and image rotation LCLBP-OR images are applied on LBP images of texton shapes in stage .later in stage three the GLCM is constructed on CLLBP-OR and first and second order statistical features are evaluated for precise and accurate classification results indicate the proposed LCLBPCM method classification performance is superior to that LBP, Gabor and other methods.

II. OBSERVATION BASED ON LITERATURE SURVEY

The basic LBP operator LBP/C proposed is monotonic invariant to gray scale change and computationally cheap.Unsupervised texture segmentation of texture feature using LBP/C operator is not sensitive to the selection of parameter values, does not require any prior knowledge about the number of textures or regions in the image, and seems to provide significantly better results than existing unsupervised texture segmentation approaches Multiresolution gray scale and rotation-invariant lbp operator is very robust because operator is invariant for both gray scale and rotation and computationally simple with a few operations in a small neighborhoods & a look up table.

Multi-scale binary pattern operator is a novel way of extending the lbp for multiple scale, but incapable to cope up with a large no of local neighborhood. This operator increases the classification accuracy but with increased computational burden.For color texture discrimination, color and texture information should be processed separately. Multidimensional local binary pattern texture feature data can be visually explored and analyzed by utilizing ISOMAP for lbp texture feature data and perform non-linear dimensionality reduction for the data.

An associated completed LBP (CLBP) scheme is developed for texture classification. A local region is represented by its center pixel and a local difference sing-magnitude transforms (LDSMT) and demonstrates that the sign component is more important than the magnitude component in preserving the local difference information. Texture classification using multimodal invariant lbp achieves better accuracy for classifying multimodal images. Classification accuracy for same modality is relatively lower compared to other lbp based method.The CS-LBP descriptor combines the strength of two well-known methods, the SIFT descriptor and the lbp texture operator. CS-LBP has many features which make it suitable for real-world texture data like face recognition and face attitude recognition.Image descriptor based on local phase quantization that is robust to centrally symmetric blur. The descriptor referred to as local phase quantization (LPQ) can be used to characterize the image texture. These operators have slightly varying performance under different blurring conditions. In all test cases, including also sharp images, the new descriptors can outperform two state-of-the-art methods, namely, local binary pattern and Gabor filter.Facial features are extracted and compared using K nearest neighbor classification. Experiments were conducted on JAFFE female, CMU-PIE and FRGC version2 databases. The results show that CS-LBP consistently performs much better than LBP, Multivariate LBP and LBP variance operator. By combining the Logical Compact LBP with OR operator (LCLBP-OR), with

GLCM approach and using LCLBPCM in three stages. LCLBPCM method classification performance is superior to that LBP, Gabor and other methods. Because The LCLBP-OR reduces the texture unit size from 0 to 255 to 0 to 15 and achieves much better rotation invariant classification than conventional LBP.

2.1 Objective

Some research work has been done about texture analysis using LBP Operators, like LBP/C, grayscale rotation- invariant, multi-scale analysis, illumination- invariant, CS-LBP and blur invariant operators etc. however LBP Operator which is illumination invariant, blur invariant using gradient difference to reduce the computational complexity has not been attempted. Therefore generation of new LBP Operator by using two existing operators MI-LBP (2011) & CS-LBP (2012) is proposed. MILBP operator is illumination invariant and CS-LBP operator is suitable for face recognition, hence good results can be expected for face image analysis in any imaging condition like, light intensity variation, change in view point and for out of focus imaging conditions.

III. CONCLUSION

MICS-LBP is a variant of LBP operator, which can reduce the dimensionality of LBP features and capture the gradient information better than basic LBP. In future framework, we can utilize MICS-LBP operator three times to extract three-level face features, which include abundant and discriminative texture features. For capturing face spatial information, the algorithm divides each level face feature into the same size of cells. Then, face images are represented by concatenating the spatial histogram of each cell sequentially. In classification phrase, a nearest neighbor classifier is used to choose the minimum Euclidean distance for testing face images.

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