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TERNARY PATTERNS AND MOMENT INVARIANTS FOR TEXTURE CLASSIFICATION

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Abstract

Texture extraction and classification is the key feature that is used in pattern recognition and classification. Binary patterns are very powerful discrimination operators that are able to extract texture features irrespective of its illumination changes. This paper mainly focuses on extraction of fabric texture patterns that are used in discriminating the defects and the non-defects. A ternary pattern is a powerful tool for extracting the microstructures of the images, used for feature extraction that has robustness towards the illumination invariance. On the other hand, a Zernike moment which is simultaneously invariant to similarity transformation and rotation is also explained. Experimental analysis is conducted both on standard texture images and fabric images. The performance of the proposed approach is evaluated using SVM, KNN and Bayes classifiers.

Keywords:

SVM Classification, Texture Extraction, Ternary Patterns, Moment of Invariants

1. INTRODUCTION

Most of the texture classification algorithms assume that the unknown samples are identical to the training samples properties. However in real world the texture may occur differently varying in illumination, rotation and resolutions. This paper focus on such dissimilarities, providing a solution with ternary patterns and moment of variants.

Kashyap et al. in [1] studied the rotation-invariant texture classification by using a circular auto regressive model. Initially many mixture models were explored to study rotation invariance for texture classification, including hidden Markov model [2] and Gaussian Markov random filed [3]. Varma et al. in [4] proposed to learn a rotation invariant texton dictionary from a training set, and then classify the texture image based on its texton distribution. Ojala et al. in [5] proposed to use the Local Binary Pattern (LBP) histogram for rotation invariant texture classification. LBP is so simple and efficient operator to describe local image pattern, and has achieved impressive classification results on different texture databases.

LBP itself is sometimes used as a lighting normalization stage for other methods [6]. However, in practice the reliability of LBP decreases significantly under large illumination variations. Lighting effects involve complex local interactions and the resulting images often violate LBP's basic assumption that gray level changes monotonically. Another limitation of LBP is its sensitivity to random and quantization noise in uniform and near-uniform image regions. To overcome this Tan et.al in [7] extends LBP to Local Ternary Patterns (LTP), a 3-valued coding that includes a threshold around zero for improved resistance to noise. LTP inherits most of the other key advantages of LBP such as computational efficiency.

This paper is organized as follows, section 1 discusses about the description of texture patterns and the previous done by researchers, section 2 explains briefly about the ternary pattern and it's different from binary pattern. Section 3 clearly depicts the proposed approach concluding with the experimental results that are analyzed in section 4.

2. BACKGROUND

2.1 LOCAL TERNARY PATTERN (LTP)

The local binary pattern (LBP) texture analysis operator is defined as a gray-scale invariant texture measure, derived from a general definition of texture in a local neighborhood. The local binary pattern (LBP) operator was first introduced by Ojala et al. as a complementary measure for local image contrast [6,7]. Since the LBP was, by definition, invariant to monotonic changes in gray scale, it was supplemented by an orthogonal measure of local contrast. Two-dimensional distributions of the LBP and local contrast measures were used as features.

i_0	i_1	i_2
i_3	i_4	i_5
i_6	i_7	i_8

(a)

1	2	4
128	0	8
64	32	16

(b)

Fig.1. (a) LBP Operator Binary Sequence (b) Weighted Thresholds

So this can described mathematically as,

$$LBP\left(x_c, y_c\right) = \sum_{n=0}^{7} s\left(i_n - i_c\right) \cdot 2^n \tag{1}$$

Local ternary pattern extends LBP to '3' value codes in which gray levels in a zone of width 't' around 'i_c', and the binary code is replaced by LTP code. Ternary pattern is given as,

$$LTP\left(u, i_c, t\right) = \begin{cases} 1 & u \geq i_c + t \\ 0 & \left|u - i_c\right| < t \\ -1 & u \leq i_c - t \end{cases} \tag{2}$$

78	99	50
54	54	49
57	12	13

Threshold

1	1	1
0		0
0	-1	-1

Ternary Code: 1100(-1)(-1)00

Fig.2. (a) LTP operator binary sequence (b) Binary outputs

When using LTP for visual matching we could use 3^n valued codes, but the uniform pattern argument also applies in the ternary case.

2.2 ZERNIKE MOMENTS

Zernike polynomials are orthogonal over the unit disk and are specified in polar coordinates in terms of a real valued radial component $R_{nl}(r)$ which is a polynomial of order '*n*', and a complex exponential component, l- is called as repetition.

The radial moment of order '*p*' with repetition '*q*' of image intensity function $f(r,\theta)$ is defined as,

$$D_{p,q}^{(f)} = \int_0^{2\pi}\int_0^1 r^p e^{-jq\theta} f\left(r,\theta\right) dr d\theta \tag{3}$$

where, $0 \le r \le 1$, $p \ge 0$, $q = 0, \pm 1, \pm 2$……...

The Zernike moment of order '*p*' with repetition '*q*' of $f(r,\theta)$ is defined as [8,9],

$$Z_{p,q}^{(f)} = \frac{p+1}{\pi}\int_0^{2\pi}\int_0^1 R_{p,q}\left(r\right) e^{-jq\theta} f\left(r,\theta\right) dr d\theta \tag{4}$$

3. PROPOSED APPROACH

The proposed approach is a mixture of ternary patterns and Zernike moments. Main objective of this paper is to provide an efficient image classification which is robust against illumination and rotation. The concept is implemented for real time fabric images which consist of both defectives and non-defectives. The procedure for the proposed approach is as follows

1. Read an image, preprocess and normalize
2. Apply ternary pattern to extract the texture code
3. Apply Zernike moments of order 5 and extract the moment invariants
4. These invariants are stored as feature vector for an image.
5. To evaluate the performance of the image, dataset are divided into training and testing subsets
6. Classification of the features are done with SVM (Support vector machines), KNN (K-nearest Neighborhood).

3.1 PRE-PROCESSING (CONTRAST ENHANCEMENT)

Contrast: This refers to the differences in luminance between the object and its surroundings. In psycho visual studies the contrast '*C*' of an object with luminance '*f*' against its surrounding '*b*' is defined as [13],

$$c = \frac{f-b}{f+b} \tag{5}$$

Many approaches have been proposed by the researchers so far to get more appropriate results out of the image that were obtained from the sensors/camera. In this paper the contrast enhancement is based on Contrast-Limited Adaptive Histogram Equalization (CLAHE).

This method is based on the general idea of adaptive histogram equalization but the limitation of the conventional Adaptive Histogram Equalization (AHE) is with the slope of window cumulative distribution function, if it is too high then the resultant image would be noisy. This limitation can be overcome in CLAHE by limiting each bin of histogram to a certain maximum value, any value more than this is uniformly distributed to the remaining bins which will be reducing the slope of the CDF and eliminates many of the artifacts that were produced with the conventional AHE. Processing images with CLAHE gives a natural appearance as it provides comparison of area within the image. On the other hand, enhancement with CLAHE may hinder the aptitude of the observer to distinguish some important gray scale levels [14].

3.2 SVM CLASSIFIER

SVM is an extensively used classification tool accommodating a great deal of success in many applications. This perform pattern recognition between two classes by finding a decision surface that has the maximum distance to the closest point in the training set. Assuming linearly separable data, the goal of maximum margin classification is to separate the two classes by a hyper-plane such that the distance to the support vectors is maximized. This hyper-plane is called as the optimal separating hyper-plane (OSH) which has the form,

$$f\left(x\right) = \sum_{i=1}^{1} \alpha_i y_i x_i \cdot x + b \tag{6}$$

The coefficients in the above equation are the solutions of a quadratic problem. Classification of the new data point *x* is performed by computing the sigh of the right side of the equation. So this will allow applying multi class classification.

$$d\left(x\right) = \frac{\sum_{i=1}^{1} \alpha_i y_i x_i \cdot x + b}{\left\| \sum_{i=1}^{l} \alpha_i y_i x_i \cdot x + b \right\|} \tag{7}$$

The sign of *d* is the Classification result for *x* and |*d*| is the distance from *x* to the hyper plane [10,11,12].

Different types of kernels are used like,

i. Linear $K\left(x,y\right) = x.y$

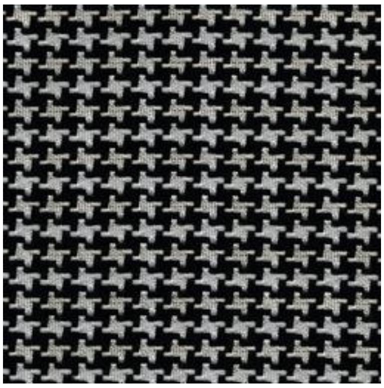
ii. Polynomial $K\left(x,y\right) = \left(\gamma x.y + c\right)^{\text{degree}}$

iii. Radial Basis Function $K\left(x,y\right) = e^{-\gamma|x-y|^2}$

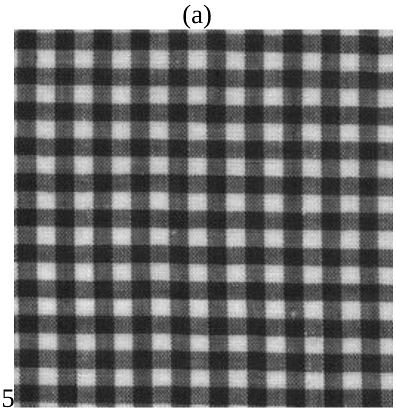
iv. Sigmoid $K\left(x,y\right) = \tanh\left(\gamma x.y + c\right)$

4. EXPERIMENTAL RESULTS

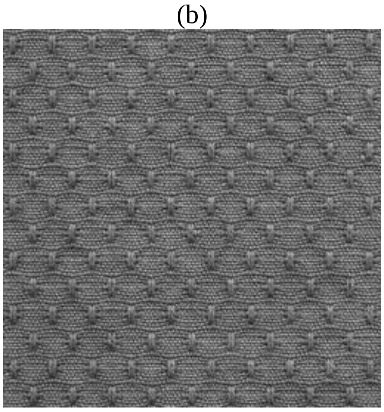
In this paper to assess the performance analysis of the proposed approach two datasets are considered for texture analysis Brodatz texture database [15] and Fabric Texture database [16]. Few sample test images are shown below in Fig.1. The classification is performed using SVM and KNN approaches.



(a)



(b)



(c)

Fig.2. Fabric Images (a) Star type (b) Square type (c) Mesh Type

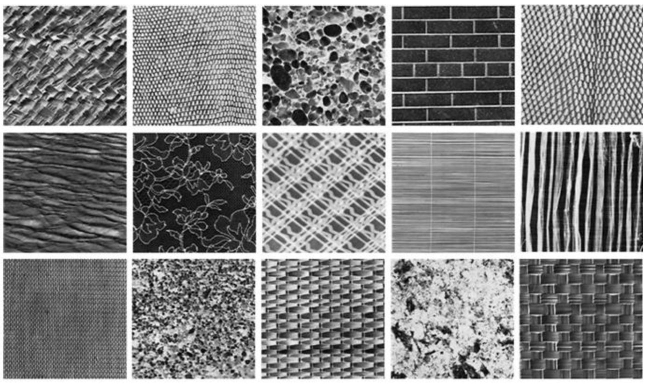


Fig.3. Brodatz texture images

The experiments were conducted on Matlab tool. The images are rotated with 10, 20 45 degrees in clock wise and counter clockwise direction and they are also scaled with different factors.

Feature extraction is done according to the algorithm mentioned in section 3. The classified results are represented graphically in Fig.4 and Fig.5. For the analysis, the original images have been trained, however, for testing the images are scaled and rotated as mentioned above. For the evaluation of performance, the analysis was performed on 200 images and the mean accuracy is represented.

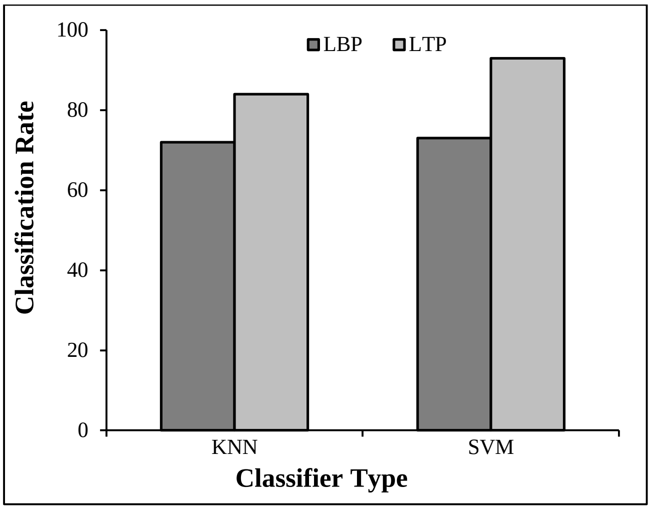


Fig.4. Classification analysis for fabric dataset images using SVM and KNN

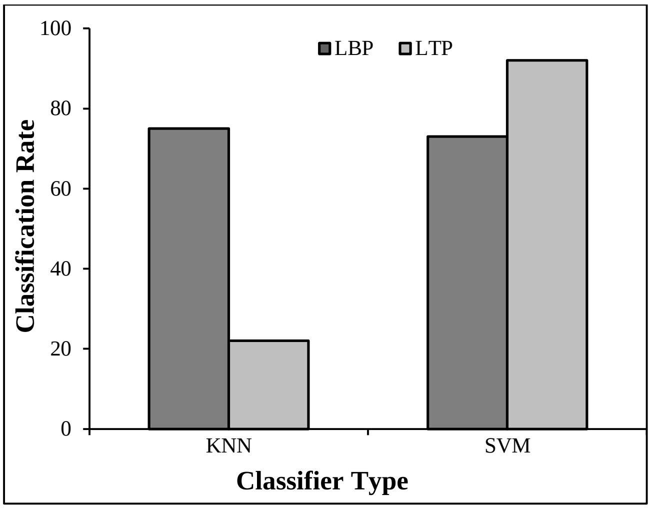


Fig.5. Classification analysis for Brodatz dataset images using SVM and KNN

5. CONCLUSION

The present research paper discuss as about the application of ternary patterns for texture extraction and pattern recognition which is classified using SVM classifier. The proposed approach also discuss about the Zernike moments for feature analysis. This approach was tested on two dataset and found that the present ternary approach is yielding an improvement in classification of about 23% on an average with two different classification approaches. So it is here by concluded that the ternary patterns are very much suitable for extraction of complex textures than binary patterns. This work can be further extended by using more sophisticated classifiers like Bayes and neural networks.

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