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Texture Classification using Local Binary Patterns and Modular PCA

Sayanshree Ghosh, Srimanta Kundu and Sayantari Ghosh

***Abstract*— Texture classification is one of the traditional challenges in the field of pattern recognition. In this paper, we propose a technique to classify textures using two very powerful tools: Modular PCA (m-PCA) and Local Binary Patterns (LBP). Being an advanced version of conventional PCA, m-PCA focuses more on various portions of a texture, which results into enhanced recognition and improved robustness. On the other hand, LBP is a well-known texture operator, which has been used for object segmentation. The proposed algorithm combines these two feature extraction approaches into one. We get highly competitive results which prove the effectiveness of the proposed methodology.**

***Index Terms*— LBP, m-PCA, Texture Recognition.**

I. Introduction

Texture analysis is one of the classic problems in pattern recognition and computer vision [1]. Though there is no precise definition for textures, but these are repetitive patterns, identifiable by humans, and they are very important in perceiving the 3D shapes of physical objects. That is why textures are considered to be essential source of visual information. The major issues that are generally addressed in texture analysis can have several branches, like, texture classification [2, 3], feature extraction [1], texture discrimination [2], reconstruction of 3D shapes from textures [4,5], understanding surface geometry by texture analysis [1] etc.

Texture classification, as the name suggests, is a process to assign a particular texture into one of the predefined categories, which are generally referred as *texture classes*. This has immense opportunity of application in the fields of industrial surface inspection, biomedical diseased state detection, satellite image identification etc. [6]. To classify different texture segments, various pattern recognition tools have been used so far. The most popular algorithms with this particular application are Bayesian decision theory [7], nonparametric *k*-nearest neighbor classifier [8], and various neural network based approaches, like multilayer perceptron [9].

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***Sayanshree Ghosh**, Wipro Technologies, Kolkata, India, Mobile No: (+91)9614487565*

***Srimanta Kundu**, Dynamic Digital Private Limited, Kolkata, India, Mobile No: (+91) 988322152.*

***Sayantari Ghosh**, Amity University, Kolkata, India, Mobile No: (+91) 8902217293.*

An effective classification tool involves an extensive description of texture features. Local Binary Pattern (LBP) is known as one of the strongest feature extractor tools in texture domain [10, 11]. In this paper, we have combined LBP with another powerful technique, modular PCA (m-PCA), which has already proved its effectiveness on face recognition. Gottumukkal and Asari have shown in their paper how it works better than conventional PCA in different conditions like variation in expression and illumination [12]. In our paper we have used LBP as a feature extractor from the images. Different properties of LBP (like rotation invariance, uniformity etc.) has been used to generate the feature strip from the images. The output of this step, which is a normalized LBP histogram, has been fed to m-PCA module. The flowchart in the following section will indicate the major steps of the process. We have proved the superiority of our method over m-PCA; one sample result has been provided for Brodatz dataset. This paper has been organized as follows: after the introduction, Section 2 will give the brief description of the mathematical formulas for m-PCA and LBP consecutively. Section 3 will show the process in flow chart format. Section 4 presents one sample result and the relevant references are given in Section 5.

II. MATHEMATICAL MODELS

A. *Modular Principal Component Analysis (m-PCA)*

In m-PCA [12] algorithm, the original image is divided into equal sized sub images for enhancement. Suppose, there are total K number of images in the database. Each image has a size of $L\times L$. M number of images are considered as the training set. In the database, suppose there are Γ number of images of a particular texture pattern, and among those, S number of individual textures are taken into the training set. For m-PCA, each image in the training set is divided into N smaller images; these sub-images can be represented mathematically as,

$$I_{ij} = I_i\left(\frac{L}{\sqrt{N}}(j-i) + m, \frac{L}{\sqrt{N}}(j-i) + n\right) \ \forall i,j \quad (1)$$

where, i varies from 1 to M, j varies from 1 to N, and m (as well as n) vary from 1 to $\frac{L}{\sqrt{N}}$.

So, for the training set images average image can be denoted as A and compute as below,

$$A = \frac{1}{M.N}\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ij} \quad (2)$$

So, as per traditional PCA method, the normalized training set will as below,

$$Y_{ij} = I_{ij} - A \quad \forall i,j \tag{3}$$

and, the covariance matrix can be calculated as,

$$C = \frac{1}{M.N}\sum_{i=1}^{M}\sum_{j=1}^{N} Y_{ij} . Y_{ij}^{T} \tag{4}$$

Suppose, eigenvectors $(E_1 E_2, \dots, E_{M'})$ associated with M' largest eigenvalues have taken into account, and the weight values are computed as,

$$W_{snjK} = E_K^T . (I_{snj} - A) \quad \forall s,n,j,K \tag{5}$$

where, K varies from 1 to M', n varies from 1 to Γ and s varies from *1* to S. So, mean weight will be,

$$V_{sjK} = \frac{1}{\Gamma}\sum_{K=1}^{M'}\sum_{n=1}^{\Gamma} W_{snjK} \quad \forall s,j \tag{6}$$

Weights for the testing set can be evaluated as,

$$W_{test\ jK} = E_K^T . (I_{test\ j} - A) \quad \forall j,K \tag{7}$$

Finally, to calculate the distance below equation can be followed,

$$D_{sj} = \frac{1}{M'}\sum_{K=1}^{M'} |W_{test\ jK} - V_{sjK}| \tag{8}$$

$$D_s = \frac{1}{N}\sum_{j=1}^{N} D_{sj} \tag{9}$$

So, if $Min(D_s) < \Theta_i$ for a particular value of s, the corresponding texture pattern in the training set is recognized as belonging to the s^{th} texture class.

B. Local Binary Patterns (LBP)

Local Binary Patterns (LBP) [13-18] is a well built feature extraction tool in pattern recognition. It follows the two axioms - gray scale invariance and rotation invariance. For these two important properties, LBP has been used successfully in different domains of computer vision like face detection, facial expression recognition, brain MR image analysis etc.

The mathematical formulation has been composed using the neighborhood point's pixel value. LBP can be defined by using a texture T in a local neighborhood of a pixel. Texture T can be defined and evaluated in the following way:

$$T = t(n_c, n_0, n_1, n_2 \dots n_{P-1})$$
$$T = t(n_c, n_0 - n_c, n_1 - n_c, n_2 - n_c \dots n_{P-1} - n_c)$$
$$T \approx t(n_c)t(n_0 - n_c, n_1 - n_c, n_2 - n_c \dots n_{P-1} - n_c)$$
$$T \approx t(n_0 - n_c, n_1 - n_c, n_2 - n_c \dots n_{P-1} - n_c)$$
$$T :\approx t(sign(n_0 - n_c), sign(n_1 - n_c) \dots sign(n_{P-1} - n_c))$$

where
$$sign(x) = \begin{cases} 0 & if\ x \le 0 \\ 1 & if\ x > 0 \end{cases} \tag{10}$$

Here n_c is the gray value of the centered pixel and n_p $(i = 0, 1, 2 \dots P-1)$ corresponds to the gray values of equally spaced pixels on a circle of radius R $(R > 0)$ that form a circularly symmetric neighbor set. Here 'R' is called spatial resolution and 'P' is called angular resolution. Considering n_c as origin, then the coordinate point of n_i is given by,

$$(x_{ni}, y_{ni}) = (-Rsin(2\prod i/P), Rcos(2\prod i/P)) \tag{11}$$

Derived mathematical form the LBP formulation will be like [10, 13],

$$LBP_{P,R} = \sum_{i=0}^{P-1} (sign\ (n_i - n_c) 2^i) \tag{12}$$

Rotation invariant property will modify the above form as follows [10, 13],

$$LBP_{P,R}^{ri} = \min\{ROR(LBP_{P,R}, i)\}$$
$$where, i = 0, 1, 2 \dots P-1 \tag{13}$$

where $ROR(x, i)$ performs a circular bit-wise 'i' times right shift on the P bit number x; 'min' operator will just take the minimum decimal values from different patterns.

A binary pattern is called "uniform" if it contains at most *2* spatial transitions (bitwise 0/1 changes). Based on this uniformity concept, a new LBP value ($LBP_{P,R}^{riu}$)can be computed by summing up the bit values A binary pattern is called "uniform" if it contains at most *2* spatial transitions (bitwise 0/1 changes). Based on this uniformity concept, a new LBP value ($LBP_{P,R}^{riu}$)can be computed by summing up the bit values of a rotation invariant binary pattern if it is uniform, or a miscellaneous label *P+1* can be assigned if it is non-uniform. The uniform property is defined as follows [10]:

$$LBP_{P,R}^{riu2} = \sum_{p=0}^{P-1} \left(sign\ (n_p - n_c)\right) \ if, U(LBP_{P,R} \le 2$$
$$= (P+1) \quad otherwise$$

where,

$$U(LBP_{P,R}) = |sign\ (n_{p-1} - n_c) - sign\ (n_0 - n_c)|$$
$$+ \sum_{p=1}^{P-1} |(sign\ (n_p - n_c) - sign\ (n_{p-1} - n_c)| \tag{14}$$

Signed differences $(n_i - n_c)$ are not affected by changes in mean luminance because if a pixel is affected by noise then there is a high chance that its neighborhood pixels will be affected by it more or less in same manner.

C. Collaboration of Principal Component Analysis and Local Binary Pattern

PCA and LBP collaboration has been used for the first time for face recognition in the year of 2011. Md. Jan Nordin and Abdul Aziz K. Abdul Hamid [19] presented an improved face recognition performance by a combination of two techniques, one appearance-based and the other, feature-based, on the T-Zone face area. This study shows that the combined technique of LBP and PCA provides a significant impact on the face recognition rate. Experiments have been carried out on the different sets of the Olivetti Research Laboratory (ORL) database. High recognition rates are obtained when compared to other face recognition methods of the same class. Mirzaei and Toygar [20] used subpattern-based approaches to solve the age classification problem on facial images. Subpattern-based LBP, sp-PCA and m-PCA are used for feature extraction on different datasets selected from FG-NET and MORPH databases.

In this paper, for the first time, to the best of our knowledge, m-PCA and LBP collaboration has been applied for texture images. We have experimented with different texture datasets using our algorithm. In the following sections, the algorithm and sample results have been described.

III. ALGORITHM

Local Binary Pattern is a powerful feature extractor tool and the main advantage of using PCA [21] is data compression, by reducing the number of dimensions. In our proposed algorithm, we have used LBP and Modular PCA one after another. A block diagram of the basic steps of the algorithm is shown in Fig. 1. Firstly the texture images have been partitioned into equal sized regions; the number of regions may vary. Each sub-image has been directly feed to the LBP algorithm. In LBP, we have set different experimental parameters as follows: angular resolution (P) as 8, spatial resolution (R) as 1 and most importantly the type of LBP used in our experiment is uniform (u2). Using (P = 8, R = 1), the number of features has become 59 [10] for each sub-image. All the region based outputs are appended and ultimately it contains global information together. So, if we consider number of regions as 16, then the total number of attributes will be $16 \times 59 = 944$ for a single image.

The sub-image strip [10] produced by LBP algorithm has been used as the input of m-PCA. This is nothing but the LBP Histogram. In statistical analysis, a histogram is a representation of the distribution of different parameters in an event. We can store the LBP information of a particular image in histogram form and then analyze that histogram using some statistical operators for example Chi-square, Log statistic etc or we can apply some soft computing tools on it like SVM, MLP etc. Here the histogram strips are divided into smaller strips and the PCA approach is applied to each of the small part.

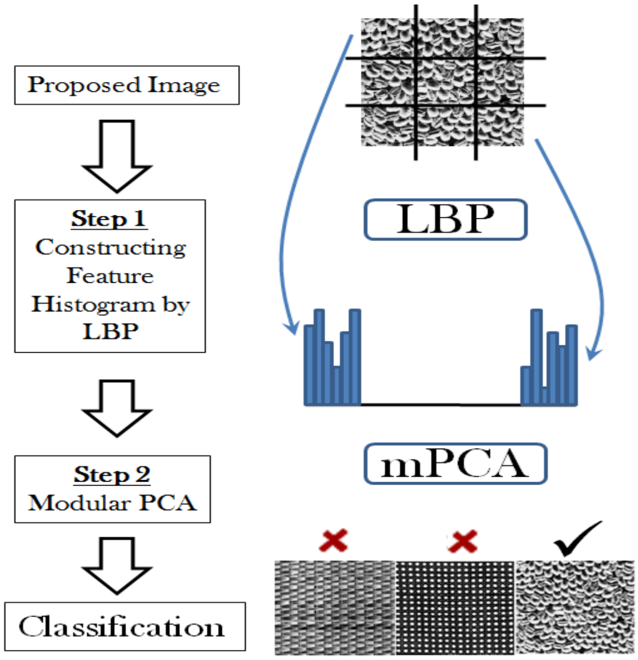

Figure 1: Block Diagram of the proposed algorithm

IV. RESULTS

Texture classification methods usually have two steps: learning and detection [1]. In learning phase the goal is to build a model for the specific texture contents (such as, spatial structure, contrast, roughness, orientation etc.) of the training set and define each of the texture classes. Then, in the detection phase, the texture features of the unknown samples are compared to the classes using some classification algorithm.

The competence of a classification tool is estimated by several aspects. Firstly it should cope with the rotational and spatial scale variability. Next, the algorithm should be illumination invariant and it should sustain under unstable lighting conditions. The model should also be robust under noisy input images; along with that, the minimum sample size needed for a meaningful classification is another vital point to take care of. Finally, for real-time visual inspection and retrieval of large databases, the computational complexity of the algorithm should be taken into account.

Table: 1 Broadatz Dataset: Feature u2						
16 Sub-images						
Reduced Dimension	Training 10%		Training 20%		Training 25%	
	mPCA	LBP_mPCA	mPCA	LBP_mPCA	mPCA	LBP_mPCA
60%	59.26%	83.67%	64.06%	93.44%	63.33%	97.78%
80%	64.35%	85.65%	61.98%	95.83%	62.78%	98.89%
100%	59.72%	87.96%	60.94%	97.40%	67.22%	99.16%
25 Sub-images						
Reduced Dimension	Training 10%		Training 20%		Training 25%	
	mPCA	LBP_mPCA	mPCA	LBP_mPCA	mPCA	LBP_mPCA
60%	65.74%	93.52%	68.75%	95.13%	68.33%	96.67%
80%	64.81%	93.06%	64.06%	95.31%	68.89%	98.89%
100%	65.74%	96.57%	65.10%	96.88%	64.44%	99.16%

Table 1: Comparison of the proposed methodology with the existing methods for Broadatz Dataset. For 16 and 25 sub-images, for different training set fraction, the percentage of successful detections have been charted here. We have compared the successful classification with only modular PCA, with that of the prescribed LBP-mPCA technique. A clear rise in efficiency has been detected. Results are shown for different reduced dimensions.

We performed extensive experiments to test the effectiveness of our algorithm under all the criteria mentioned above. We have used Broadatz Dataset for our experiments [22]. As already discussed earlier, for the Modular PCA, we need to divide the texture image into number of regions, or *sub-images*. In our case, for each image we have decided to proceed with 16 (or 25) equal sized sub-images. A subset of the data has been used to train during the learning phase to build the texture model. We have chosen three separate percentages (10, 20 and 25) of the total number of images for this training, which restricts the *training sample size*. After getting the feature histogram from LBP, we proceeded with Modular PCA where three different percentages of the reduced dimension has been taken into account. For each specific case, the experiment has been done for 20 times and the average has been shown in Table 1.

From the results, it can be seen that efficiency is increased with increasing Training percentage and decreasing reduced dimension percentage. But, irrespective of these parameters, LBP and mPCA collaboration outperform Modular PCA in every scenario. Our algorithm is also proved to be efficient under different rotational effects. There are different angles of rotation among the images of the dataset. We have verified the efficiency, by training with only the zero rotation images, and by testing with rotated versions. Fig. 2 is representing the performance of our method for rotation invariance.

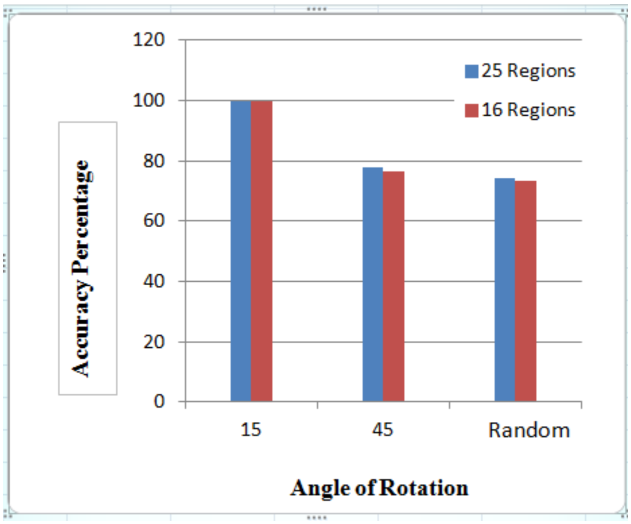

Figure 2: Experimental results for rotational invariance. The bar chart shows the percentage of accurate detections when the training set is consisting of only zero rotation textures and the test set contained rotated figures of the same texture. We are reporting here three sets of experimental results, while the rotation in the test set was (a) 15 degrees, (b) 45 degrees and (c) any random angle. We have performed the test run with both 16 and 25 sub-images.

V. CONCLUSION

The prescribed methodology, combining of LBP and mPCA, is proved to be competent with all the aspects mentioned above. It performs better than mPCA in texture domain and resulted significant improvement in recognition accuracy. For image data LBP itself acts as a strong feature extractor which leads mPCA to produce good outcome. Supremacy of the algorithm has been proved by showing different results on the texture image databases. More than 30% improvement we have achieved in some cases.

Though texture classification has various possible applications, dealing with real textures are difficult. Most of the times, these images are not uniformly illuminated. Other features that cause specific complexities are contrast, directionality, granulation, density, coarseness, regularity, linearity, frequency, randomness, perceived lightness etc. As a scope of improvement we can use the riu2 type of LBP as it is operating on texture images. On the other hand weight factor can be adaptively set in mPCA to make algorithm more effective. Among all the variants of PCA, sub-pattern PCA [23, 24] can be also used for betterment as it has been delivered promising outputs for many research areas. We plan to proceed with these ideas in future.

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Sayanshree Ghosh is a young researcher from Calcutta. She completed her B.Tech. (2011) from West Bengal University of Technology. She qualified Graduate Aptitude Test for Engineers (GATE) and has just completed her M.Tech. (2015) in Computer Technology from Jadavpur University, Kolkata. Her research interests lie in pattern recognition, facial recognition, general classification and segmentation techniques etc. She is currently an employee of Wipro Technologies, Kolkata.

Srimanta Kundu did his Bachelor of Engineering (2009) and Master of Engineering (2011) both from Jadavpur University. Currently he is working at Polaris Networks as a Senior Software Engineer. He has Scored 98.13 percentile in GATE 2009, Computer Science and got the MHRD GATE scholarship. He has received the ERASMUS MUNDUS INDIA4EU scholarship to study in Universidad Politecnica de Madrid (Spain) as an exchange student from Jadavpur University for a period of 10 months in 2010 during his Masters.

Sayantari Ghosh did her Ph.D. degree from Bose Institute, Kolkata in 2014. She received the Msc. degree in Physics from Jawaharlal Nehru University Delhi, India, in 2008. She worked in IIT Delhi for sometimes. She has 4 yrs of teaching experience. Her research interest includes 'Non linear dynamics', 'Image Processing' etc.