M^3 Robust Noise Resistant Extended Linear Binary Pattern Exclusively for Hand Geometry and Iris Images

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***Abstract*— Linear Binary Patterns consists of the most efficient pattern recognition technique to extract patterns. But Linear binary pattern are most sensitive to noise. To avoid this problem, in this paper a novel new idea of m^3 robust noise resistant extended local binary pattern technique is taken and it is tested with the palm and iris images. The proposed technique is different from other existing techniques where in traditional LBP the small pixel value is most vulnerable to noise, whereas in this technique the noise patterns are encoded as non-uniform codes. Thus the noise patterns appear very less frequent than uniform codes. Additionally, the proposed scheme also computes multiscale LBP that identifies both microstructure and macrostructure information. Thus our proposed technique produces the best noise tolerance score as 99.89%, 99.37% and 99.66%. CASIA Iris image database and CASIA Hand geometry Image database are used to compare the results with existing systems. Application areas are surveillance systems and on various applications the proposed technique demonstrates than traditional techniques.**

Keywords*— Linear binary pattern, feature extraction, Threshold detection, authentication, feature extraction.

I. INTRODUCTION

Linear Binary Pattern converts an image into array of integer images which explains about the pixel pattern and its immediate neighbors. LBP technique [1]- [5] encodes the pixel difference of image as its binary code. Thus the images are used to analyze further. LBP techniques are used in facial analysis, human detection, texture classification and many applications. Many of the existing techniques are not having the capability of performing better for real world application. In this proposed work the concentration is made on extracting powerful texture features like high quality description and low computational complexity. Texture classification is one of the most important issues in texture analysis to know how the texture recognition process works in various applications of computer vision and image processing. High quality descriptors are known as providing distinctiveness, due to wide range of robustness, texture classification, scale, blur and noise. Representing low dimension relates to running the entire application task in real time. Many research works has been carried out to achieve strict quality and low computational speed.

Linear binary patterns are the most emerging texture descriptors where it is used in the field of computer vision and image analysis. Linear image analysis has many advantages such as easy to implement, low computational complexity and invariance to illuminating changes. Even though LBP method is used for texture analysis, it has been successfully applied to many real world problems like dynamic texture recognition, visual inception, face image analysis, motion analysis, edge detection and environment modeling. In LBP is used to limit the noise in LBP histogram. The LBP codes are defined as uniform patterns from 0 to 1 or vice versa. The mapping of LBP mapping is used for each uniform pattern and all non-uniform patterns are accumulated in a single bin. Thus the noises in non-uniform patterns are statistically insignificant and probabilistically more reliable.

Principal component analysis approach and random sequence approach were utilized on uniform and non-uniform patterns to extract information [6]-[10]. Non uniform codes are used to extract the information in this technique. These approaches still sensitive to noise. There are many techniques which describe about the various extensions of LBP. Completed Local Binary Pattern (CLBP) [11], Extended Local Binary Pattern (ELBP), Discriminative Local Binary Pattern (disCLBP) [12]-[14], Dominant Local Binary Pattern (DLBP) are used to increase robustness of the system. But they have image blur and corrupted noise. It also suffers from increased computational complexity. In order to overcome the shortcomings of the existing techniques we propose a simple and efficient computational technique known as M^3 Robust Noise Resistant Extended Linear Binary Pattern technique which uses Hand Geometry and iris images. M^3 means is a combination of Mean, Median and Mode. These three Ms are combined in a well suited ratio and the desired results are obtained. The contributions of the proposed technique are highlighted as follow:

- Encode noise resistant LBP
- Find local mean, median and mode using novel sampling technique
- Evaluate the proposed method on various benchmark texture datasets.

The reminder of this paper is organized as follows. Section II explains about the related work. Section III explains the proposed methodology. Section IV presents the experimental results. Section V concludes this paper.

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II. RELATED WORK

In this approach robustness of noise is improved using fuzzy LBP (FLBP)[15]. In order to do that they used linear fuzzy membership function. The Gaussian membership function is also used. Ojala et al proposed another technique which uses spatial structure. The local image is patched by encoding the central point and pixel values between the neighbors. They propose that certain LBP patterns uses fundamental texture microstructures and these microstructures group the uniform patterns as p+1 invariants.

Extended binary pattern is used to find the relationship between the central point and its neighbors. Their approach is known as ELBP[16] which encodes the local regions and that contains spatial information. This technique finds the intensity of the center pixel, neighbor pixel and the differences in radius. LBP technique is most popular because of its simplicity in nature and robust to various illumination variations. In uniform LBP all histogram bin are applied to each pattern and the other non-uniform bins are used in single bin. The uniform patterns are statistically more insignificant and thus they are noise prone. The non-uniform bins are grouped into one label but the noise pattern for non-uniform pattern is suppressed and the number of patterns are reduced significantly.

The dominant LBP patterns are classified as the frequent texture image. Completed Local Binary Pattern (CLBP) is used to find the discriminative features. Many authors worked regarding Local Ternary Pattern (LTP)[17] where the image noise is tackled in uniform regions. In their technique the pixel difference is encoded as 3-valued code. The ternary code is split into positive and negative dimension. The two threshold values are used to reduce the dimensionality of the data. LTP is very less sensitive to noise in uniform regions. In order to deal with gray scale intensity changes LTP is used as four binary code values. The center symmetry LTP is proposed to reduce high dimensionality of LTP. In local adaptive ternary pattern a constant threshold is calculated for each window using some local statistics. A special case of LTP is proposed where the equality is modeled as a separate state and a tristate pattern is formulated. The variants of LTP solve the noise sensitive problem. The proposed work uses noise resistant m^3 binary pattern is used. M^3 binary pattern and local quantization techniques are used to find noise resistant local binary pattern.

The ELBP approach uses joint probability distribution that produces good texture classification performance. The ELBP approach proposed is subjected to very sensitive to image blur and noise. This technique also fails to catch texture macrostructure and provides high feature dimensionality. The topology and neighborhood sampling techniques are used to provide geometric local texture patterns on neighborhood images. Medical image texture analysis technique uses different neighborhood topology and encoding the LBP variants for medical image texture analysis. Three patches LBP and four patches LBP is used to find the average path difference magnitudes. In order to improve discriminative power three strategies are used. They are discriminative cluster, exploring co-occurrences and combine discriminative cluster with other texture. Soft LBP[18] histograms are used to enhance the robustness by using fuzzy membership function. Retinal sampling grid uses sampling structure and patch to mimic the retinal grid. Second order derivatives are used in the circular direction. Noise robustness is improved by soft LBP that enhances the fuzzy membership to find local texture primitive. Fuzzy LBP uses binary patterns to generate each pixel position but improves computational complexity. The noise resistant scheme is used to provide most efficient variant. Even though [19][20] many techniques are proposed in literature provides solution the proposed methodology with hand geometry and iris images provides novel and efficient binary pattern technique.

III. PROPOSED METHODOLOGY

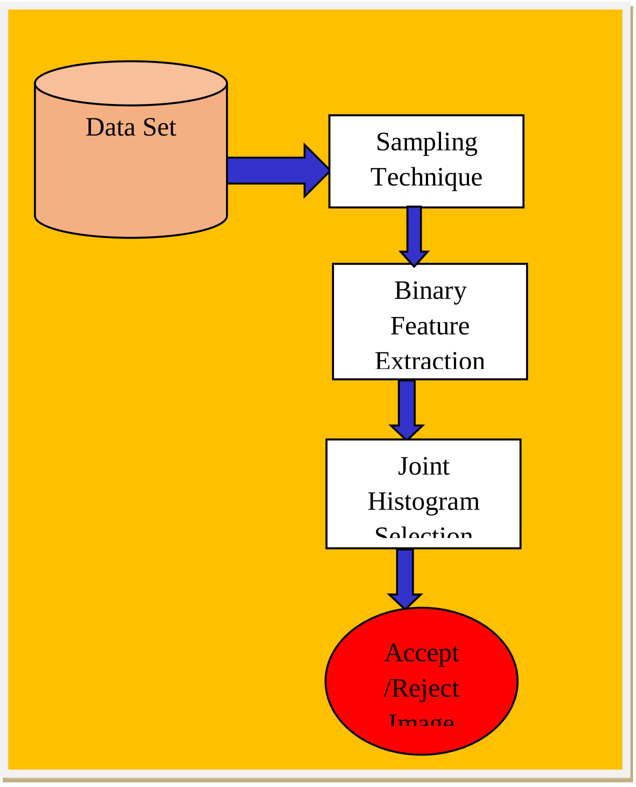

Fig 1. Proposed Technique

Dataset collection and Sampling Technique

The Data set is collected from CASIO database version 4.0 and also hand geometry is obtained in person in Muthayammal and KSR engineering colleges. The sample input images are shown in Fig 2.a,b,c,d.

Fig 2.a

Fig 2.b

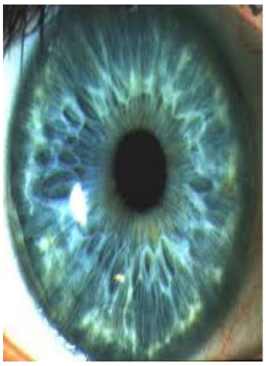
Fig 2.c


Fig 2.d

In order to avoid noise the proposed technique uses small pixel difference as an uncertain bit. The pixel difference is determined into following three states as follows.

$$b_p^N = \begin{cases} 1 & \text{if } z_p \geq t, \\ X & \text{if } |z_p| < t, \\ 0 & \text{if } z_p \leq -t. \end{cases}$$

States 1 and 0 represents positive and negative states. Further if the mode value is repeated more than 5 positions among eight neighbors then it is stated as 0 in addition.

X state is known as uncertain state where the pixel difference is very small. Then the uncertain code is represented by c(x) as follows:

$$\overrightarrow{b_{P-1}^N b_{P-2}^N \ldots b_1^N b_0^N} = C(\mathbf{X}).$$

The uncertain bits are derived from the certain bits from one or more codes of image local structures. The uniform patterns are represented by spot, flat, edge and corner. The non-uniform patterns occur. We have adapted the technique to normalize the image are given between the RELBP and ELBP. The central pixel representation using RELBP technique is given by the following formula,

$$\text{RELBP\_CI}(x_c) = s(\phi(\mathbf{X}_{c,w}) - \mu_w)$$

The neighbor representation is given by the following formula,

$$\text{RELBP\_NI}_{r,p}(x_c) = \sum_{n=0}^{p-1} s(\phi(\mathbf{X}_{r,p,w_r,n}) - \mu_{r,p,w_r})2^n$$

$$\mu_{r,p,w_r} = \frac{1}{p}\sum_{n=0}^{p-1} \phi(\mathbf{X}_{r,p,w_r,n})$$

In the proposed RELBP Gaussian M^3RELBP is adapted that applies sampling after the smoothing with Gaussian, and then the following M^3 are calculated. Mode is calculated if the centre value is repeated more than 5 times in those eight neighbors then the value zero is assigned to the function or else average/ Mean RELBP is calculated with regional mean and finally calculated Median RELBP is calculated for regional median.

Feature Extraction

The Gaussian logarithmic scale is used to extract the underlying information from the iris and hand geometry feature set. The feature set of iris pattern and hand geometry is generated by convolving the normalized iris pattern and hand geometry with 1D Log-Gabor filter. The Gaussian logarithmic scheme is given by the following equation,

$$G(f) = exp\left(\frac{-\log\left(\frac{f}{f_o}\right)^2}{2\log\left(\frac{\sigma}{f_o}\right)}\right)$$

By applying 1d log-Gabor clear out, the 2d normalized pattern is divided into a number of 1d signals and those are convolved with 1d Gabor wavelets. The rows of the 2d normalized sample are taken as the 1d signal; each row corresponds to a round ring at the iris location. The angular path is taken, which corresponds to columns of the normalized pattern, on the grounds that maximum independence happens within the angular path. The filter is built via calculating the radial filter out issue which includes middle frequency of clear out and normalized radius from the center of frequency plan. The resultant complex capabilities are phase quantized and encoded into binary iris template and hand geometry.

Joint Histogram Selection

In order to find the independence between various images the histogram features are used as the concentration over multiple scales. Histogram feature vectors classification is used in M^3RELBP technique. The following Fig 3 illustrates about the histogram construction for the proposed work.

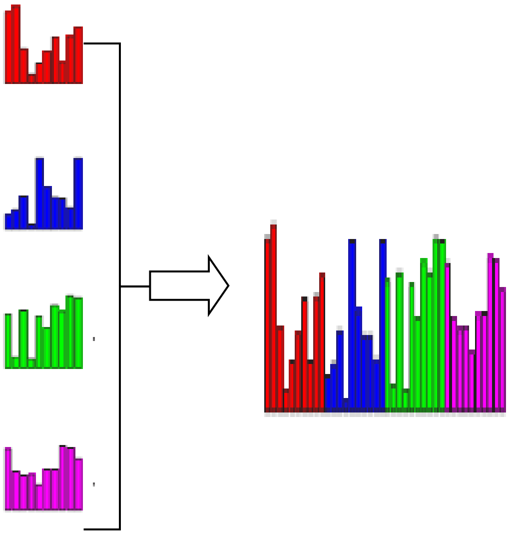

Fig 3. Histogram Concatenation

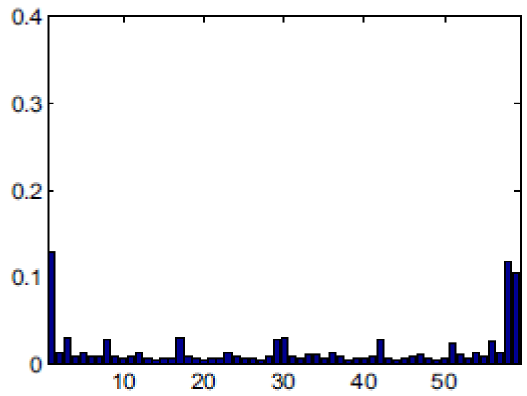

Fig 4. Median Robust Noise Resistant Extended Robust Binary Pattern

The above Fig 4 illustrates the samples from where the histograms are got for the proposed technique. First we concatenated the histogram. Our proposed technique corrects the non-uniform pattern into uniform pattern.

IV. EXPERIMENTAL RESULTS

In this section various numbers of experiments are performed using Matlab 7.0 on an intel Pentium IV 3.0 GHZ processor with the memory of 1 GB memory. Additionally 300 images from 100 people are used. In order to do evaluate the proposed technique training and testing, both CASIO 4.0 database and real world dataset from users are used. The users are aged between age 20 to 50. There were 75% men and 25% women. In this experiment the outputs are compared with proposed technique, LBP and NRLBP. Experimental results proved that the proposed M^3 Robust Noise Resistant Linear pattern out performs all the existing techniques.

Table 1: Performance Comparison of the Proposed Technique with other existing technique

Algorithm	Gaussian Noise	Gaussian Blur
LBP	12.7	89.0
ELBP	12.3	93.8
CLBP	13.5	89.3
NTLBP	15.6	82.1
MRLBP	91.5	97.9
Proposed Technique	99.89	99.39

Table 1 is the performance comparison of the proposed technique with existing technique against noise robustness. The proposed technique has exceptional noise tolerance than other existing techniques. Thus the proposed technique correctly identifies the input image.

CONCLUSION

In the proposed work a novel and efficient approach which is known as M^3 robust noise resistant existent linear binary pattern is implemented. As it is claimed the proposed technique is noise resistant, the experimental results also prove that the technique is noise resistant. It is also proved that the proposed approach also corrects non-uniform patterns to uniform patterns. This method can be accomplished with image patching and object recognition as the future work.

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