TEXTURE CLASSIFICATION USING OPTIMAL LOCAL TERNARY PATTERN WITH NOISE RESISTANT LOCAL BINARY PATTERN

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ABSTRACT

Optimized local Ternary Patterns a new model for texture analysis, already many texture model has been introduce in few years, but more simple and efficient method is Local Binary Pattern (LBP). LBP has some problem like feature vector generation and to handle the challenges like gray scale variation, illumination variation, rotation variation and noise. Optimal Local Ternary Pattern(OLTP) introduce for feature vector generation. The proposed approach LTP extended from LBP. LBP and LTP still have a challenge in noise, so new method has been introduce to reduce the noise namely NRLBP and ENRLBP to capture line patterns both are more resistant to noise compared with LBP, LTP and many other variants. Already the experiment result also refered in proposed texture model improves the classification accuracy and speed the classification process.

***Keywords:* Center-Symmetric Local Ternary Pattern , Extended Noise-Resistant Local Binary Pattern , fuzzy Local Binary Pattern, Local Binary Pattern , Local Ternary Pattern , Noise-Resistant Local Binary Pattern and Optimal Local Ternary Pattern.**

I INTRODUCTION

Image processing is used to extract the useful information from image has an input and extract useful information from the digital image. Image segmentation, Image compression, Image correspondence are some image analysis. Feature extraction is task for sub process in image analysis a feature like color texture and shape from a digital image.Textures are defined as wide variability and is structure composed of large number of more or less similar elements or patterns. Texture has different shapes and model is not adequate for a variety of texture. A texture analysis have four categories they are statistical methods and signal processing methods.

LBP operator transforms an image into an array or image interger labels for micropatterns it has been formed by pixels and immediate neighbours[2].LBP encodes the sign of pixel to pixel difference in neighbourhood to a binary code.The histogram of such code in an image block can be used in texture classification[2],dynamic texture recognition, facial analysis, human detection and many other tasks.LBP is less sensitive to illumination variation extracting histogram of micropatterns in a patch location information is preserved.

1.1 Literature Review and Related Work

Ojala and Pietikyinen, et al proposed In the digital images, the spatial distributions of grey values decide the textural features and hence, statistical methods analyze the spatial distribution of pixel values in the digital image. Based on the number of pixels defining the local feature, statistical methods can be classified into first-order statistical methods, second-order statistical methods and higher-order statistical methods.

Moasheri and Azadinia et al a large number of statistical texture approaches have been proposed, ranging from first order statistics to higher order statistics. As first orderstatistical methods cannot model the texture perfectly, higher order statistics are widely used for texture analysis .

G Haralick et al., proposed Grey level cooccurrence matrices grey level differencesc Weszka et al., and Local Binary Patterns Ojala et al., proposed some of the popular second-order statistical texture methods for texture analysis. Galloway et al and after some years Tsatsanis and Giannakis et al have proved that at the cost of computational complexity, higher than second-order statistical methods could also be used for statistical texture analysis.Geometrical methods are based on the concept that texture could be considered as a spatial organization of texture primitives.

Fu et al proposed an idea in which the texture image is viewed as texture primitives, which are arranged according to a placement rule and texture analysis is a process of identifying those primitives or the placement rule. Matsuyama et al used Fourier spectrum of a texture image to detect texture periodicity for the texture analysis. Liu et al examined the structures of texture patterns in terms of their translation symmetries for the texture analysis.

Xia et al., proposed In model-based methods, mathematical models are used to represent the textures in an image such as fractals random field models by Zhu et al., and so on. Signal processing methods consider the frequency domain of the digital images for the texture feature extraction. Coggins and Jain et al tested multichannel filtering approach using frequency and orientation selective filters for the texture analysis. Under signal processing methods, usage of Gabor filters Daugman, et al and pyramids Heeger et al and Bergen, et al have also been successfully investigated.

II.EXISTING WORK

2.1 Local Binary Patterns (LBP)

The texture model Local Binary Patterns was first developed in [1]. For a 3×3 neighborhood around a centre pixel in an image, the LBP operator. This LBP operator considers a local neighborhood with a certain radius around every pixel in the image and all the neighboring pixels are encoded by thresholding against the centre pixel of the neighborhood by using the piecewise function s(u). Then all the encodedneighboring labels are concatenated to form a binary pattern string and finally the histogram of all these binary pattern strings is used as the texture descriptor. Ojala *et al.* extended their earlier work in the name of Uniform Local Binary Patterns (ULBP) by introducing a new concept called “Uniform patterns”. By considering the uniform patterns, total number of patterns in LBP is reduced from 256 to 58 and it is observed that in a texture image, for a 3´3 neighborhood, nearly 90% of encoded labels are uniform patterns only.

Even after ten years of its introduction, still there have been various extensions and modifications from the original LBP operator, because it is computationally simple and very robust in terms of rotational and gray-scale variations. Some recent developments in medical imaging [1] moving object detection [7] and facial expression recognition [8] prove that the LBP texture model is still receiving a lot of attention. However LBP texture model is considered to be sensitive to noise especially in uniform regions [9] Moreover, it supports only a binary level comparison for encoding and thereby it is inadequate to represent the local texture information.

2.2 Local Ternary Patterns (LTP)

As LBP may be sensitive to noise, a 3-valued pattern instead of a binary pattern was introduced by [1] When a 3´3 neighborhood around a[1] centre pixel in an image is considered, the LTP operator.

Although LBP has gained much popularity because of its simplicity and robustness to illumination variations, its sensitivity to noise limits its performance [2]. In [2], uniform LBP was proposed to reduce the noise in LBP histogram. The LBP codes are defined as uniform patterns if they have at most two circularly bitwise transitions from 0 to 1 or vice versa, and non-uniform patterns if otherwise. In uniform LBP mapping, one separate histogram bin is used for each uniform pattern and all non-uniform patterns are accumulated in a single bin. Most LBPs in natural images are uniform patterns [2]. Thus, uniform patterns are statistically more significant, and their occurrence probabilities can be more reliably estimated. In contrast, non-uniform patterns are statistically insignificant, and hence noise-prone and unreliable. By grouping the nonuniform patterns into one label, the noise in non-uniform patterns is suppressed. The number of patterns is reduced significantly at the same time. In [2].information in non-uniform patterns is extracted and also used for classification.

Liao et al. proposed dominant LBP patterns that consider the most frequently occurred patterns in a texture image Zhou et al. and Fathi et al. proposed to extract information from non-uniform patterns based on pattern uniformity measure and the number of ones in the LBP codes. Principal Component Analysis and random subspace approach [2]. were utilized to extract information from the whole LBP histogram including both uniform patterns and non-uniform patterns. These approaches extract some useful information from non uniform codes. However, they tend to be sensitive to noise. “Soft histogram” is another approach to improve the robustness to noise, e.g. a fuzzy LBP (FLBP) using piecewise linear fuzzy membership function [2]. and another using Gaussian-like membership function [2].

A comprehensive comparison between LBP and fuzzy LBP in classifying and segmenting textures is given in [2]. Instead of hard-coding the pixel difference, a probability measure is utilized to represent its likelihood as *0* or *1*. However, the probability is closely related to the magnitude of the pixel difference. Thus, it is still sensitive to noise. Local ternary pattern (LTP) was proposed in [2] to tackle the image noise in uniform regions. Instead of binary code, the pixel difference is encoded as a 3-valued code according to a threshold t. Then, the ternary code is split into a positive LBP and a negative LBP in order to reduce the dimensionality. LTP was shown less sensitive to noise, especially in uniform regions [2]. Subsequently, many LTP variants were proposedin the literature.

Nanni et al. proposed a quinary code of five values according to two thresholds [2] and then split it into four binary codes similarly as LTP. As LTP is not invariant under scaling of intensity values, Liao et al. proposed Scale Invariant Local Ternary Pattern to deal with the gray scale intensity changes in a complex background [2] In order to reduce the high dimensionality of LTP, Center-Symmetric LTP was proposed in [2] Instead of the pixel difference between the neighboring pixel and the central pixel, the pixel difference between diagonal neighbors is calculated. In Local Adaptive Ternary Patterns [2] and extended LTP [2] instead of using a constant threshold, the threshold is calculated for each window using some local statistics, which makes them less sensitive to illumination variations. In Local Triplet Pattern [2] the equality is modeled as a separate state, and a tri-state pattern is formulated. It can be viewed as a special case of LTP [2] LTP and its variants partially solve the noise-sensitive problem. However, they lack a mechanism to recover the corrupted image patterns. Here a Noise- Resistant LBP (NRLBP) and an Extended Noise-Resistant LBP (ENRLBP) is proposed to address this issue.

III.PROPOSED WORK

3.1 Proposed Noise-Resistant LBP

LBP is sensitive to noise. Even a small noise may change the LBP code significantly. Thus, we propose to encode the small pixel difference as an *uncertain* bit X first and then determine X based on other certain bits of the LBP code. For the pixel difference between the neighboring pixel and the central pixel, then encode it into one of the three states

States *1* and *0* represent two strong states where the pixel difference is almost definitely positive and negative, respectively. Noise can unlikely change them from *0* to *1* or from *1* to *0*. State *X* represents an *uncertain* state where the pixel difference is small. A small pixel difference is vulnerable to noise if we only take its sign. More specifically, noise can easily change its LBP bit from *0* to *1* or vice versa. Therefore, encode it as an *uncertain* state regardless its sign.

After derive the *uncertain* code, and determine the *uncertain* bits based on the values of the other certain bits to form one or more codes of image local structures. Uniform patterns represent local primitives, including spot, flat, edge, edge end and corner. They appear much more often than nonuniform patterns in natural images. Since uniform patterns occur more likely than non-uniform ones, we assign the values of *uncertain* bits X so as to form possible uniform LBP codes. A non-uniform pattern is generated only if no uniform pattern can be formed.

Algorithm 1 Histogram construction of the proposed NRLBP
for Every pixel in a patch **do**
1. Derive the *uncertain* code C(X) as in Eqn. (5), (6).
3. Search *uncertain* bits X in the space {0, 1}n so that
C(X) forms uniform LBP codes as in Eqn. (7).
4. Construct the histogram.
if m = 0 **then**
Accumulate the non-uniform bin with 1.
else
Accumulate the bin of each pattern in SNRLBP with
1/m.
end if
end for

. **Figure (1) histogram of LBP, LTP and NRLBP**

The proposed NRLBP corrects noisy non-uniform patterns back to uniform pattern. Figure (1) shows the histogram of LBP, LTP and NRLBP .The threshold t is chosen as 10 for LTP and NRLBP. LTP histogram is the concatenation of positive LBP histogram and negative LBP histogram. The last bin of each histogram is corresponding to non-uniform patterns, and other bins are corresponding to uniform patterns. Clearly, compared with LBP histogram and LTP histogram, non-uniform patterns in NRLBP histogram are reduced significantly from about 35% to about 10% only.

The proposed NRLBP corrects a large amount of non-uniform patterns that are corrupted by the noise back to uniform patterns. The proposed NRLBP is different from LBP and LTP in many other aspects besides the capability of noise resistance and error-correction. The LBP code is one of the NRLBP code set if it is uniform.

The only exception is that the LBP code is non-uniform and is corrected back to uniform code in NRLBP. Compared with LTP, the treatment of *uncertain* state is totally different for NRLBP. For LTP, all *uncertain* bits are set to *0* for positive half and *1* for negative half whereas for the proposed NRLBP, do not hurry for a decision of the *uncertain* bits.

To treat them as if they could be encoded as *1* and/or *0*, and determine their values based on the other bits of the code. Mathematically, for LTP, for positive half and for negative half, value is determine for NRLBP. The number of histogram bin is also different. LTP histogram consists of 118 bins, whereas NRLBP histogram only has 59 bins. For implementation, a look-up table from the *uncertain* code to the feature vector of NRLBP histogram can be precomputed. Then, the feature vector of local image patch can be easily obtained by summing up the feature vector of each pixel in this image patch.

3.2 Proposed Extended Noise-Resistant LBP

The local primitives represented by uniform LBP mainly consists of spots, flat region, edges, edge ends and corners [1], However, a large group of local primitives are totally discarded, e.g. lines patterns, Although those patterns may not appear as frequently as uniform patterns, they represent an important group of local primitives that may be crucial for recognition tasks. Grouping them with other non-uniform patterns into one bin may result in information lost. Therefore, we introduce an extended set of uniform patterns to preserve line patterns. Among all possible line patterns, diagonal lines appear less frequently. In order to keep the feature vector compact, we only choose nearly horizontal or vertical lines.

The proposed extended set of uniform patterns consist of 48 patterns. Including 58 uniform patterns, we derive the extended uniform patterns. Similarly as NRLBP, we can derive the extended NRLBP (ENRLBP). Instead of forming uniform patterns, we form extended uniform patterns as our ENRLBP pattern. In such a way, line patterns are preserved during the encoding process. The number of bins of ENRLBP histogram is 107, which is smaller than LTP histogram that has 118 bins.

3.3 Description of an Optimal Pattern

A uniform pattern is said to be an optimal pattern, if it satisfies the following criteria:

- The pattern string must not contain more than 3 transitions between the successive encoded values (sub patterns) in the pattern string.
- The level of optimality must be greater than or equal to 2.

3.4 Optimized Local Ternary Patterns (OLTP)

The following texture model, Optimized Local Ternary Patterns (OLTP) which is rotational invariant, gray-scale invariant, image histogram equalization invariant and noise resistant is proposed. OLTP operator uses only optimal set of patterns for describing a local image texture This newly proposed texture model, OLTP uses a total number of 24 unique optimal patterns for texture representation. All other patterns are termed as “suboptimal” patterns and grouped under one label 25.

Therefore the dimension of pattern spectrum has been reduced from 6561 to 25, that too with optimal set of patterns. Among these 24 unique optimal patterns, 17 patterns are having a maximum of 2 transitions in their sub patterns 3 patterns are having and there are 4 patterns for some of the pattern strings with relevant details of their uniformity, level of optimality and whether they are optimal patterns or not. some selected texture images from Brodatz album and their corresponding pattern spectrum of the optimal patterns
obtained through proposed OLTP texture model.

IV. CONCLUSION

This study proposed a new spatial method of texture modeling approach called Optimized Local Ternary Patterns (OLTP). This study also introduced a new concept called, “Level of Optimality”, which is very simple and computationally efficient, to select the optimal patterns among the uniform patterns. On one hand, like conventional LBP approach, the proposed method OLTP has the properties of rotation invariant and gray-scale invariant.

On the other hand, like LTP, it has the ability to with stand against the noise also. LBP is sensitive to noise. Even a small noise may change the LBP pattern significantly. LTP partially solves this problem by encoding the small pixel differences into the same state. However, both LBP and LTP treat the corrupted patterns as they are, and lack a mechanism to recover the underlining image local structures. As the small pixel difference is most vulnerable to noise, we encode it as *uncertain* bit first, and then determine its value based on the other bits of the LBP code to form a code of [2] image local structure.

The proposed approaches show stronger noise-resistance compared with other approaches. Inject Gaussian noise and uniform noise of different noise levels on the AR database for face recognition and the Outex-13 dataset for texture recognition. Compared with FLBP, the proposed approaches are much faster and achieve comparable or slightly better performance. They consistently achieve better performance than all other approaches.

Further, it was also experimentally proved that this newly proposed texture model is histogram equalization invariant. The quality of the proposed approach was validated with many numbers of experiments to prove that this OLTP is robust to grey-scale variation, rotation variation, histogram equalization and noise.

This proposed OLTP texture method on one side gives better classification accuracy than recently introduced LTP texture approach. On the other side, it uses only half the number of uniform patterns of LTP method. It was experimentally in [1] proved that the optimal patterns of the proposed texture model OLTP are the fundamental properties of textures and they are the dominant patterns in the uniform patterns of the LTP model. Since the proposed OLTP is robust in every aspect it can be a good replacement for both LBP and LTP. the future work, the proposed texture model OLTP can be tested for image texture segmentation problems. The proposed approach can also be checked for color texture images.

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