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# SOIL TEXTURE CLASSIFICATION AND ANALYSIS WITH LOCAL TERNARY PATTERN (LTP) TECHNIQUE

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**Abstract:**

Texture analysis is one of the significant and useful task in image processing application. A lot of texture analysis models hae been developed and implemented over past few years. Though Local Binary Pattern (LBP) offers robust performance and of simple and dynamic approach, Local Binary Pattern (LBP) is very sensitive to noise and illumination change and gives wrong code. The Proposed paper utilizes Local Ternary Pattern (LTP) to extract the local features of soil texture. Test Soil images features are compared with all the training images using Euclidean's distance. The image with lowest Euclide4an distance is recognized as the true image. If the distance between test image and training images is more than test image is compared as unrecognized image or match not found.

**Keywords**: Local Binary Pattern (LBP), Soil texture, Euclidean distance, Local Ternary Pattern (LTP).

## I. Introduction

Image processing is done to derive useful information from digital images. Image segmentation, image classification, image correspondence and image compression are some of the areas where image analysis is used. Feature extraction is one of the major step in every image analysis. Feature extraction is a sub-process in image analysis in which it derives some of the important features like colour, texture and shape from digital image. Among all the features, texture p[lays a important role in many image analysis tasks. Image analysis based on texture feature is known as texture analysis.

In this paper a novel method for soil texture classification and analysis. Using Local Ternary Pattern this classification is done. Euclidean classifier is used to recognize the test images. Soil texture classification helps in agriculture. Texture analysis is a process of extracting information from the texture images, which defines the spatial variations within the image by using mathematical processes and examples.

## II. Background

In the digital images, the textural features are decided by the spatial distribution of gray values hence, the spatial distribution of pixel values in the digital image can be analyzed by statistical methods. Statistical methods can be classified into first-order statistical methods, second-order statistical methods and higher-order statistical methods [1,2] based on the number of pixels defining the local feature. Many statistical texture methods have been proposed, which are varying from first order statistics to higher order statistics. As first order statistical methods cannot model the texture perfectly, higher order statistics are widely used for texture analysis [3]. Grey level concurrence matrices [4], grey level differences [5] and Local Binary Patterns [6] are some of the popular second-order statistical texture methods for texture analysis. Geometrical methods are based on the concept of texture that could be considered as a spatial organization of texture primitives. Fu [7] proposed a concept in which the texture image can be observed as texture primitives. In this texture primitives are arranged according to the placement rule. The process of analyzing those primitives of the placement rule is known as texture analysis.

### LOCAL INARY PATTERNS:

In previous, local binary patterns (LBPs)[13] have aroused increasing interest structure of images efficiently by comparing each pixel with its adjoining pixels. Tolerance to monotonic illumination changes and computational simplicity are the main properties of local binary pattern. LBP was originally proposed for texture analysis and later it became a strong approach to relate local structures. By using of decimal numbers the actual LBP operator labels the pixels of an image, which are known as LBP codes. These codes encode the local structure for each pixel. It represents as illustrated in Fig. 1.Every pixel is compared with its eight neighbors in a 3 × 3 neighborhood by subtracting the center pixel value; the obtained negative values are encoded with 0 and the positive values with 1. For each given pixel, a binary number is formed by concatenating all these binary values in a clockwise direction, starting from the top-left neighbor. The decimal value of the generated binary number is then used for labeling the given pixel. The derived binary numbers are known as LBPs or LBP codes.

$$LBP_{P,R} = \sum_{i=0}^{P-1} s(P_i - P_c) \times 2^i, s(x) = \begin{Bmatrix} 1\ if\ x > 0 \\ 0\ otherwise \end{Bmatrix}$$

where P is the number of the sampling pixels on the circle, R is the radius of the circle, pc corresponds to the gray value of the central pixel and pi corresponds to the gray value of each sampling pixel on the circle.

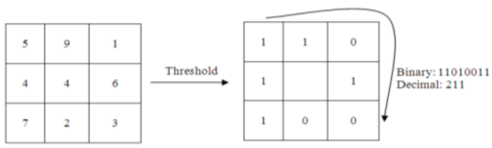


**Figure 1.** An example of the basic LBP operator.

Later LBP technique has been developed with large number of variations to improve performance in different applications of image processing. These variations target is to improve the discriminative capability of it. The ELBP [15] is an approach to improve the discriminative capability of LBP. The ELBP operator performs binary comparison between the central pixel and its neighbours. By using some additional binary units it encodes their exact gray-value differences (*GDs*). Especially, the ELBP feature consists of several LBP codes at multiple layers, which encodes the grey value difference between the central pixel and its neighbouring pixels. As shown in Fig. 2, the first layer of ELBP is actual LBP code that encodes the sign of grey alue difference. The following layers of ELBP then encode the absolute value of *GD*. Now, each absolute grey value difference value is first encoded in its binary representation, and then all the binary values at a given layer result in an additional LBP. For example, in Fig. 4, the first layer is the original LBP code that encodes the sign of *GD*, thus yielding a decimal number of 211 from its binary form (11010011)2. The absolute values of *GD*, i.e., 1, 5, 3, 2, 1, 2, 3, and 0, are first encoded in their binary numbers: (001)2 , (101)2 , (011)2 , (010)2 ,. . ., etc. Using same weight scheme of LBP on all the binary bits, its ELBP code of the corresponding layer can be generated e.g., *L*2 is composed of (01000000)2 , and its decimal value is 64; *L*3 is composed of (00110110)2 , and its decimal value is 54; finally, *L*4 is composed of (11101010)2 , and its decimal value is 234. As a result, when describing similar local textures ,although the first layer LBP is not discriminative enough, the information encoded in the additional layers can be utilized to distinguish them. Its downside is that ELBP increases feature dimensionality to a large extent.

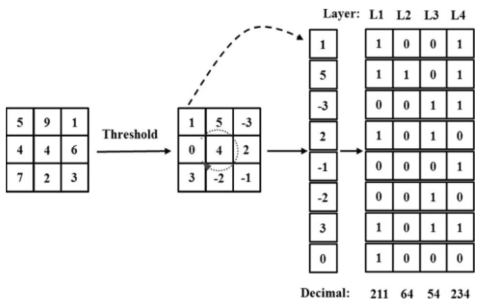


**Figure 2**. Example of the ELBP operator

## III. Proposed Work

### Local Ternary Pattern:

The LBP is sensitive to noise, because a small gray change of the central pixel may cause different codes for a neighborhood in an image, especially for the smooth regions. In order to overcome such a flaw, Tan and Triggs extended the basic LBP to a version with three-value codes, which is called the local ternary pattern (LTP). In LTP, the indicator s (x) is further defined as:

$$LTP_{P,R,T} = \sum_{i=0}^{P-1} s(P_i - P_c) \times 3^i, s(x) = \begin{Bmatrix} 1\ if\ x \geq T \\ 0\ \ if\ IxI < T \\ -1\ if\ x \leq\ -T \end{Bmatrix}$$

where T is a threshold specified by the user. In order to reduce the feature dimension, a coding scheme is also represented by Tan and Triggs by splitting each ternary pattern into two parts: the positive part and the negative part, as illustrated in Figure 3. Though the LTP codes are more resistant to noise, it is no longer strictly invariant to gray-level transformations, because _ is constant in feature extraction for all neighborhoods and all images in the database.

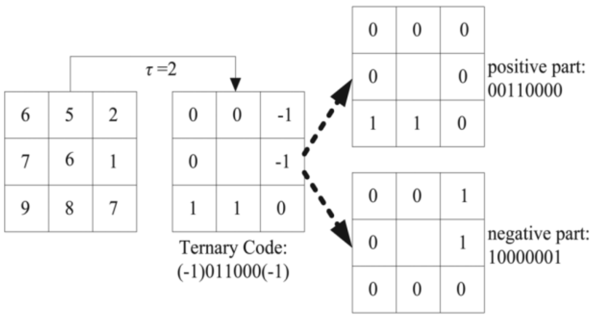


**Figure 3.** Calculation of the LTP with eight neighboring pixels.

This paper proposes a navel method for extraction of features using Local Ternary Pattern (LTP) and signed bit multiplication, which uses central pixel for feature computation. The extracted features are main component of the initial set of learning images (training set).Once the features of test images are extracted, the image is classified by comparing its feature vector with other train vectors in database using Euclidean classifier. If the minimum Euclidean distance of test image is more than threshold that means test image is not present in train database and displayed as match not found otherwise the train image which has minimum Euclidean distance is displayed as recognised image. Even in the presence of occlusion, pose variation, expression and illumination change face recognition technique should provide good recognition rate. The advantage of this approach is over other face recognition system is its simplicity, speed and sensitivity to small or gradual changes on face. The workflow process of face recognition system is shown in Figure 4.

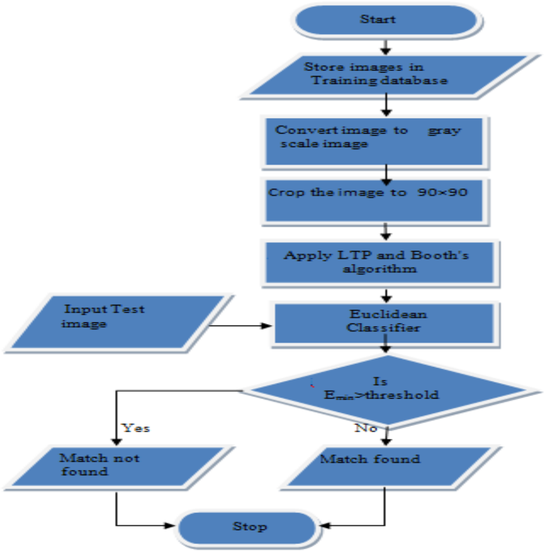


**Figure 4**: Workflow process of face recognition system

## IV. Experiment Results

In order to verify the effectiveness of the segmentation process using the proposed method, a group of images of different kinds were tested. The performance evaluation of two methods has been described based on tables of values and graphs shown in the paper. Three texture images of Pebbels and beach of different soil images have been shown in Fig 5 & Fig 6 of size 256X256 were considered in this experiment. Each test sample is compared using LBP and proposed method and classified. Table1 & Table2 show the classification performance of the proposed texture model and ELBP. Proposed method is considered as a good texture classifier, it clearly classifies all three types of images. Among the two texture methods under consideration, the proposed texture method delivers superior classification.

**Figure 5**.Pebbel images

| IMAGE | Pebbel LTP | Beach LTP |
|---|---|---|
| I1 | 0.224 | 0.240 |
| I2 | 0.231 | 0.252 |
| I3 | 0.234 | 0.241 |
| I4 | 0.236 | 0.249 |
| I5 | 0.240 | 0.257 |
| I6 | 0.248 | 0.267 |
| I7 | 0.250 | 0.268 |
| I8 | 0.250 | 0.271 |
| I9 | 0.253 | 0.294 |
| I10 | 0.254 | 0.318 |

**Table 1.** ELBP

### V. Conclusion

The LBP operator has been theoretically simple yet a very powerful method of analyzing textures. Through the extension developed during this paper, the **LTP** operator was made a really powerful measure of image texture showing outstanding results in terms of accuracy and computational complexity in many empirical studies. In this paper, we analyzed ELBP and consequently a new scheme, namely LTP is proposed. Two operators, ELBP and LTP are defined to classify the texture images. Finally, LTP operator gives much better texture classification accuracy than ELBP operator which obtained.

**Figure 6**.Beach images

| IMAGE | Pebbel ELBP | Beach ELBP |
|---|---|---|
| I1 | 0.039 | 0.026 |
| I2 | 0.0431 | 0.031 |
| I3 | 0.044 | 0.041 |
| I4 | 0.048 | 0.042 |
| I5 | 0.048 | 0.045 |
| I6 | 0.05 | 0.048 |
| I7 | 0.054 | 0.063 |
| I8 | 0.054 | 0.063 |
| I9 | 0.06 | 0.066 |
| I10 | 0.065 | 0.067 |

**Table 2.** LTP

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