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Texture Classification Using High-Order Local Derivative Pattern and KNN Classifier

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Abstract- Texture classification is a fundamental issue in image processing and computer vision. It has been used in material classification, surface analysis, document analysis, and industrial automation. In this paper, a texture classification algorithm based on Local Derivative Pattern (LDP) is proposed. The algorithm extracts high-order directional texture features from grayscale images and represents them using normalized histograms. A K-Nearest Neighbor (KNN) classifier with cosine distance is employed to classify texture images into multiple categories. Simulation experiments on a practical texture image database demonstrate that the proposed algorithm can achieve accurate classification results with low computational complexity.

Index Terms - Local Derivative Pattern, Texture Classification, High-Order Descriptor, Cosine Distance, KNN, Image Texture Analysis.

I. INTRODUCTION

Texture is a prominent visual cue that can be defined as the spatial arrangement of intensity variations in an image. Texture analysis has numerous applications in computer vision, including material analysis, biomedical image analysis, surface defect detection, remote sensing, and document analysis [1],[2],[9],[10]. A good texture representation should be able to extract local structural information and be insensitive to illumination changes and noise. Early texture classification methods mainly relied on statistical and spectral techniques such as gray-level co-occurrence matrices (GLCM), autocorrelation functions, and Fourier-based representations [3]. Although these approaches provide useful global texture information, they often fail to capture fine local variations that are critical for distinguishing visually similar textures. Local pattern-based descriptors received more attention owing to their high discriminative power and efficiency. Among these descriptors, the Local Binary Pattern (LBP) operator was one of the most popular texture descriptors [4]. LBP describes the local texture pattern by comparing the central pixel with its neighboring pixels and assigning a binary pattern to it. Because of its simplicity and invariance to gray scale, LBP has been successfully used in several texture classification tasks [5],[17],[18]. Although LBP is very effective, it only captures first-order local intensity variations and does not consider the directional derivative information. This means that it might not be able to capture complex textures with higher-order spatial relationships. To overcome this problem, high-order local descriptors have been proposed. The Local Derivative Pattern (LDP) was introduced as a high-order local texture feature that describes the changes of directional derivatives rather than pixel values [6]. The use of derivative direction variations allows LDP to offer more detailed texture information and enhance the discrimination power for complex textures. In this paper, we investigate the use of Local Derivative Pattern for texture classification. Local Derivative Pattern features are derived from texture images and represented by normalized histograms. A K-Nearest Neighbor classifier with cosine distance is used for classification. The performance of the proposed method is tested on a multi-class texture database. The remaining part of this paper is organized as follows. Section II discusses related work in texture classification. Section III describes the proposed approach. Section IV discusses implementation. Results are presented in Section V, while conclusions are drawn in Section VI.

II. RELATED WORK

Texture classification has been widely researched in the literature of image processing. Statistical techniques like GLCM describe second-order statistics of pixel intensity distributions, but their results are highly sensitive to parameter tuning and image resolution [3]. Frequency domain techniques, such as Gabor filtering and wavelet analysis, examine textures at various scales and orientations [7],[11]. While these techniques offer detailed descriptions of textures, they can be computationally expensive. Local pattern-based features, especially LBP and its variants, have gained popularity because of their ease of use and effectiveness [4],[5]. Various modifications of LBP have been proposed to enhance robustness and feature discriminability, including uniform LBP and rotation-invariant LBP. To describe higher-order information, Local Derivative Pattern (LDP) was proposed as an extension of LBP [6]. Unlike LBP, LDP describes the transitions of directional derivatives, which is more appropriate for describing complex texture layouts. Recent research has shown that LDP performs better than LBP in various pattern recognition problems, particularly in the context of textured surfaces and detailed structural variations [6],[12],[14]. In recent years, local pattern-based descriptors have become popular due to their efficiency and reliability. Among these, the Local Binary Pattern (LBP) method stands out; it works by evaluating each pixel in relation to its surrounding neighbors and encoding these comparisons as binary sequences. Mathematically, the LBP operator is defined as:

$$LBP(x,y) = \sum_{p=0}^{p-1} s(I_p - I_c)2^p$$

where I_c is the center pixel and I_p represents neighboring pixels.

Although LBP performs well for many texture problems, it fails to capture higher-order variations. To overcome this limitation, Local Derivative Pattern (LDP) was introduced, which encodes changes in derivative directions instead of raw intensity differences. High-order LDP descriptors have been shown to improve discrimination capability for complex textures.

III. PROPOSED METHODOLOGY

A. Local Derivative Pattern (LDP)

Local Derivative Pattern is a high-order local texture descriptor that captures directional derivative transitions [6]. Unlike LBP [4],[5], which encodes pixel-level comparisons, LDP encodes the relationship between local derivatives [6].

First-order derivatives of an image along four directions are defined as:

$$D_0 = I(x,y) - I(x,y-1)$$
$$D_{45} = I(x,y) - I(x-1,y+1)$$
$$D_{90} = I(x,y) - I(x-1,y)$$
$$D_{135} = I(x,y) - I(x-1,y-1)$$

The second-order LDP encodes changes in derivative signs using a binary coding function:

$$f(a,b) = \begin{cases} 1, & if sign(a) \neq sign(b) \\ 0, & otherwise \end{cases}$$

The final LDP code is formed by concatenating directional patterns, resulting in a 32-bit descriptor per pixel.

B. Histogram-Based Feature Representation

After computing the LDP image, a histogram is generated to represent texture distribution:

$$H(k) = \frac{1}{2} \sum_{i=1}^{N} \delta(LDP_i = k)$$

Where:

- N is the total number of pixel
- $k \epsilon [0, 255]$
- δ is the Kronecker delta function

Histogram normalization ensures scale invariance and robustness.

C. Classification Algorithm

For texture classification, the K-Nearest Neighbor classifier is utilized. K-Nearest Neighbor is a classical non-parametric classifier that has been broadly utilized for pattern recognition [15], [16]. Cosine distance is utilized for the computation of the similarity between two feature vectors:

$$d(X,Y) = 1 - \frac{X.Y}{||x|| y ||}$$

The class label is assigned based on the nearest neighbor.

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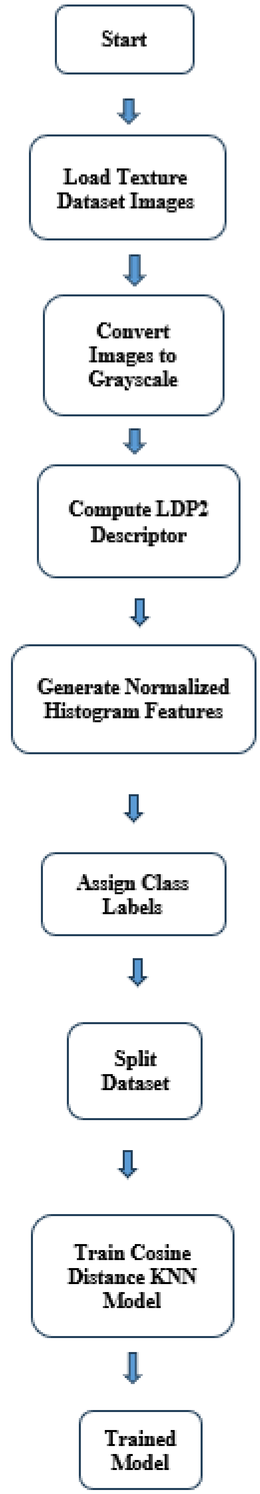
D. Algorithm

Texture Classification Algorithm
Input: Texture Dataset
Output: Predicted Texture Class

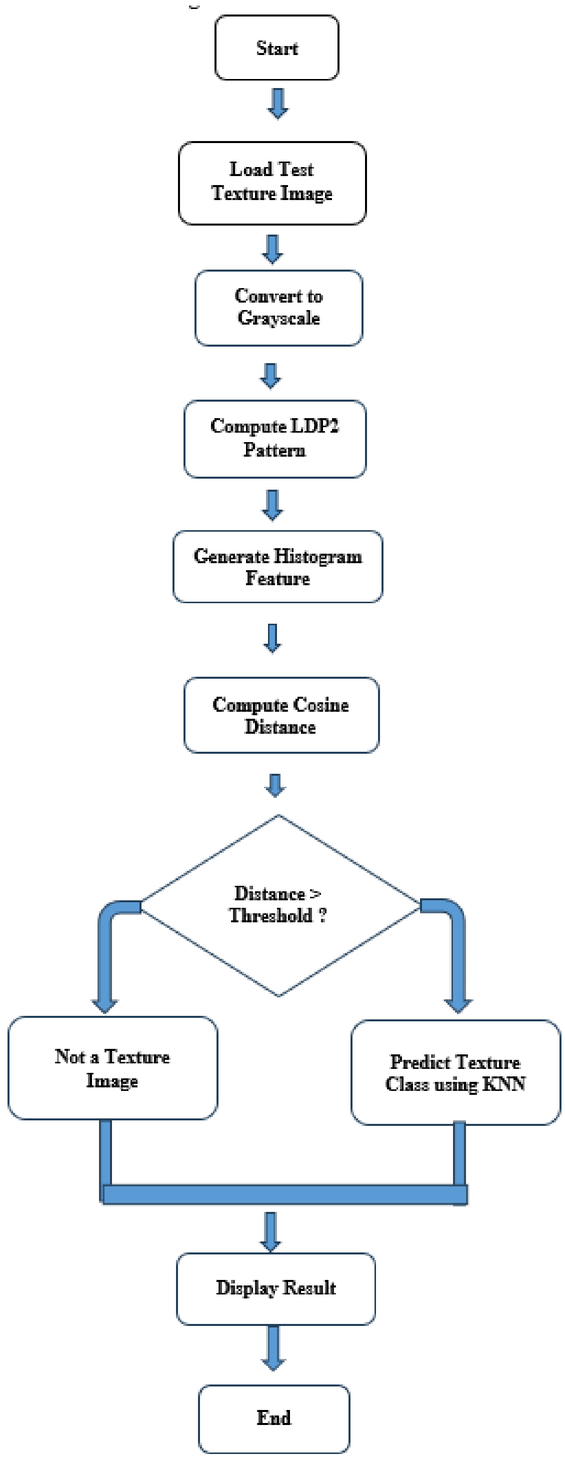
Steps:
1. Read input texture image
2. Convert image to grayscale
3. Apply LDP operator
4. Compute LDP histogram
5. Compute LDP histogram
6. Split dataset into training and testing sets
7. Train KNN classifier
8. Classify test images
9. Compute accuracy and confusion matrix

E. Flow Chart

I. Training Phase Flowchart



II. Testing Phase Flowchart



IV. IMPLEMENTATION

The proposed texture classification system is developed using MATLAB because of its excellent support for matrix manipulation and image processing. The system is developed in a well-organized manner involving dataset preparation, feature extraction, model training, and testing. The texture image dataset is stored in a class-wise directory organization, where each directory corresponds to a separate texture class. Each image in a class is processed separately. During system execution, each texture image is loaded from the dataset directory and transformed into grayscale to simplify the processing and maintain the necessary texture details. Local Derivative Pattern (LDP) features are extracted through a systemically developed code without using any third-party toolboxes [6]. The first-order directional derivatives are calculated in four major directions, and second-order derivative changes are encoded to obtain a 32-bit LDP descriptor for each pixel . The extracted LDP descriptors are combined to obtain an LDP image, which effectively captures the local texture details. A histogram of LDP codes is calculated for each texture image to show the distribution of local patterns . The histogram is then normalized to obtain a compact and scale-invariant feature vector. These feature vectors are stored along with their respective class labels to create the feature database. For classification purposes, a K-Nearest Neighbor (KNN) classifier is used [15],[16]. The database is randomly split into 70% for training and 30% for testing to assess the performance of the system. Cosine distance is used as the distance metric, and the number of nearest neighbors is fixed to one. Besides the evaluation based on the dataset, the system is also capable of testing on new images of textures. The test image is processed through the same preprocessing and feature extraction phases, and the feature vector is then matched with the trained feature database. A distance threshold is used to decide if the input image is from a valid texture class or not. Performance analysis of the classification is done through accuracy measures and confusion matrix analysis, which give information on the class-level recognition accuracy. The implementation shows that the proposed approach is computationally efficient and easy to implement.

V. RESULTS AND DISCUSSION

The proposed texture classification system is tested using a texture image dataset with various texture classes. The texture image dataset is split into training and testing subsets with a 70:30 ratio. This ensures that the training and testing processes are balanced. The

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texture images are processed one by one to extract the Local Derivative Pattern (LDP) features. The performance of the proposed system is tested using the classification accuracy rate. The results show that the LDP feature descriptor is capable of describing the higher-order directional information of textures. The K-Nearest Neighbor classifier with one nearest neighbor and cosine distance performs well on all texture classes. The cosine distance measure is found to be efficient in calculating the similarity between the normalized histogram feature vectors, and this results in better separation of classes. The confusion matrix is employed to examine the performance of the classifier on each class. The test samples are correctly classified with only slight errors being noticed among the visually similar texture classes. This confirms the effectiveness of the proposed feature extraction method. The system is also tested with new texture images, and the classifier correctly identifies the valid texture classes. The experimental results validate the proposed LDP-based texture classification method to be accurate with low computational complexity.

Table I: Dataset Description and Experimental Settings

Parameter	Description
Number of texture classes	5
Texture categories	Cracker, Cotton, Linen, Aluminium Foil, Mail
Image format	PNG
Feature descriptor	Local Derivative Pattern (LDP)
Feature representation	Normalized LDP histogram
Classifier	K-Nearest Neighbor (KNN)
Distance metric	Cosine distance
Training–testing split	70% training, 30% testing

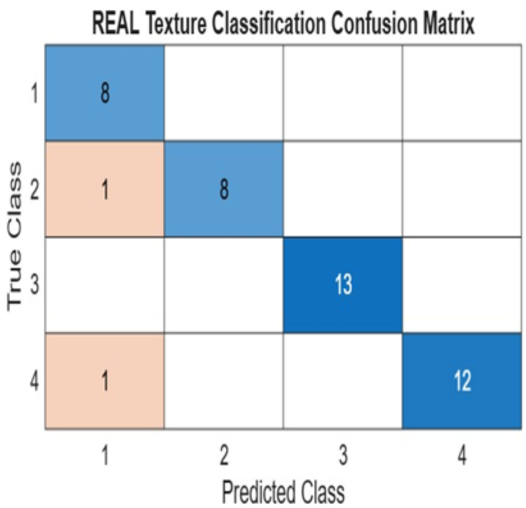
The details of the dataset and the experimentation parameters are given in Table I. The texture image is arranged in a class-wise manner, and each image is processed separately. The Local Derivative Pattern (LDP) features are employed. The texture image is divided into training and testing subsets in a fixed ratio to assess the performance of the texture classification method.

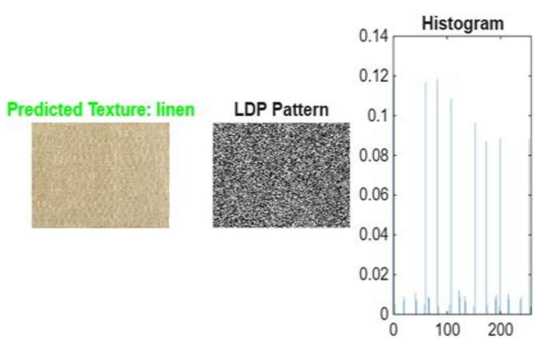
Table II. Performance Comparison with Existing Method

Feature	Existing Method (LBP)	Proposed Method (LDP + KNN)
Texture descriptor	Local Binary Pattern	Local Derivative Pattern
Order of information	First-order	Higher-order directional
Feature representation	Binary pattern histogram	Normalized LDP histogram
Sensitivity to noise	Moderate	Low
Discriminative power	Limited	High
Classifier	KNN / basic classifier	KNN (k = 1)
Distance metric	Euclidean	Cosine
Overall accuracy	Moderate	High

Table II shows the comparison of the proposed method for texture classification with the existing method using the Local Binary Pattern. The comparison shows the effectiveness of the proposed method for the representation of higher-order textures using the Local Derivative Pattern. The proposed method represents the texture using the LDP-based descriptor, which shows the effectiveness of the representation for noise and illumination variations. The representation of the features using the normalized histogram shows the effectiveness of the features. The use of the cosine distance measure by the KNN classifier shows the effectiveness of the similarity measurement. The proposed method shows high accuracy and low misclassification error. The proposed method also shows the effectiveness of the low computational complexity.

The experimental results show that the proposed LDP-based texture classification system has better performance than the traditional LBP-based methods [4],[5]. The LDP method is able to capture the complex local texture variations due to the use of the high-order directional information [6]. Moreover, the use of the cosine distance metric for the KNN classifier improves the separability between the different classes of images. Although the LBP method uses the basic intensity information, it sometimes fails to discriminate between the different textures, especially when the textures have similar intensity distributions. However, the proposed method has better discrimination ability with a slight increase in the computational complexity. The results show that the proposed method has a good trade-off between the accuracy, robustness, and simplicity





Texture Dataset LDP Feature Extraction Completed

REAL Texture Classification Accuracy=95.35 %
Predicted Texture Class: linen
Minimum Distance = 0.0010

VI. CONCLUSION

This paper introduced a texture classification technique using Local Derivative Pattern and KNN classification. The proposed technique is capable of extracting high-order texture information and providing reliable classification results. Because of its simplicity and robustness, the proposed technique can be applied to real-world texture analysis tasks. Future research directions include multi-scale LDP and more sophisticated classifiers.

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