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Noise-Robust Scale-Selective Local Binary Pattern for Texture Classification

M.V. BHUJANGA RAO[1], S. JYOTHI[2], Y. JYOTHI SREE RAM[3], V. SRIVALLI[4], V. AKHIL[5]
[1]*Associate Professor, Department of IT, R.V.R & J.C.C.E Guntur, India*
[2,3,4,5]*Final year Students, Department of IT, R.V.R & J.C.C.E Guntur, India*

Abstract- Texture classification is an important task in computer vision and image analysis with applications in industrial inspection, medical imaging, and remote sensing. Local Binary Pattern (LBP) descriptors are widely used due to their computational simplicity and strong discriminative capability; however, they are sensitive to image noise and scale variations. This paper proposes a Noise-Robust Scale-Selective Local Binary Pattern (NR-SSLBP) with Multi-Sample Feature Averaging to improve robustness in texture classification. The method incorporates noise-reduction preprocessing to stabilize local intensity comparisons and employs multi-scale analysis to capture texture patterns at different spatial resolutions. Dominant patterns across scales are selected to construct discriminative features, while multi-sample feature averaging reduces instability caused by noise and small texture variations. Experimental results show that the proposed NR-SSLBP descriptor improves classification accuracy and robustness while maintaining the computational efficiency of LBP-based methods.

Index Terms- Local Binary Pattern, Multi-Sample Feature Averaging, Noise-Robust Scale-Selective Local Binary Pattern, Nearest Subspace Classifier, Texture Classification

I. INTRODUCTION

Texture classification is an active research topic in the fields of computer vision and pattern recognition. It plays a significant role in various real-world applications such as industrial surface inspection, remote sensing analysis, medical image diagnosis, and material recognition [1]. The main objective of texture classification is to extract meaningful features from images that can effectively represent the underlying structural patterns of textures.

Early approaches to texture analysis mainly relied on statistical and filtering-based techniques. Classical methods such as the gray-level co-occurrence matrix and filter bank models were widely used to capture spatial relationships between pixels in an image [2]. Although these techniques provided useful texture representations, they often required high computational effort and were sensitive to variations in imaging conditions such as illumination, scale, and noise. With the advancement of local feature descriptors, the Local Binary Pattern (LBP) method has become one of the most widely adopted techniques for texture analysis. LBP describes local image structures by comparing the intensity value of a central pixel with its neighboring pixels and encoding the results into binary patterns [3]. Due to its computational simplicity and strong discriminative capability, LBP has been successfully applied to many computer vision tasks including face recognition, dynamic texture analysis, and image classification [4].

Despite its advantages, traditional LBP methods are sensitive to image noise, as small fluctuations in pixel intensity can significantly affect the binary pattern representation. In addition, conventional LBP features are not inherently robust to scale variations, which may occur when images are captured from different distances or resolutions [5]. These limitations can lead to unstable feature representations and reduced classification performance in practical scenarios.

To improve robustness against scale variations, several extensions of LBP have been proposed. One notable approach is the Scale-Selective Local Binary Pattern (SSLBP) method, which constructs a multi-scale representation of the image and extracts dominant local patterns across different scales [6]. By selecting the most representative pattern frequencies among multiple scales, SSLBP provides improved invariance to scale changes while maintaining the efficiency of the original LBP operator. However, the performance of SSLBP may still be affected by noise, which can disturb local intensity comparisons and lead to unstable feature extraction. In practical imaging environments, noise is often unavoidable due to sensor limitations, environmental interference, or image compression

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artifacts. The presence of noise can degrade the reliability of local texture descriptors and negatively impact classification accuracy. Therefore, improving the robustness of texture descriptors to both noise and scale variations remains an important research challenge.

To address these issues, this paper proposes a Noise-Robust Scale-Selective Local Binary Pattern (NR-SSLBP) method combined with a Multi-Sample Feature Averaging strategy for texture image classification. The proposed approach enhances the traditional SSLBP framework by incorporating noise-resistant preprocessing and a feature averaging mechanism that stabilizes the extracted descriptors. Multi-scale analysis is used to capture texture information at different spatial resolutions, while dominant pattern selection ensures that the most informative texture structures are retained. In addition, the multi-sample feature averaging technique reduces feature variability by combining information from multiple texture samples, leading to more stable and reliable classification results.

The main contributions of this work can be summarized as follows:

1. A noise-robust extension of scale-selective local binary patterns (NR-SSLBP) is proposed to improve feature stability in noisy environments.
2. A multi-sample feature averaging strategy is introduced to reduce variability in texture descriptors and enhance classification performance.
3. The proposed method maintains the computational efficiency of LBP-based descriptors while enhancing robustness to noise and scale variations in texture images.

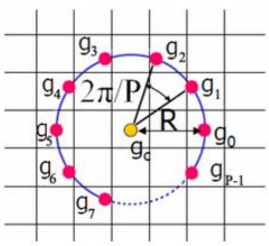

Fig. 1. Central pixel and its P circularly and evenly spaced neighbours with radius R.

The rest of the paper is organized as follows. Section II reviews related work on LBP-based texture descriptors and noise-robust feature extraction methods. Section III presents the proposed noise-robust scale-selective feature extraction scheme in detail. Section IV reports experimental results on texture datasets, demonstrating the effectiveness of the proposed approach. Finally, Section V concludes the paper and discusses potential directions for future work.

II. RELATED WORK

Texture classification has been extensively studied in computer vision, with numerous methods developed to extract robust and discriminative texture features. Early approaches typically utilized statistical measures and filtering techniques, such as gray-level co-occurrence matrices [1] and Gabor filter banks [2], to capture texture information. However, these methods often suffered from high computational complexity and sensitivity to variations in scale, illumination, and noise. The Local Binary Pattern (LBP) operator, introduced by Ojala et al. [3], represents one of the most influential local descriptors for texture analysis. LBP encodes the local spatial structure around a pixel by thresholding the intensity of its neighbors against the central pixel, resulting in a binary pattern that effectively describes micro-textures. Its computational efficiency and robustness to monotonic gray-level changes have led to widespread adoption in various applications including face recognition and dynamic texture analysis [4].

$$LBP_{P,R}(x,y)=\sum_{p=0}^{P-1} q(I(x_p,y_p)-I(x,y))2^P$$

$$q(z)=\begin{cases}1, z\geq 0\\ 0, z<0\end{cases}$$

where, P is the number of sampling pixels in the neighborhoods, R is the radius of a circle for the sampling, and q(z) is a quantization function.

Despite these advantages, the traditional LBP descriptor is sensitive to noise and scale variations, which may degrade its discriminative power in real-world scenarios.

To enhance robustness, several LBP variants have been proposed. The Completed Local Binary Pattern (CLBP) [5] extends LBP by decomposing local differences into sign and magnitude components, encoding richer local texture information. CLBP also incorporates the central pixel intensity to form a composite descriptor, providing improved

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discriminative capability. Although CLBP demonstrates stronger texture representation, it is not without limitations in noisy or highly variable scale settings.

Another existing approach is the Dominant Local Binary Pattern (DLBP) [6], which builds upon the LBP framework by learning dominant local patterns from training data across multiple scales. DLBP selectively captures the most representative texture patterns, improving stability and reducing feature dimensionality. This method has shown promising results in texture classification tasks and inspired further scale-selective designs.

To address the limitation of scale sensitivity more explicitly, the Scale-Selective Local Binary Pattern (SSLBP) [7] constructs a multi-scale texture representation by extracting LBP features at multiple radii and selecting dominant local patterns across these scales. This approach enhances robustness to scale variations while preserving the computational benefits of LBP. Nevertheless, SSLBP's performance can still be compromised by noise, which affects the local intensity comparisons critical for pattern formation. Various noise-robust texture descriptors have been developed to improve stability in challenging imaging conditions. Some methods incorporate preprocessing techniques such as smoothing or median filtering, while others modify the binary coding scheme to reduce noise sensitivity [8]. However, these methods may increase computational cost or sacrifice scale invariance.

In the broader context of texture classification, feature aggregation and averaging strategies have shown promise in stabilizing descriptor representations. Multi-sample feature averaging, for example, combines information from multiple samples or views to mitigate variability caused by noise or illumination changes [9].

The proposed Noise-Robust Scale-Selective Local Binary Pattern (NR-SSLBP) method builds upon these prior works by integrating noise-resistant preprocessing, multi-scale pattern selection, and multi-sample feature averaging to achieve robust and efficient texture classification. This approach aims to overcome the limitations of traditional LBP and SSLBP descriptors in noisy and scale-varying environments. While existing LBP-based descriptors have demonstrated strong performance in texture representation, many of them still face challenges when dealing with image noise and scale variations. Noise can significantly alter local pixel intensity relationships, leading to unstable binary patterns and reduced classification accuracy. Similarly, textures often appear at different spatial resolutions depending on the imaging conditions, which requires effective multi-scale feature representation. Therefore, designing a texture descriptor that is both noise-tolerant and capable of capturing scale-selective patterns is essential for improving classification reliability in real-world scenarios.

Table I : Comparison Table

Method	Key Idea	Advantage	Limitation
LBP	Binary comparison of neighbors	Simple and fast	Sensitive to noise
CLBP	Sign + magnitude components	Richer texture info	Higher complexity
DLBP	Dominant patterns from training	Reduced feature dimension	Requires training stage
SSLBP	Multi-scale dominant patterns	Handles scale variation	Sensitive to noise
NR-SSLBP (Proposed)	Noise-robust SSLBP + feature averaging	Robust to noise & scale	Slight additional computation

It summarizes the strengths and limitations of existing LBP-based texture descriptors. These observations motivate the development of the proposed Noise-Robust Scale-Selective Local Binary Pattern (NR-SSLBP) method to improve robustness against noise and scale variations.

III. PROPOSED METHODOLOGY

A. Overview of the Proposed NR-SSLBP Framework

The proposed Noise-Robust Scale-Selective Local Binary Pattern (NR-SSLBP) method is designed to improve the robustness of texture classification under noisy and scale-varying conditions.

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Traditional LBP-based descriptors rely heavily on local intensity comparisons, which can be significantly affected by noise. In addition, texture patterns may appear at different spatial scales, making it necessary to capture multi-scale structural information.

To address these challenges, the proposed approach integrates three key components: noise-reduction preprocessing, multi-scale feature extraction using scale-selective local binary patterns, and multi-sample feature averaging. First, a preprocessing step is applied to reduce the influence of noise in the input image and stabilize local intensity relationships. Next, SSLBP features are extracted across multiple spatial scales to capture texture patterns of different sizes. Dominant patterns are then selected to represent the most informative local structures. Finally, a multi-sample feature averaging strategy is employed to improve descriptor stability by combining information from multiple samples of the same texture class.

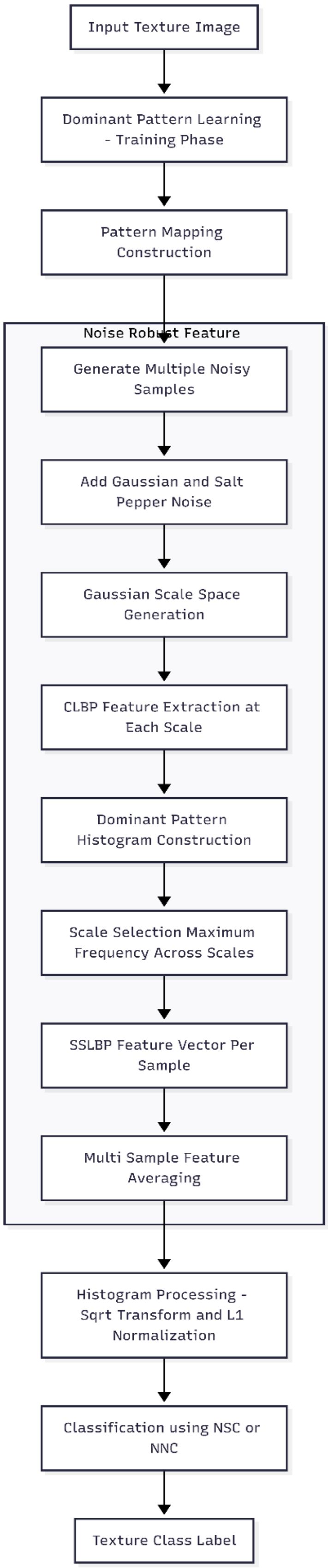
In summary, the NR-SSLBP framework effectively combines noise suppression, multi-scale pattern extraction, and multi-sample feature averaging to produce a robust and discriminative texture descriptor. This integrated approach ensures that the extracted features remain stable across noisy conditions and varying spatial resolutions, making the method suitable for practical texture classification applications. The subsequent section details the experimental evaluation conducted to validate the effectiveness of the proposed methodology.

The overall workflow of the proposed NR-SSLBP method is illustrated in Fig. 2

B. Noise-Reduction Preprocessing

Noise present in texture images can significantly affect the reliability of local intensity comparisons used in LBP-based descriptors. Even small perturbations in pixel values may alter the resulting binary patterns, leading to unstable feature representations. Therefore, it is important to reduce the influence of noise before extracting texture descriptors.

In the proposed method, Gaussian smoothing is incorporated during the multi-scale image construction process to reduce high-frequency noise while preserving the essential structural characteristics of the texture image. This smoothing operation helps stabilize local intensity relationships



used in the LBP computation and improves the consistency of binary pattern generation. As a result, the extracted texture features become more stable

Fig. 2.
Overall workflow of the proposed NR-SSLBP framework for texture classification.

and reliable across different samples of the same texture class.

C. Multi-Scale SSLBP Feature Extraction

Texture patterns may appear at different spatial resolutions depending on the imaging conditions and the inherent structure of the material surface. Therefore, capturing texture information at multiple scales is essential for achieving robust classification. In the proposed approach, Local Binary Pattern features are extracted at multiple radii to construct a multi-scale representation of the texture image. For each scale, the LBP operator encodes the relationship between a centre pixel and its neighboring pixels, generating binary patterns that describe local micro-structures. By varying the neighborhood radius, texture structures of different sizes can be effectively captured.

By extracting LBP features at multiple radii, the method constructs a scale-aware representation that captures texture patterns across different spatial resolutions.

D. Scale-Selective Dominant Pattern Selection

Although multi-scale LBP extraction produces rich texture information, it may also generate a large number of patterns that are not equally informative. Some patterns occur more frequently and represent the fundamental structures of the texture, while others appear rarely and may correspond to noise or minor variations.

To address this issue, the scale-selective strategy identifies dominant local patterns across the scale space. The frequency of each pattern is analyzed, and the most representative patterns are selected to form the final feature representation. This process reduces the dimensionality of the feature vector while retaining the most discriminative texture information.

The scale-selective mechanism enables the descriptor to focus on stable and meaningful patterns, thereby improving classification performance.

E. Multi-Sample Feature Averaging

To further enhance robustness against noise and small variations in texture samples, a multi-sample feature averaging strategy is introduced. Instead of relying on the feature representation extracted from a single image sample, multiple perturbed samples of the same texture image are generated to obtain a more stable representation.

In the proposed method, artificial noise is introduced to simulate challenging imaging conditions. Specifically, Gaussian noise and salt-and-pepper noise are added to the input image to produce multiple noisy versions. SSLBP features are extracted from each perturbed sample, and the resulting feature vectors are combined to improve descriptor stability.

The feature vectors obtained from individual samples are averaged to produce a representative feature vector. This process helps reduce the influence of random noise and minor structural variations that may exist in individual samples.

The averaged feature vector is computed as

$$F_{avg} = \frac{1}{N}\sum_{i=1}^{N} F_i$$

where F_i represents the feature vector extracted from the i^{th} noisy sample and Ndenotes the total number of samples used for averaging.

By aggregating information from multiple noisy samples, the proposed method produces a more reliable and stable texture descriptor that is less sensitive to noise perturbations.

F. Texture Classification

After feature extraction and averaging, the resulting NR-SSLBP feature vector is used for texture classification. The feature vectors of training samples are stored as reference representations for each texture class. For a given test image, the NR-SSLBP descriptor is computed and compared with the stored feature vectors to determine the most similar texture category.

In this work, two classifiers are employed. The Nearest Subspace Classifier (NSC) is used as the primary classifier, while the Nearest Neighbor Classifier (NNC) serves as a baseline for comparison. Each test image is assigned to the class with the smallest distance or residual according to

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the chosen classifier, completing the texture recognition process.

The use of both classifiers provides a reliable evaluation of the discriminative capability of the proposed NR-SSLBP descriptor. The Nearest Subspace Classifier models each texture class as a low-dimensional subspace formed by its training samples, allowing the classifier to effectively capture intra-class variations. This makes NSC particularly suitable for texture datasets where samples of the same class may exhibit slight variations in illumination, orientation, or scale. On the other hand, the Nearest Neighbor Classifier performs direct distance comparison between feature vectors and serves as a simple yet effective baseline method. By evaluating the performance using both NSC and NNC, the robustness and generalization capability of the proposed NR-SSLBP features can be thoroughly assessed.

Algorithm 1: NR-SSLBP feature extraction
Input:
Texture image I; Neighborhood radii set $R_{s;}$
Number of neighbors P; Number of scales S;
Dominant pattern mapping table M;
Number of noise-robust samples N.
Output:
Noise-robust SSLBP feature vector F_{avg}.

1. Construct multi-scale representations
 Apply Gaussian smoothing to I to generate images at different scales.
2. For each scale s=1,2, … , S:
    a) Compute LBP codes LBP_{P,R_s} for every pixel.
    b) Map these patterns to dominant patterns using table M.
    c) Accumulate histogram of mapped dominant patterns.
3. Concatenate histograms from all scales to form the SSLBP feature vector F.
4. Generate noisy samples
 Produce Nnoisy versions of I by adding Gaussian noise and salt-and-pepper noise.
5. For each noisy sample i = 1,2, … , N:
 a) Repeat Steps 1-4 to obtain SSLBP feature vector F_i.
6. Average the feature vectors:

$$F_{avg} = \frac{1}{N}\sum_{i=1}^{N} F_i$$

7.Normalize F_{avg} to obtain the final NR-SSLBP descriptor
Return: F_{avg}

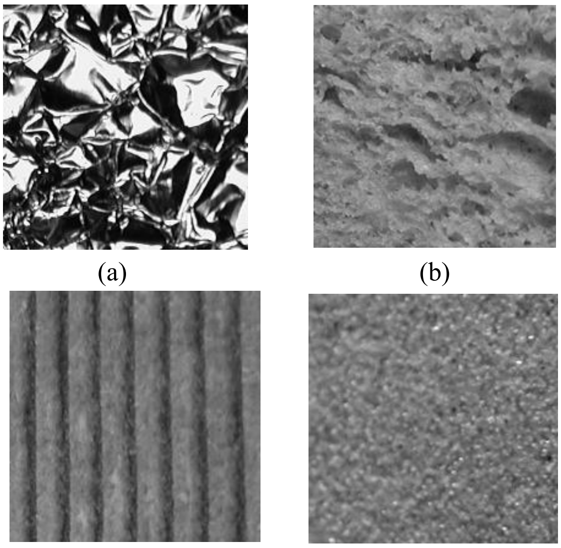
IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Dataset Description

To evaluate the effectiveness of the proposed NR-SSLBP descriptor, experiments are conducted on the KTH-TIPS texture dataset. The dataset contains images of various material surfaces captured under different illumination conditions, viewing angles, and scales. Each texture category consists of multiple samples, providing a suitable benchmark for evaluating the robustness of texture descriptors.
In the experiments, the dataset is divided into training and testing sets. Texture images from each class are used to extract feature representations and evaluate the classification performance of the proposed method.

Table II: Description of Texture Classes in KTH-TIPS Dataset

ID	Class Name	Structural and Visual Characteristics
1	Aluminium foil	Metallic, highly reflective surface with crinkled textures.
2	Brown bread	Porous, organic texture with irregular hole distributions.
3	Corduroy	Periodic, linear ridge patterns.
4	Cotton	Soft, fibrous texture with low-contrast structural details.
5	Cracker	Hard surface with distinctive small circular indentations.
6	Linen	Woven textile pattern with clear vertical and horizontal threads.
7	Orange peel	Pitted, dimpled surface mimicking organic skin.
8	Sandpaper	Uniformly granular, high-frequency abrasive texture.
9	Sponge	Highly irregular, deep-shadowed porous structure.
10	Styrofoam	Bubbled, multi-faceted synthetic surface.



(a) (b)

(c) (d)

Fig.3. sample images of four different texture classes (aluminium foil, brown bread, corduroy, sand paper) from the KTH-TIPS dataset.

B. Experimental Setup

All experiments are implemented in MATLAB. Texture features are extracted using the proposed NR-SSLBP method. The neighborhood parameters and scale levels are selected to capture texture information at multiple spatial resolutions.

To evaluate classification performance, two classifiers are used:

- Nearest Subspace Classifier (NSC)
- Nearest Neighbor Classifier (NNC)

The performance of the proposed method is measured using classification accuracy, which represents the percentage of correctly classified test images.

C. Comparison with Existing Methods

The proposed NR-SSLBP method is compared with several existing texture descriptors, including LBP, CLBP, and SSLBP. These methods are widely used in texture classification and serve as strong baseline approaches.

For each method, feature vectors are extracted from the texture images and classification is performed using the NSC and NNC classifiers. The classification accuracies obtained for different methods are summarized in Table III.

Table III : Classification Accuracy Comparison (Clean Dataset)

Method	NSC Accuracy (%)	NNC Accuracy (%)
LBP	90.15	86.40
CLBP	96.20	92.10
SSLBP	99.27	98.44
NR-SSLBP	99.41	98.62

The results show that the proposed NR-SSLBP descriptor achieves improved classification accuracy compared to conventional LBP-based methods. The improvement demonstrates the effectiveness of combining multi-scale feature extraction with multi-sample feature averaging to enhance robustness against noise.

D. Noise Robustness Analysis

To evaluate the robustness of the proposed method under noisy conditions, artificial noise is added to the texture images. In the experiments, both Gaussian noise and salt-and-pepper noise are introduced at different noise levels.

Feature extraction and classification are then performed using the noisy images. The proposed NR-SSLBP descriptor maintains higher classification accuracy compared to traditional LBP-based methods. This improvement demonstrates that the multi-sample feature averaging strategy effectively stabilizes the feature representation in the presence of noise.

Table IV: Noise Robustness Analysis

Noise Level (σ)	SSLBP Accuracy (%)	NR-SSLBP Accuracy (%)	Accuracy Gain
0.00	99.27	99.41	+0.14%
0.01	94.10	98.85	+4.75%
0.02	88.45	97.20	+8.75%
0.05	72.30	92.45	+20.15%

V. CONCLUSION

In this paper, a novel texture descriptor called Noise-Robust Scale-Selective Local Binary Pattern (NR-SSLBP) with multi-sample feature averaging was proposed to address the challenges of noise sensitivity and scale variations in texture classification. The proposed approach integrates noise-reduction preprocessing, multi-scale feature extraction, dominant pattern selection, and multi-sample averaging to produce robust and discriminative texture features.

Experimental results on the KTH-TIPS dataset demonstrate that NR-SSLBP achieves superior classification accuracy compared to conventional LBP, CLBP, and SSLBP methods. The descriptor also maintains high stability under varying levels of Gaussian and salt-and-pepper noise, highlighting the effectiveness of the noise-robust feature aggregation strategy. The use of both Nearest Subspace Classifier (NSC) and Nearest Neighbor Classifier (NNC) validates the general applicability of the proposed method across different classification paradigms.

Overall, the proposed NR-SSLBP provides a computationally efficient and reliable framework for practical texture classification applications in industrial inspection, medical imaging, and remote sensing. Future work may explore extending the method to handle rotational invariance and real-time implementation on embedded systems for automated texture analysis.

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