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Signature Verification Using Local Optimal-Oriented Pattern (LOOP)

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Abstract- Signature verification is a challenging biometric problem due to high intra-class variation and skilled forgeries. Traditional texture-based descriptors such as Local Binary Pattern (LBP) and Local Directional Pattern (LDP) have been widely used for this task; however, their sensitivity to rotation limits robustness. This work presents an offline signature verification system based on the Local Optimal-Oriented Pattern (LOOP), which inherently embeds rotation invariance into its formulation. Experimental evaluation on genuine and forged signatures demonstrates that LOOP-based features achieve superior discrimination compared to LBP and LDP.

Index Terms- Local Binary Pattern, Local Directional Pattern, Local Optimal-Oriented Pattern, Rotation Invariance, Texture Descriptors, Pattern Recognition

I. INTRODUCTION

Handwritten signatures are still one of the most widely accepted methods of personal verification in banking, legal, and administrative transactions[18]. Automatic offline signature verification[18] is the process of checking the authenticity of a signature from its static image captured after the signature is written, without using any dynamic information such as pen pressure and writing speed, making offline signature verification much more difficult than online signature verification. The major problem in offline signature verification is due to large intra-class variations, where the signatures of the same person can be quite different, and skilled forgeries can be very similar to the original signature[18]. Moreover, inter-class similarities, variations in writing instruments, scanning resolution, and background noise make offline signature verification a more difficult task[18]. Thus, the performance of an offline signature verification system largely depends on its capability to extract robust features that can capture the fine details of the signature strokes and are invariant to the above-mentioned variations[3].In recent years, local texture-based feature descriptors have gained significant attention due to their ability to model subtle structural patterns present in handwritten signatures[1]. Among these, rotation-invariant descriptors play a crucial role in improving verification accuracy under varying orientation[8].

1.1 Applications of Signature Verification

Offline signature verification systems[18] are commonly used in bank cheque handling, document verification, forensic analysis, and access control systems[1]. Automation of verification can minimize human error, accelerate the verification process, and enhance security in large-scale applications[8].

1.2 Literature Survey

Traditional methods for offline signature verification were based on global features like aspect ratio, projection profiles, and contour features[18]. Later, local descriptors like Local Binary Pattern (LBP)[1], which is a texture-based feature, gained popularity due to its simplicity and discriminative ability. LBP is a local intensity variation descriptor, but it is sensitive to rotation[1].Local Directional Pattern (LDP)[6] was proposed to make the descriptor more robust to noise by using edge response with directional masks. LDP is a better descriptor than LBP in terms of directional information, but it is still rotation-sensitive due to the use of fixed positional weights[6].Recent studies have demonstrated that rotation-invariant descriptors can enhance verification performance, which led to the development of Local Optimal-Oriented Pattern (LOOP)[8] that combines directional strength with the encoding process[8].

1.3 Motivation

The primary drive of this research is to counter the rotation sensitivity that is implicit in LBP[1] and

LDP[6] descriptors. In offline signatures, local stroke orientations may change because of the scanning angle, signing posture, or natural variations[18]. The LOOP method[8] overcomes this problem by using weights according to the local directional strength[8].

1.4 Objectives of the Project

The objectives of this project are: - To study and analyze LBP and LDP descriptors for offline signature verification[18] - To implement LOOP for extracting rotation-invariant local features - To compare the performance of LBP, LDP, and LOOP using distance-based classification - To show the effectiveness of LOOP[8] in distinguishing genuine and forged signatures[18]

1.5 Scope of the Work

This research is based on offline signature images and does not take consideration dynamic characteristics[18]. The proposed method is tested using texture-based features[1] and histogram comparison[3].

1.6 Signature Databases

The experimental setup employs the use of real and fake signature image datasets stored in different folders. The images are all preprocessed through grayscale conversion, binarization, and normalization.

II. VARIANTS OF LOCAL PATTERN DESCRIPTORS

2.1 Local Binary Pattern (LBP)

2.1.1 Introduction

Local Binary Pattern is a simple yet effective texture feature descriptor that captures the relationship between a pixel and its neighbors[1]. It has been widely applied in texture-based classification and biometric systems owing to its simplicity and effectiveness in describing local micro-patterns like edges, spots, and flat areas[1]. The standard LBP operator is based on a fixed neighborhood and produces a binary code by thresholding the neighboring pixel values with respect to the central pixel[1].One of the major strengths of LBP is its ability to handle monotonic gray-scale transformations, making it applicable to handwritten signature analysis, where illumination changes can occur[1]. However, the standard LBP operator assigns fixed positional weights to the neighboring pixels, resulting in a change in the produced pattern when the image is rotated[1]. Although rotation-invariant versions of LBP have been developed, they tend to increase computational complexity or decrease discriminative ability[3]. Consequently, the standard LBP operator is highly sensitive to rotation and not very effective in offline signature verification tasks, where orientation changes are common[18].

2.1.2 Methodology

In the Local Binary Pattern (LBP), every pixel in the grayscale image is evaluated by comparing it with its neighboring pixels in a predefined 3×3 window. The threshold value is the intensity of the central pixel. If the intensity of the neighboring pixel is greater than or equal to the intensity of the central pixel, then the neighboring pixel is assigned a binary value of 1; otherwise, it is assigned a value of 0.

The mathematical expression for the LBP value of a pixel located at position (x, y) is given by:

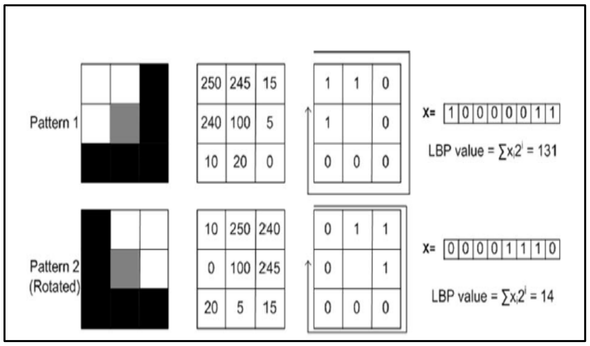
$$\boxed{\mathrm{LBP}(x,y) = \sum_{n=0}^{7} s(I_n - I_c)\, 2^n}$$

Where I_c denotes the gray-level intensity of the central pixel I_n represents the intensity of the n^{th} neighboring pixel,and s(.) is a thresholding function defined as:

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

The binary sequence thus obtained from the comparison of the neighborhood is then converted into a decimal value, which corresponds to the LBP code of the pixel. By calculating the LBP code for all pixels in the image, a histogram of the LBP values is obtained. This histogram is used as the feature vector that describes the texture information of the signature image.The histogram-based representation technique used in LBP enables the description of the local pattern distribution and is robust to small intensity changes.

However, due to the fixed order of the neighborhood, the LBP code is sensitive to rotation. This leads to the investigation of more sophisticated features such as LDP and LOOP in the next sections.



2.2 Local Directional Pattern (LDP)

2.2.1 Introduction

Local Directional Pattern (LDP) is an extension of Local Binary Pattern that uses directional edge information derived with compass masks[6]. Unlike LBP, which is based solely on intensity values, LDP conveys the directional information of local image patterns, making it more robust to noise and subtle changes in illumination[6]. This is particularly beneficial in offline signature verification, where the edges of strokes and directional changes contain valuable information[18].In LDP, the response values calculated in multiple directions are used to measure the strength of local directional patterns at a given image location[7]. By focusing on the most dominant directional responses, LDP highlights structural information about pen strokes and curves in handwritten signatures[7]. Although LDP is superior to LBP in the representation of directional information, it retains fixed positional encoding, which is sensitive to rotation[6]. This drawback triggers the need for more sophisticated descriptors that can attain rotation invariance[3].

2.2.2 Methodology

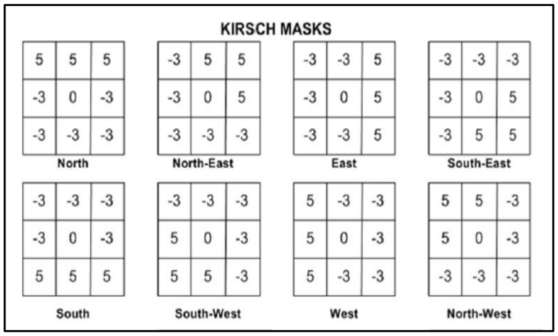
The Local Directional Pattern (LDP) feature extracts texture information based on the analysis of directional edge responses around each pixel. Unlike LBP, which uses only intensity values for comparison, LDP uses a series of directional compass masks to extract edge information based on different orientations. This helps LDP to better capture structural information like stroke direction and curvature in handwritten signatures.For each pixel, eight Kirsch compass masks are applied to a 3×3 neighborhood to calculate edge response values.let R_k denote the response obtained by convolving the image with the K^{th} directional mask where K=0,1,2,3,…..,7 These responses represent the strength of edges in different orientations.The LDP code for a pixel is generated by selecting the top mmm most significant directional responses. A binary encoding is then formed such that:

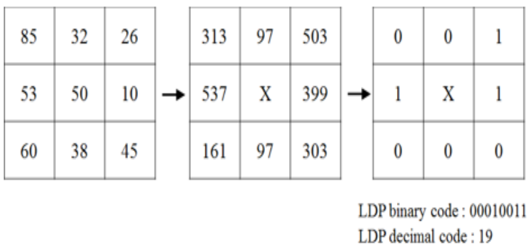
$$\mathrm{LDP}(x,y) = \sum_{k=0}^{7} b_k \cdot 2^k$$

where

$$b_k = \begin{cases} 1, & \text{if } R_k \text{ is among the } m \text{ highest responses} \\ 0, & \text{otherwise} \end{cases}$$

The binary pattern produced highlights the dominant directions of edges and ignores the weaker responses. This process is repeated for all pixels in the image to produce an LDP-coded image. A histogram of the LDP is then created and used as the feature vector for signature verification. Although LDP is more robust to noise and illumination changes by highlighting the directional edge information, the binary weights are fixed position-wise, which makes the descriptor still sensitive to rotation. This means that rotated copies of the same signature pattern produce different LDP codes.As a result, additional preprocessing steps such as image alignment or normalization may be required to improve rotational consistency. The effectiveness of LDP largely depends on accurate edge extraction and proper parameter selection. Despite this limitation, LDP remains effective in capturing fine texture variations present in handwritten signatures. Therefore, it is widely used in signature verification systems where directional structural information plays an important role.





III. PROPOSED METHODOLOGY

3.Local Optimal-Oriented Pattern (LOOP)

3.1 Introduction

Local Optimal-Oriented Pattern (LOOP) is a rotation-invariant local texture descriptor that aims to address the shortcomings of conventional local pattern descriptors, such as LBP and LDP[8]. Although LBP is based solely on intensity comparison and LDP is based on directional edge information, both of them assign fixed positional weights to neighboring pixels, which makes them rotation-sensitive[1]. LOOP, on the other hand, leverages the benefits of both techniques and removes their dependency on rotation[8].The basic concept of LOOP is to assign weights to neighboring pixels based on the relative strength of directional edge responses rather than their fixed positions[8]. By ranking the directional responses and using the ranking to define the binary weight positions, LOOP ensures that the dominant orientation always makes a consistent contribution to the final pattern, irrespective of the rotation of the image, which inherently makes it a rotation-invariant technique[8].In the offline signature verification problem, rotation invariance is especially valuable because of the possible variations in the angle of signing, placement of documents, and scanning orientation[18]. LOOP is able to capture the local properties of signatures effectively, including the direction, while being invariant to the orientation variations[8]. Hence, LOOP is able to provide a better feature representation for distinguishing between genuine signatures and forgeries than LBP and LDP[8].

3.2 Methodology

Local Optimal-Oriented Pattern (LOOP) computes rotation-invariant local features by combining directional edge responses with adaptive weighting. Unlike LBP and LDP, which employ fixed positional weights, LOOP weights the responses dynamically according to the relative strength of the directional responses, thus inherently being rotation invariant.For each pixel in the signature image, a 3×3 neighborhood is examined. Directional edge responses are computed by convolving the neighborhood with a set of eight compass (Kirsch) masks.let denote the response obtained from the k^{th} directional mask, where k=0,1,…7.These responses represent the local edge strength along different directions.The directional responses are then ranked in descending order of magnitude. Based on the ranking, adaptive weights are assigned such that the direction with the strongest response receives the highest weight, and the weakest response receives the lowest weight.Let W_k denote the weight assigned to the k^{th} direction after ranking, where $W_k \in \{0,1,2,\ldots,7\}$.Following the LBP principle, a binary comparison is performed between each neighboring pixel intensity I_n and the center pixel intensity $I_c$defined as:

$$b_k = \begin{cases} 1, & I_n \geq I_c \\ 0, & I_n < I_c \end{cases}$$

The final LOOP code for the pixel is computed as a weighted sum of these binary comparisons:

$$\mathrm{LOOP}(x, y) = \sum_{k=0}^{7} b_k \cdot 2^{W_k}$$

This expression guarantees that the binary weights are dependent on the dominant orientation and not on fixed spatial locations. Consequently, when the image is rotated, the relative ranking of the directional responses does not change, resulting in a consistent LOOP code for the rotated patterns.This rotation-invariant property makes LOOP more stable for real-

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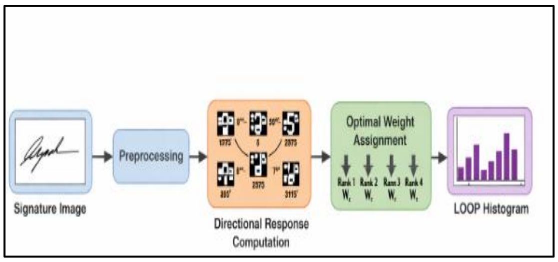
world signature samples where slight angular variations are common. By assigning weights according to the strength order of directional responses, LOOP overcomes the positional rigidity found in traditional descriptors. It effectively preserves the structural characteristics of strokes even under geometric transformations. As a result, the extracted features remain discriminative and reliable for verification tasks.The LOOP code is calculated for all pixels in the image to produce a LOOP-coded image. A normalized histogram of the LOOP values is then created and used as the feature vector describing the signature image.A block diagram describing the LOOP feature extraction process is shown below:



IV. COMPARATIVE STUDY OF LOCAL PATTERN DESCRIPTORS ON SIGNATURE DATA

4.1 Introduction

This chapter provides a comparative performance analysis of three popular local texture descriptors, namely Local Binary Pattern (LBP), Local Directional Pattern (LDP), and Local Optimal-Oriented Pattern (LOOP), in the context of offline handwritten signature verification. The comparison is made to assess their performance in distinguishing real signatures from skilled forgeries. As handwritten signatures are prone to rotation, orientation, and scanning differences, the capability of the descriptor to adapt to these differences is an important factor in the verification process. Histogram-based feature extraction with distance-based similarity computation is used for the comparison.

4.2 Performance Evaluation

4.2.1 Performance Metrics

To calculate the similarity between the feature spaces of the test and reference signatures, the Chi-square distance metric is used. The Chi-square distance metric is appropriate for histogram-based features, as it highlights the differences in corresponding histogram bins.

The Chi-square distance between two normalized histograms H1 and H2 is given by:

$$\chi^2(H_1, H_2) = \sum_{i=1}^{N} \frac{(H_1(i) - H_2(i))^2}{H_1(i) + H_2(i) + \epsilon}$$

4.2.2 Comparison Using LBP, LDP, and LOOP

Preprocessing steps, feature extraction process, and distance measure to make a fair comparison. The experimental results indicate that LBP has a limited discriminative power because of its rotation and orientation sensitivity. LDP outperforms LBP by considering the directional edge information, but it is still rotation partially dependent because of the fixed directional encoding. LOOP, on the other hand, has shown superior discriminative power between the genuine and forged signatures in all cases. The adaptive weight assignment based on the ranking of the directional response helps LOOP to provide consistent feature extraction even in the presence of rotation, resulting in better separation between the genuine and forged signatures.

Table : Qualitative comparison of the three descriptors.

Table 4.1: Comparison of Local Pattern Descriptors

Descriptor	Rotation Invariance	Discrimination Ability
LBP	No	Low
LDP	Partial	Medium
LOOP	Yes	High

4.2.3 Classifier Analysis

A decision rule based on minimum distance is used for classification. The feature histogram extracted from the test signature is compared with the histograms of genuine and forged reference signatures with respect to the Chi-square distance. The test signature is classified based on the minimum distance. If the minimum distance is to the genuine reference

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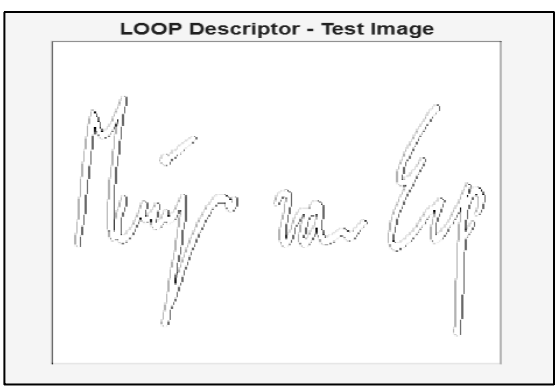
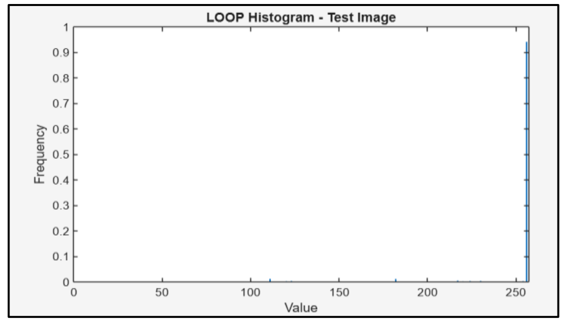
signature, the test signature is classified as genuine; otherwise, it is classified as forged. The simple classifier emphasizes the discriminative capability of the extracted features without adding complexity to the classifier.

4.3 Results and Discussion

The experimental outcome reveals that LOOP is more robust and accurate compared to both LBP and LDP. The property of rotation invariance of LOOP makes it capable of extracting fixed local patterns from the signatures even after rotation. Although LDP is more accurate compared to LBP due to the directional encoding scheme, its partial rotation sensitivity limits its performance. In conclusion, LOOP is a more accurate and robust feature extraction method for offline signature verification and can be appropriately utilized in biometric authentication systems. Moreover, LOOP performs better in distinguishing real and forged signatures when histogram-based distance metrics are used. The robustness of LOOP features with respect to different orientations of signatures also enhances the reliability of signature verification.Moreover, the computational simplicity of LOOP makes it suitable for real-time and large-scale signature verification applications.This efficiency reduces processing time without compromising recognition accuracy. It also minimizes memory requirements, making it practical for embedded and resource-constrained systems. Therefore, LOOP provides a balanced combination of accuracy, robustness, and computational efficiency for signature-based authentication.





V. CONCLUSION AND FUTURE WORK

5.1 Conclusion

This study proposed an offline signature verification system using the Local Optimal-Oriented Pattern (LOOP) descriptor. By incorporating rotation invariance into the feature extraction process, the LOOP descriptor is able to successfully address the drawbacks of conventional local pattern descriptors, including LBP and LDP. The experimental results clearly show that the LOOP descriptor is able to achieve enhanced robustness and higher verification accuracy by effectively capturing local patterns in varying signature orientations. The comparison study has confirmed that the LOOP descriptor is suitable for offline signature verification and can be used as an effective feature extraction method for biometric authentication systems.

5.2 Future Scope

Future research may involve the combination of LOOP with more advanced machine learning and deep learning classifiers to further improve the classification accuracy. The proposed approach can also be extended to multi-scale or multi-resolution analysis to analyze the fine and coarse details of the signatures. Further validation of the applicability of LOOP can also be done by testing its performance on larger public signature datasets.

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