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Local Gradient Hexa Pattern: A Descriptor for Signature Verification

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Abstract - Signature verification plays a crucial role in biometric authentication systems. Traditional local texture descriptors such as Local Binary Pattern (LBP), Local Directional Pattern (LDP), and Local Tetra Pattern (LTrP) exhibit limitations in capturing detailed gradient variations in signature strokes. This paper proposes a novel Local Gradient Hexa Pattern (LGHP) descriptor for robust feature extraction in offline signature verification. The proposed method encodes gradient magnitude and directional information into a six-pattern structure, enhancing discrimination capability. Experimental evaluation is performed on standard signature datasets using a Minimum Distance Classifier. Performance comparison demonstrates that the proposed LGHP achieves improved verification accuracy and reduced false acceptance rate compared to existing descriptors. The results confirm the effectiveness and robustness of the proposed approach for biometric authentication systems.

Index Terms - Signature Verification, Local Binary Pattern (LBP), Local Directional Pattern (LDP) Local Gradient Hexa Pattern (LGHP), Forgery Detection.

I. INTRODUCTION

A. Background

Signature verification is an important biometric authentication technique used to validate personal identity in financial transactions, legal documentation, access control systems, and administrative processes [9], [10]. Unlike physiological biometrics such as fingerprint or iris recognition, signature verification is categorized as a behavioral biometric since it reflects the dynamic and individual writing characteristics of a person [11]. The individuality of handwriting and signing behavior makes signatures a socially accepted and non-intrusive means of authentication [10], [12].

Offline signature verification, which operates on scanned or captured images of signatures, has gained considerable attention due to its practical applicability in real-world scenarios [12], [15]. However, offline systems rely solely on static image information, making the feature extraction process more challenging compared to online systems that utilize dynamic stroke information such as speed and pressure [11]. Therefore, robust feature representation plays a crucial role in enhancing verification accuracy.

B. Limitations of Existing Methods

Several local texture descriptors have been employed for feature extraction in signature verification systems. Local Binary Pattern (LBP) [1], [2], Local Directional Pattern (LDP) [3], Local Ternary Pattern (LTP) [4], and Local Tetra Pattern (LTrP) [6] are widely used techniques for capturing local structural information. These descriptors encode neighborhood relationships around each pixel to represent texture characteristics.

Although these methods have demonstrated effectiveness in various pattern recognition tasks, they exhibit certain limitations when applied to signature verification. LBP primarily captures intensity variations and is sensitive to noise and illumination changes [2]. LDP improves robustness by incorporating directional edge responses [3], yet it may still fail to adequately model complex gradient transitions present in handwritten strokes. LTP enhances noise resistance using a ternary encoding scheme [4], while LTrP incorporates derivative information for directional representation [6].

Despite these advancements, most existing descriptors focus either on intensity comparison or limited directional encoding, and do not fully exploit gradient magnitude and multi-directional transitions simultaneously. As a result, distinguishing between genuine signatures and skilled forgeries remains challenging, particularly under variations in stroke width, writing pressure, and signing speed [8], [15].

C. Motivation

In offline signature verification, the discriminative power of the system heavily depends on its ability to capture subtle stroke patterns, edge continuity, and directional flow. Skilled forgeries often imitate the global structure of a signature, making it necessary to analyze fine-grained local gradient relationships.

Motivated by these challenges, there is a need for a descriptor that integrates both texture and gradient-based directional information to achieve improved robustness and discrimination capability. A representation that captures multi-directional gradient transitions and structural variations can significantly enhance the system's ability to detect forged signatures under complex writing conditions.

II. RELATED WORK

In the area of signature verification, various local pattern descriptors have been proposed to efficiently describe the structural and texture properties of signature images [9], [10]. Since signatures contain unique stroke patterns, curves, and directional intensity variations, local texture descriptors are very useful in extracting these distinctive features [1], [2].

Some of the popular local descriptors are Local Binary Pattern (LBP) [2], Local Directional Pattern (LDP) [3], Local Ternary Pattern (LTP) [4], and Local Tetra Pattern (LTrP) [6]. These techniques describe the local neighborhood information of each pixel differently to enhance the distinction between real and forged signatures [3], [6], [13].

A. Local Binary Pattern (LBP)

Introduction

Local Binary Pattern (LBP) is one of the most widely used local texture descriptors in image processing and biometric recognition systems [1], [2]. Due to its computational simplicity and strong discriminative capability, it has been extensively applied in offline signature verification [9], [10].

Handwritten signatures exhibit micro-level structural variations such as stroke thickness changes, curvature transitions, and localized ink distribution differences. Capturing these local spatial patterns is essential for distinguishing genuine signatures from skilled forgeries. LBP encodes such micro-textural information into a compact representation by analyzing the local neighborhood of each pixel [2].

Methodology

LBP operates by comparing the gray-level intensity of a central pixel with its neighboring pixels within a local window (commonly 3×3). The mathematical representation of LBP at a pixel (xc ,yc) is given by:

LBP(xc ,yc) = $\sum_{i=0}^{P-1} s(n_i - g_c)$ 2i

The thresholding function, which is defined as :

$$s(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & otherwise \end{cases}$$

In practical, a 3×3 neighborhood is typically considered. Each neighboring pixel intensity is compared with the central pixel intensity gc. If the neighbor's value is greater than or equal to gc, the corresponding bit is assigned 1; otherwise, it is assigned 0 [2].

This comparison produces a binary sequence of length P. Each bit is weighted by 2i based on its position, and the weighted sum yields a decimal value representing the LBP code for that pixel.

To represent the entire signature image, LBP codes are computed for all valid pixels, and a histogram of these codes is constructed. This histogram forms the feature vector used for classification in signature verification systems [9].

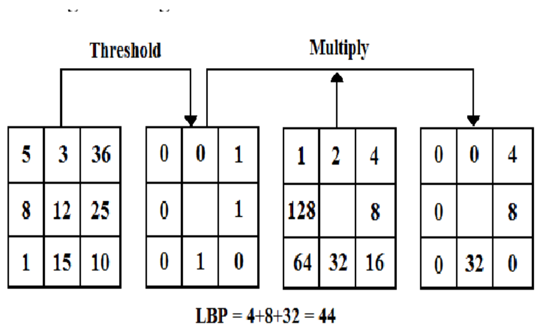

Fig 1 : LBP computation of center pixel

Limitations

Despite its simplicity and effectiveness, LBP has certain limitations when applied to offline signature verification. Since it relies solely on gray-level intensity comparison, it is sensitive to noise and illumination variations introduced during scanning or image acquisition [2]. Even minor intensity fluctuations can alter the binary encoding pattern.

Moreover, LBP does not explicitly capture gradient magnitude or directional stroke flow information, which are critical in modeling handwriting dynamics. Skilled forgeries often replicate global structural patterns while differing subtly in stroke pressure and directional consistency. Because LBP primarily encodes intensity differences, its discriminative capability may be insufficient for capturing these fine-grained variations [10].

B. Local Directional Pattern (LDP)

Introduction

Local Directional Pattern (LDP) was proposed as an improvement over intensity-based descriptors such as LBP, with the objective of enhancing robustness against illumination variations and noise [3]. Instead of directly comparing gray-level intensities, LDP focuses on capturing dominant edge responses in multiple orientations within a local neighborhood.

In the context of offline signature verification, directional stroke information plays a significant role in distinguishing genuine signatures from forgeries. Handwritten signatures consist of directional curves, intersections, and stroke continuities that reflect the writer's unique motor behavior. By encoding edge orientation information rather than simple intensity differences, LDP aims to provide a more structurally meaningful representation of signature textures [3], [9].

Methodology

LDP computes edge responses in different orientations using directional compass masks, commonly Kirsch masks, which extract gradient information in eight principal directions (North, North-East, East, South-East, South, South-West, West, and North-West) [3].

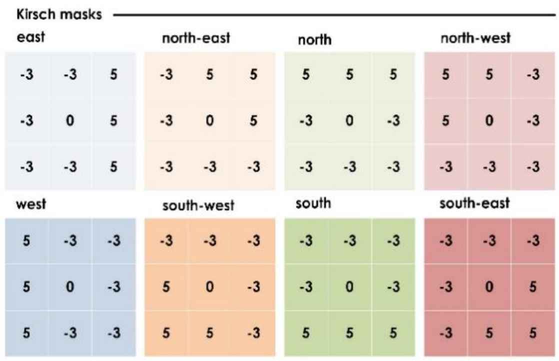

Fig 2 : Kirsch Masks

For a given pixel at location (xc,yc), eight directional responses m0,m1,...,m7 are obtained by convolving the local 3×3 neighborhood with the corresponding masks.

The LDP code for the central pixel is defined as:

LDPk (xc,yc) = $\sum_{n=0}^{7} s(m_n - m_k).2n$

The threshold function s(x) is defined as:

$$s(x)=\begin{cases}1, & if\ x \geq 0\\ 0, & otherwise\end{cases}$$

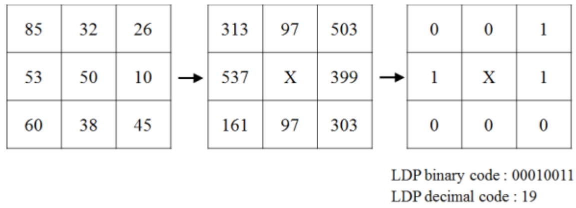

Fig 3: LDP computation

In practice, the eight directional responses are ranked in descending order, and the top k responses (commonly k=3) are selected as dominant directions [3]. These dominant directions are assigned a binary value of 1, while the remaining directions are set to 0.

This process generates an 8-bit binary code representing the prominent structural orientation around the pixel. Similar to LBP, a histogram of LDP codes is computed over the entire signature image to form the final feature vector used for classification [9].

Limitations

Although LDP improves robustness compared to LBP by incorporating directional edge responses, it still exhibits certain limitations. The descriptor primarily emphasizes dominant edge directions while suppressing weaker gradient information. In skilled forgery cases, subtle stroke variations may not appear as dominant edges, potentially reducing discriminative performance.

Furthermore, LDP does not explicitly encode gradient magnitude variations across multiple orientations. The reliance on selecting only the top k responses may lead to partial loss of structural information, particularly in complex signature regions containing overlapping or intersecting strokes.

Additionally, the computational cost of applying multiple directional masks is higher than simple

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intensity comparison methods, which may affect efficiency in large-scale verification systems [3], [10].

C. Local Ternary Pattern (LTP)

Local Ternary Pattern (LTP) is an extension of Local Binary Pattern introduced to improve robustness against noise and minor illumination variations [4]. Unlike LBP, which uses binary thresholding, LTP employs a three-level encoding scheme controlled by a threshold parameter T. For a pixel at LTP is defined as:

LTPP, R $= \sum_{p=0}^{P-1} s\left(g_p - g_c\right)$ .2p

The ternary threshold function s(x) is defined as:

$$s(x) = \begin{cases} 1, & x \geq t \\ 0, & |x| < t \\ -1, & x \leq -t \end{cases}$$

By introducing a tolerance interval, LTP reduces sensitivity to small intensity fluctuations commonly observed in scanned signature images. For practical implementation, the ternary pattern is divided into positive and negative binary patterns, and their histograms are concatenated to form the final feature vector [4], [9]. Although more stable than LBP, the descriptor depends on appropriate threshold selection and does not explicitly capture multi-directional gradient information.

III. PROPOSED METHODOLOGY

The proposed signature verification scheme employs the Local Gradient Hexa Pattern (LGHP) descriptor to extract distinctive texture information from signature images. LGHP efficiently describes the directional gradient relationships, which are very effective in representing the distinct stroke patterns of signatures.

The complete process involves gradient calculation, pattern coding, multi-distance feature extraction, feature image formation, and histogram-based feature description. The multi-distance analysis enhances the system's capability to extract the fine and coarse details of signatures

A. Image Pre-processing

First, all the input signature images are transformed into grayscale images to remove color information and simplify computations. Additionally, since the signature images may vary in size, all the images are resized to a standard resolution of 128 × 128 pixels. Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to improve the contrast of the signature image and make the signature strokes more visible. This method helps to highlight the fine structural details of the signature image. The pre-processing operation can be expressed as:

Ie = CLAHE(Is)

Where, Is is the input signature image

Ie is the enhanced image

B. First-Order Gradient Computation

After the preprocessing, the gradient values are calculated to identify the intensity changes in the signature image. The intensity changes include significant structural information such as edges, curves, and direction of strokes in the signature.

For each reference pixel p0 , gradients are calculated in four directions. Horizontal(00), Right diagonal(450), Vertical (900) and Left diagonal(1350).

The gradient in direction α at distance D is defined as:

$G_{\alpha,D}(P_0) = I(P_0) - I(P_{\alpha+1,D})$

Where, I(P0): Intensity of the reference pixel

I(Pα+1,D): Intensity of neighboring pixel located at direction α and distance D.

These gradients represent directional stroke transitions in the local neighborhood.

C. Second-Order LGHP Encoding

Second-order LGHP LGHP2(P0) at distance *D* is calculated by evaluating the first-order gradient derivatives for different pairs of directions (α,β) through the encoding function C(·,·), and then taking the encoded binary responses for all pairs of gradients to obtain the final LGHP pattern at the center pixel binary responses for all pairs of gradients to obtain the final LGHP pattern at the center pixel.

$$LGHP^2(P_0) = \sum_{(\alpha,\beta \in Pairs)} C\left(G_{\alpha,D}(P_0), G_{\beta,D}(P_0)\right)$$

where α, β ϵ 0°, 45°, 90°, and 135°.

The encoding function C(., .) for any point P in the derivative space is defined as

$$C(G\alpha,D,G\beta,D) = \begin{cases} 1, & \text{if } G_{\alpha,D} \geq G_{\beta,D} \\ 0, & Otherwise \end{cases}$$

Pairs include combinations like (0°, 45°), (0°, 90°), (0°, 135°), (45°, 90°), (45°, 135°), (90°, 135°).

Since six directional pairs exist, each pixel produces a 6-bit LGHP code, forming the Hexa Pattern representation.

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D. Multi-Distance Extension

To enhance robustness and capture multi-scale structural information, LGHP encoding is performed at multiple distances:

D=1,2,3,…,R

The multi-distance LGHP descriptor is given by:

LGHPR(P0)={LGHPD(P0)|D=1,2,3,…,R}

For each distance D, six binary patterns, which are obtained from gradient pairs, constitute the LGHP descriptor. The Combination of the descriptors at various distances gives the final multi-scale feature vector that describes the signature structure.

Smaller distances capture fine stroke details, while larger distances encode broader structural relationships. This multi-scale strategy significantly improves discriminative power in distinguishing genuine signatures from forgeries.

E. Generation of LGHP Feature Images

The binary patterns obtained from the pairwise gradient comparisons are then translated into their corresponding decimal values. This results in a series of feature images (FIs), with each feature image associated with a particular pair of gradient directions (α, β) and a distance D.

Each feature image corresponds to a specific gradient pair and distance. These images spatially encode directional gradient relationships across the signature, thereby preserving stroke continuity and structural transitions.

The generated feature images serve as intermediate representations for statistical feature extraction.

F. Histogram Feature Extraction

From each feature image, histograms are computed to summarize the distribution of LGHP codes. The histograms are normalized to ensure scale invariance and concatenated to form the final feature vector:

F=[H1,H2,…,HN]

where Hi denotes the normalized histogram corresponding to the ith feature image.

The feature maps and histogram representation are shown in Fig. 3.1, which illustrates the effectiveness of the proposed encoding scheme.

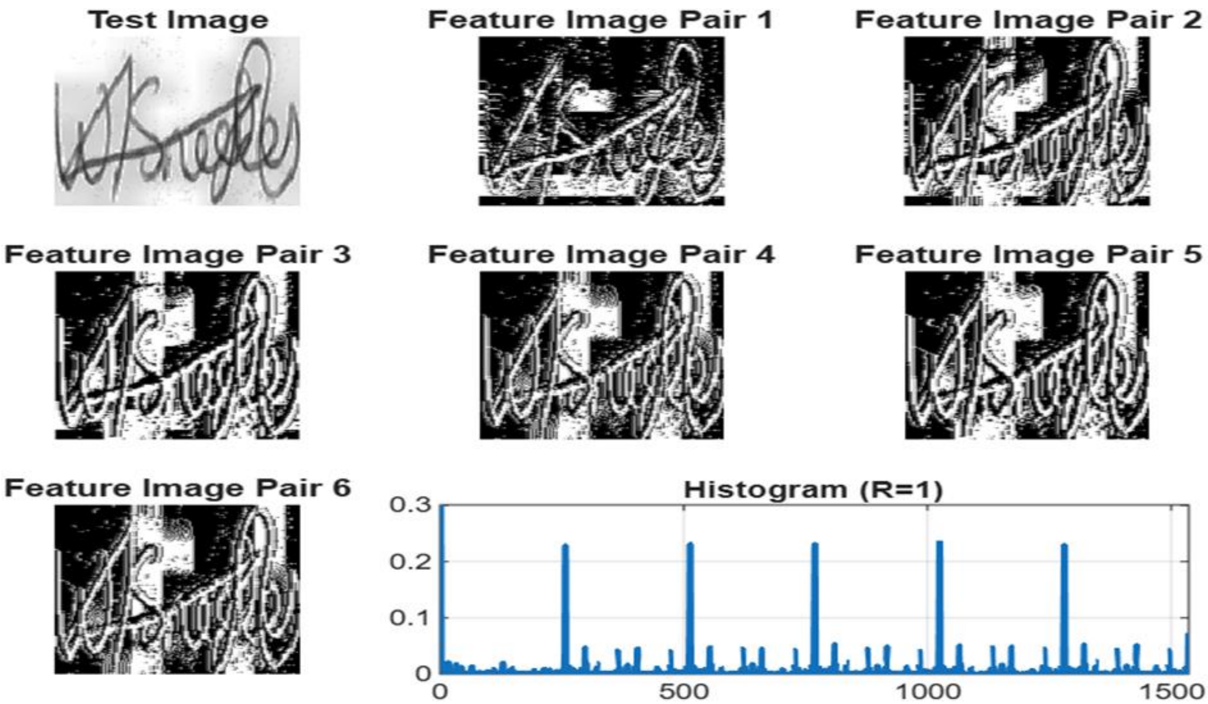

Fig 5 : Feature Images and Histogram

IV. RESULTS AND DISCUSSION

A. Experimental Setup

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The performance of the proposed LGHP-based signature verification system was evaluated using a dataset containing both genuine and forged signature samples. A total of 120 signature samples were used for training, consisting of 60 genuine and 60 forged signatures to ensure class balance during classifier learning.

For performance evaluation, 19 signature samples were used as test data. The forged samples were designed to represent variations in stroke formation and structural imitation patterns, thereby simulating realistic skilled forgery scenarios.

The objective of the experiment is to assess the ability of the proposed gradient-based descriptor to accurately discriminate between genuine and forged signatures. Performance evaluation was carried out using quantitative classification metrics derived from the prediction results.

B. Classification Method

In order to measure the similarity between the feature vector distributions of reference and query signature, a Chi-square statistical distance measure has been selected. As the feature vector extracted by the LGHP descriptor is a histogram, the Chi-square statistical distance measure is more suitable for measuring the difference between the reference and query signature feature vector distributions. The Chi-square statistical distance measure between two normalized histograms $H1$ and $H2$ is given by:

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

where N is the total number of histogram bins, and ε is a positive constant.

In the verification process, the feature vector extracted from the query signature is compared with the reference feature vector, and a classification decision is made based on a threshold condition, i.e., a smaller distance corresponds to a genuine signature, and a higher distance corresponds to a forged signature.

C. Accuracy

The performance of the system is quantified in terms of accuracy, which is calculated as the ratio of correctly classified samples to the total number of test samples:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Test Samples}}$$

Accuracy measures the proportion of correctly classified signature samples among all test instances.

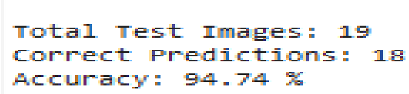

Fig 4 Accuracy Result

The accuracy achieved reveals a high recognition rate, which shows that the structural gradient information extracted is rich enough to ensure reliable verification. The system performs well on both classes, establishing the efficacy of the proposed feature representation for offline signature verification.

D. Confusion Matrix

To perform a precise class-wise performance evaluation, a confusion matrix has been created. The confusion matrix is a systematic comparison of actual class labels and predicted output obtained from the verification system. It facilitates precise analysis of classification outcomes for both genuine and forged signatures.

The confusion matrix represents the following outcomes: True Positive (TP) – Genuine signatures classified correctly as genuine, True Negative (TN) – Forged signatures classified correctly as forged, False Positive (FP) – Forged signatures incorrectly classified as genuine and False Negative (FN) – Genuine signatures incorrectly classified as forged.

From the confusion matrix(Fig. 5), it can be observed that the majority of genuine signatures are classified correctly, indicating a high sensitivity of the system to genuine signatures. A few forged signatures are incorrectly classified as genuine, indicating the presence of skilled forgery, which may have a similar structure to the original signatures.

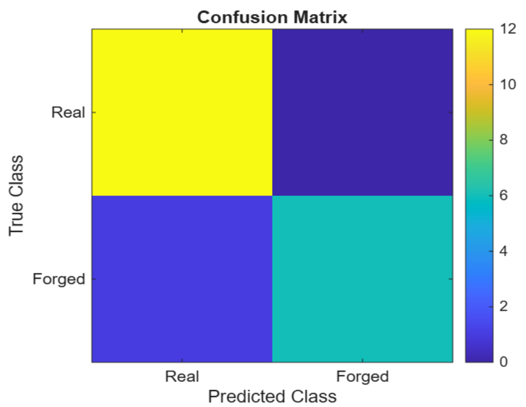

Fig 5 : Confusion Matrix

The Average Recognition Rate (ARR) indicates high overall classification consistency for all classes. Moreover, the Rejection Accuracy Rate (RAR) further confirms the effectiveness of the proposed system in accurately recognizing and rejecting the forged signatures.

V. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This study introduced an offline signature verification system based on the proposed Local Gradient Hexa Pattern (LGHP) descriptor. In this study, the LGHP descriptor takes advantage of the relationships between the gradient values to effectively represent the structural and textural characteristics associated with handwritten signatures. Through the utilization of first- and second-order gradient relationships, the LGHP descriptor effectively represents the structural characteristics associated with handwritten signatures.

The standardized preprocessing mechanism provides a sense of uniformity to the signature verification process. As a result, the LGHP-based signature verification system effectively extracts the signature characteristics. Through the experimental evaluation of the LGHP-based signature verification system, the proposed signature verification system effectively discriminates between genuine and forged signatures. As a result, the effectiveness of the gradient-based structural characteristics of handwritten signatures for signature verification applications is confirmed.

B. Future Scope

While the proposed method shows promising results, further improvements can be considered to achieve better robustness and generalization. Possible improvements for the proposed method's future direction might involve the evaluation of the proposed framework using large publicly available databases to test the adaptability of the proposed method to various writing styles and forgery types. Improvements to the discrimination ability of the proposed method using sophisticated machine learning classifiers, like deep learning classifiers, might also be considered. In addition, the fusion of LGHP with other features might be considered to improve the verification process. Finally, the extension of the proposed method to online signature verification using dynamic features might be considered.

REFERENCES

[1] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on feature distributions," *Pattern Recognition*, vol. 29, no. 1, pp. 51–59, 1996.

[2] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971–987, 2002.

[3] B. Zhang, Y. Gao, S. Zhao, and J. Liu, "Local derivative pattern versus local binary pattern: Face recognition with high-order local pattern descriptor," *IEEE Transactions on Image Processing*, vol. 19, no. 2, pp. 533–544, 2010.

[4] L. Liu, M. Guo, and D. Zhang, "Face recognition using local derivative pattern (LDP)," in *Proc. IEEE Int. Conf. Biometrics: Theory, Applications and Systems*, 2010, pp. 1–8.

[5] B. Murala, R. P. Maheshwari, and R. Balasubramanian, "Local tetra patterns: A new feature descriptor for content-based image retrieval," *IEEE Transactions on Image Processing*, vol. 21, no. 5, pp. 2874–2886, 2012.

[6] B. Murala, R. P. Maheshwari, and R. Balasubramanian, "Local gradient hexa patterns: A new feature descriptor for texture classification," *Signal Processing*, vol. 92, no. 6, pp. 1469–1479, 2012.

[7] S. Liao, Y. Mu, X. Li, A. K. Jain, and S. Z. Li, "A benchmark study of large-scale unconstrained face recognition," in *Proc. European Conf. Computer Vision (ECCV)*, 2012, pp. 1–15.

[8] R. Plamondon and G. Lorette, "Automatic signature verification and writer identification—The state of the art," *Pattern Recognition*, vol. 22, no. 2, pp. 107–131, 1989.

[9] D. Impedovo and G. Pirlo, "Automatic signature verification: The state of the art," *IEEE Transactions on Systems, Man, and*

Cybernetics – Part C, vol. 38, no. 5, pp. 609–635, 2008.

[10] S. N. Srihari, S. H. Cha, H. Arora, and S. Lee, "Individuality of handwriting," *Journal of Forensic Sciences*, vol. 47, no. 4, pp. 856–872, 2002.

[11] A. K. Jain, F. D. Griess, and S. D. Connell, "On-line signature verification," *Pattern Recognition*, vol. 35, no. 12, pp. 2963–2972, 2002.

[12] L. Nanni and A. Lumini, "Combining multiple one-class classifiers for offline signature verification," *Pattern Recognition Letters*, vol. 29, no. 12, pp. 1646–1656, 2008.

[13] S. Cai, L. Zhang, W. Zuo, and X. Feng, "A probabilistic collaborative representation based approach for pattern classification," *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2950–2959, 2016.

[14] A. Hadid, J. Heikkilä, T. Ahonen, and M. Pietikäinen, "Face and eye detection for person authentication in mobile phones," in *Proc. SPIE Biometric Technology for Human Identification*, 2007.

[15] L. Xia, J. Pan, and W. Zheng, "Offline signature verification using sparse representation classification," *Pattern Recognition*, vol. 63, pp. 444–453, 2017.

[16] V. K. Govindaraju and B. V. K. Vijaya Kumar, "Analysis of handwritten signatures," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, no. 6, pp. 648–658, 1993.

[17] F. Alonso-Ferrero, F. J. J. Galán, C. J. Ruiz, J. Fierrez, and R. Plamondon, "Off-line signature verification based on grey level information: A case study," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 22, no. 7, pp. 1349–1370, 2008.

[18] S. Chakraborty, S. K. Singh, and P. Chakraborty, "Local Gradient Hexa Pattern: A Descriptor for Face Recognition and Retrieval," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 28, no. 1, pp. 171–180, Jan. 2018.